The Classification Patterns of Bank Financial Ratios

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Abstract

Financial ratios are key units of analysis in most quantitative financial research including bankruptcy prediction, performance and efficiency analysis, mergers and acquisitions, and credit ratings, amongst others. Since hundreds of ratios can be computed using available financial data and given the substantial overlap in information provided by many of these ratios, choosing amongst ratios has been a significant issue facing practitioners and researchers. An important contribution of the present thesis is to show that ratios can be arranged into groups where each group describes a separate financial aspect or dimension of a given firm or industry. Then by choosing representative ratios from each group, a small, yet comprehensive, set of ratios can be identified and used for further analysis. Whilst a substantial part of the financial ratio literature has focused on classifying financial ratios empirically and on assessing the stability of the ratio groups over different periods and industries, relatively little attention has been paid to the classifying of financial ratios of the banking sector.

This study aims to explore the classification patterns of 56 financial ratios for banks of different type, size and age. Using data from the Uniform Bank Performance Report (UBPR), large samples of commercial, savings, and De Novo (newly-chartered) commercial banks were obtained for the period between 2001 and 2005, inclusive. Principal Component Analysis (PCA) was performed on a yearly basis to classify the banks' ratios after applying the inverse sinh transformation to enhance the distributional properties of the data. The number of patterns were decided using Parallel Analysis. The study also uses various methods including visual comparison, correlation, congruency, and transformation analysis to assess the time series stability and cross-sectional similarity of the identified ratio patterns.

The study identifies 13 or 14 ratio patterns for commercial banks and 10 or 11 ratio patterns for savings banks over the period on which the study is based. These patterns are generally stable over time; yet, some dissimilarity was found between the ratio patterns for the two types of banks – that is, the commercial and savings banks. A certain degree of dissimilarity was also found between the financial patterns for commercial banks belonging to different asset-size classes. Furthermore, four ratio patterns were consistently identified for the De Novo commercial banks in the first year of their operations. However, no evidence of convergence was found between the ratio patterns of the De Novo commercial banks and the ratio patterns of the incumbent (that is, long established) commercial banks.

The findings of this study bring useful insights particularly to researchers who employ bank financial ratios in empirical analysis. Methodologically, this research pioneers the application of the inverse sinh transformation and parallel analysis in the area of the ratio classification literature. Also, it contributes to the use of transformation analysis as a factor comparison technique by deriving a significance test for the outputs of this analysis. Moreover, this is the only large scale study to be conducted on the classification patterns of bank financial ratios.

Key Words: Bank Financial Ratios, Classification Patterns, Commercial Banks, Congruency Coefficient, De Novo Banks, Factor Analysis, Parallel Analysis, Principal Component Analysis, Savings Banks, Transformation Analysis.

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Table of Contents

List of Appendices

List of Tables

List of Figures

List of Abbreviations

Variables' Numbers and Ratios

Variable Number	Ratio	Variable Number	Ratio
X1	INT INC \ AVR AST	X29	G R TIER ONE CAP
X2	INT EXP \ AVR AST	X30	G R NET LN&LS
X3	NET INT INC \ AVR AST	X31	G R S T INV
X4	NONINT INC \ AVR AST	X32	G R S T NON CORE FUNDING
X5	NONINT EXP \ AVR AST	X33	EFFICIENCY RATIO
X6	PROVISION LN&LS LOSSES \ AVR AST	X34	AVR PERSONNEL EXP PER EMPL($000)
X7	PRETAX OPER INC \ AVR AST	X35	AST PER EMPLOYEE ($MILLION)
X8	PRETAX NET OPER INC \ AVR AST	X36	YIELD ON TOT LN&LS (TE)
X9	NET OPER INC \ AVR AST	X37	YIELD ON TOT INV SEC (TE)
X10	NET INC \ AVR AST	X38	COST OF ALL INT-BEARING FUNDS
X11	AVR EARN AST \ AVR AST	X39	S T INV \ TOT AST
X12	AVR INT-BEARING FUNDS \ AVR AST	X40	MARKETABLE EQ SEC \ TOT AST
X13	INT INC \ AVR EARN AST	X41	CORE DEP \ TOT AST
X14	INT EXP \ AVR EARN AST	X42	S T NCORE FUNDING \ TOT AST
X15	NET INT INC \ AVR EARN AST	X43	NET S T NCORE FUND DEPENDENCE
X16	NET LOSS \ AVR TOT LN&LS	X44	BROK DEP \ DEP
X17	EARN COV OF NET LOSS	X45	S T INV \ S T NCORE FUND
X18	LN&LS ALLOW \ NET LOSSES	X46	S T AST \ S T LIABS
X19	LN&LS ALLOW \ LN&LS NOT HFS	X47	NET S T LIAB \ TOT AST
X20	LN&LS ALLOW \ TOT LN&LS	X48	NET LN&LS \ DEP
X21	NON-CUR LN&LS \ GRS LN&LS	X49	NET LN&LS \ CORE DEP
X22	NET NCORE FUND DEPENDENCE	X50	TOT HTM SEC \ TOT SEC
X23	NET LN&LS \ TOT AST	X51	TOT AFS SEC \ TOT SEC
X24	TIER ONE LEVERAGE CAP	X52	PLEDGED SEC \ TOT SEC
X25	CASH DIV \ NET INC	X53	NET INC \ AVR TOT EQ
X26	RETAIN EARNS \ AVR TOT EQ	X54	G R TOT EQCAP
X27	RESTR+NONAC+RE ACQ \ EQCAP+ALLL	X55	TIER ONE RBC \ RISK-WGT AST
X28	G R AST	X56	TOT RBC \ RISK-WGT AST

Abbreviations: General

BTS	Barlett's Test of Sphercity
C	Component
CFA	Confirmatory Factor Analysis
EFA	Exploratory Factor Analysis
FA	Factor Analysis
FDIC	Federal Deposit Insurance Corporation
FFIEC	Federal Financial Institutions Examinations Council
G	Group
KMO	Kaiser-Meyer-Olkin
logit	Logistic Regression
MDA	Multiple Discriminat Analysis
MSA	Measure of Sampling Adequacy
PA	Parallel Analysis
PCA	Principal Component Analysis
UBPR	Uniform Bank Performance Report

Abbreviations of Components

Abbreviation	Component
AQ	Asset Quality
AQ-I	Asset Quality-I
AQ-II	Asset Quality-II
AQ-III	Asset Quality-III
CG	Capital Growth
Eff	Efficiency
Eff-I	Efficiency-I
Eff-II	Efficiency-II
Fnd	Funding
Fnd-II	Funding-II
Grth	Growth
IS	Investment Securities
Ln&Ls	Loans and Leases
M(Y)-I	Margin (Yield)
M(C)-II	Margin (Cost)
Prof	Profitability
RBC	Risk-Based Capital
Sh-t inv	Short-term Investment
Sh-t liq	Short-term Liquidity

Chapter 1 Introduction

1.1 Research background

The foundations of financial ratio analysis can be traced back to the last half of the nineteenth century (Horrigan, 1968). In those early years, the development of ratio analysis was dominated by the credit analysis approach rather than by managerial analysis. The first two decades of the twentieth century witnessed three main developments in ratio analysis (Horrigan, 1968, p. 285). First, a large variety of ratios was conceived; second, absolute ratio criteria began to appear (for example, the current ratio criterion of 2-to-1); third, the need for inter-firm analysis and, accordingly, the need for relative ratio criteria was recognised by some analysts. Up to now, financial ratios have been extensively used for various purposes.

There have been two main uses of financial ratios: the traditional normative use for comparison purposes and the alternative use for predictive purposes (Whittington, 1980). Traditionally, accountants have used ratios for performance evaluation by comparing the financial ratios of a firm to some standard benchmark. The benchmark may have a theoretical basis, or may be based on the firm's past performance or on a comparison with other firms (Whittington, 1980, p. 220). Alternatively, practitioners and researchers have used financial ratios in estimating empirical relationships; in general, for predictive purposes. Accountants and analysts, for instance, have utilised ratios to forecast future financial variables whereas researchers have used ratios as inputs into advanced statistical models for prediction purposes. Some noteworthy applications of ratio analysis include corporate failure, credit rating, assessment of risk and testing of economic hypotheses, amongst others (Barnes, 1987, p. 449).

Financial ratios have been subjected to close examination in order to understand their properties and enhance their usefulness. This has produced a rapidly growing body of literature that focused on different areas in relation to financial ratios. Amongst these areas the following themes have attracted the attention of researchers throughout the years: the proportionality assumption [Lev and Sundar (1979), Fieldsend et al. (1987), McLeay and Fieldsend (1987), Sundarsanam and Taffler (1995), Trigueiros (1997), and McLeay and Trigueiros (200)]; financial ratios vs. regression analysis [Wittington (1980), McDonald and Morris (1984, 1985), Berry and Nix (1991)]; cross-sectional and distributional properties [Horrigan (1965), Deakin (1976), Ricketts and Stover (1978), Bougen and Drury (1980), Barnes (1982), Horrigan (1983), Bedingfield et al. (1985), Ezzamel et al. (1987b), McLeay (1986), Kolari et al. (1989), Lee (1985), Martikainen (1991), McLeay and Omar (2000), Frecka and Hopwood (1983), So (1987), Watson (1990), Nikkinen and Sahlstrom (2004)]; time-series properties [Tippett (1990), Martikainen (1992), Rhys and Tippett (1993), Fuller-Love et al. (1995), Tippett and Whittington (1995), Wu et al. (1996), Whittington and Tippett (1999), Ashton et al. (2004) and Peel et al. (2004)]; and the adjustment process [Lev (1969), Frecka and Lee (1983), Peles and Schneller (1989), Davis and Peles (1993), Chen and Ainina (1994), Aksu et al. (1996), Gallizo and Salvador (2003), and Ioannidis et al. (2003)]. Alongside this literature, the widely cited papers of Beaver (1966), Altman (1968), Edmister (1972) and Ohlson (1980) are amongst the studies that initiated the usefulness of financial ratios in prediction research.

Whether financial ratios are used by practitioners or researchers, the question has always been: which ratios to use, given the enormous number of ratios it is feasible to calculate. Attempts to answer this question have focused on arranging financial ratios into different groups based on certain criteria. By selecting representative ratios from each group, a parsimonious yet comprehensive set can be achieved. Using such sets of carefully selected financial ratios ensure practicality and sufficiency. Practicality is ensured since analysing a small number of ratios, as opposed to the hundreds that can be calculated, requires much less effort. Sufficiency is ensured as all the financial aspects included in the large set of ratios are represented in the smaller set and no facet has been omitted. Furthermore, a small set of carefully selected ratios offers some preferred statistical properties as the ratios it includes can be chosen to have low inter-correlations. This reduces the multicollinearity amongst these ratios which leads to better estimates when these ratios are used as inputs into statistical models. Given this, the underlying question to be asked in this regard is how to classify financial ratios into groups. For this, a specific area of ratio literature evolved and has grown since the 1970s.

Literature that has focused on categorising ratios into groups can be arranged under four sections, based on the main approach it used (Salmi and Martikainen, 1994): pragmatic empiricism, the deductive approach, the inductive approach, and the confirmatory approach. The ‘pragmatic empiricism’ approach is followed to group ratios in most accounting and finance textbooks [see Lev (1974) and Foster (1986), amongst others]. This approach relies often on the personal views and experiences of the authors. The ‘deductive approach’, however, uses logic and judgment to classify ratios under pre-determined headings and sub-headings without considering the statistical relationships amongst these ratios (see, for example: Courtis, 1978). However, empirical relationships amongst financial ratios are the focus of the inductive approach. Studies that followed this approach have often utilised the multivariate data reduction technique of Principal Component Analysis (PCA) and/or one of the Factor Analysis (FA) techniques to uncover the dimensions that exist in the larger set of ratios. These dimensions are also called components, factors, classification patterns, groups, aspects and categories of ratios. These studies were pioneered by Pinches et al. (1973, 1975) who inspired all the subsequent research into the classification patterns of financial ratios. Last but not least, the confirmatory approach is a fairly recent addition to the ratio classification literature. This approach has often utilised the technique of Confirmatory Factor Analysis (CFA) to test empirically whether a set of ratios corresponds to pre-determined (either theoretically or empirically developed) groups of ratios [see Kanto and Martikainen (1992), and Chen and Olinsky (2006)].

Studies that follow the inductive approach form the core of the literature on classification. The main aim in these studies has been to identify a small set of ratios that retains most of the information contained in the larger set. Furthermore, these studies have investigated other areas in relation to the classification patterns of ratios. Amongst the most frequently investigated issues has been the stability of the identified patterns of ratios over time: short (Pinches et al., 1975) and long periods

(Pinches et al., 1973); across different industries (Ketz et al., 1990); and across countries (Yli-Olli and Virtanen, 1989). The financial patterns for manufacturing and retail industries have been investigated most (for example: Johnson, 1979). Furthermore, the majority of the classification studies have been conducted using U.S. and Finnish data [for example: Gombola and Ketz (1983b) and Martikainen (1993), respectively]. The ratio classification literature also incorporates a number of studies that have investigated ratio patterns in conjunction with different research areas, such as ratio distribution (Martikainen, 1995a), the proportionality assumption (Kallunki et al., 1996) and cash flow measures (Gombola and Ketz, 1983a), amongst other issues.

The use of PCA/FA to identify the classification patterns of ratios has primarily dominated the area of ratio classification. Although some differences exist between PCA and FA, the two terms have been used interchangeably in most classification studies. Further to identifying the empirical groups of financial ratios, it has been always crucial to gain further understanding of the extent to which the groups are stable and/or similar over time, or across different samples. Addressing the issue of stability of the patterns of ratios is believed to enhance the generalisability of the results in the classification literature. Thus, this issue has been addressed in almost every classification study where one or more factor comparison techniques have been utilised. Amongst the most frequently employed factor comparison techniques are visual comparisons, correlation analysis, congruency coefficients and, more recently, transformation analysis.

The classification literature has influenced research in different areas of finance, but mainly those which have used financial ratios as input variables in statistical models for prediction purposes. In such research, using a classification technique has become an essential step prior to performing further empirical analysis such as Multiple Discriminat Analysis (MDA) and logistic regression (logit), amongst others. The techniques of PCA and FA have become popular because of the data reduction possibilities they offer. Researchers have heavily used these techniques as a means of finding a small set of ratios that summarises the information contained in the more extensive set; more importantly, these ratios have low inter-correlations which meet the requirements of the statistical models often used in finance. Amongst the areas of finance that have utilised PCA/FA as data reduction techniques, are bankruptcy prediction [Libby (1975) and Richardson and Davidson (1984)]; bond rating [Pinches and Mingo (1973)]; and takeover, mergers and acquisitions [Stevens (1973) and Barnes (1990)].

1.2 Literature gaps and research questions

The classification patterns of financial ratios for the banking industry have not received enough attention in the ratio classification literature which has mainly focused on non-financial institutions. However, a number of banking studies provide little evidence in this regard [Whalen and Thomson (1988), Ali et al. (1995), Poon et al. (1999), Cheng and Ariff (2007), amongst others]. Banking studies, similar to other research areas in finance, utilised PCA/FA as a preliminary step prior to performing further empirical work. However, given that identifying the patterns of ratios was not the primary focus in such studies, the classification step was often addressed only at a shallow level. In addition, given the different research interests in these studies, a wide range of banking data was used. These data often compiled variables in ratio and non-ratio forms; thus, the classification patterns identified in these studies were not unique to bank ratios. Furthermore, a number of these studies used samples of banks in certain phases such as failed and non-failed, and acquiring and acquired banks. Also, these studies used data for different periods compiled into the same sample. All these make the identified financial patterns more specific to the samples used in these studies and less generalisable to financial ratios for banks in common operating conditions.

In the ratio classification literature, a number of studies focused on the ratio patterns for manufacturing firms in general (Ezzamel et al., 1987a) whereas other studies examined the stability of these patterns across different manufacturing industries (Ketz et al., 1990). Accordingly, the existing literature enables one to assess the extent to which ratio patterns are similar across the different types of manufacturing firms which in turn deepens the understanding of the properties of ratio patterns for manufacturing firms as a whole. This has not been the case concerning the patterns of bank financial ratios. Although different types of banks operate within the banking industry (for example: commercial, savings, and investment banks), the little evidence provided in this regard seems to fall short of addressing the issue of the similarity of ratio patterns across the various types of banks. As posed earlier, the classification literature lacks studies that are purely based on the banking industry; in fact, the available banking evidence is provided by studies that were not primarily focused on investigating the patterns of bank ratios. So, the available banking evidence can be considered as insufficient. Addressing the issue of similarity of the ratio patterns across the different types of banks would certainly aid in gaining further understanding of the patterns of ratios for the banking industry as a whole.

The classification patterns of ratios have been investigated for firms in different phases such as failed and non-failed firms (Martikainen and Ankelo, 1991), and firms with different lengths of operating cycles (Jensen and Ketz, 1987), amongst others. However, the effect of firm size on the classification patterns of ratios has not been addressed in the classification literature. Although the issue of size seemed to be indirectly addressed in a number of studies that focused only on small- and medium-sized firms (Martikainen et al., 1995b), to date no research has been conducted to investigate whether firm size influences the empirical classification of ratios. Furthermore, the classification literature does not seem to explore whether firms' age has an impact on the patterns of ratios. In other words, the classification literature lacks evidence on whether the financial patterns of ratios for newly started firms are similar to those of their incumbent counterparts.

Moreover, in regard to the methodologies followed in the classification literature, PCA/FA have been the popular classification techniques. However, these techniques have been often performed in an arbitrary manner. Researchers into the classification patterns of ratios generally tend to duplicate the steps followed in the seminal paper in the field, Pinches et al. (1973), without referring to the relevant PCA/FA textbooks or acknowledging the new developments in the field. This has also been the case when PCA/FA were used as data reduction techniques generally in prediction studies in finance. In regard to techniques used in the literature to compare the patterns of ratios across different samples, transformation analysis seemed to be the recent, yet the most complicated method. However, the use of this technique appeared to be associated only with a group of Finnish researchers who seemed to have access to the statistical programmes required to perform this analysis. Thus, researchers in other countries have not used transformation analysis and continued to rely heavily on the conservative methods of visual comparison and correlation and congruency coefficients to assess the similarity/stability of ratio patterns.

In accordance with the identified gaps in the literature on ratio classification, the current study focuses on answering the following four primary questions; from each of these questions a number of secondary questions have been derived:

1. What are the classification patterns of financial ratios for commercial banks?
    - To what extent are these patterns stable over a short period?

2. To what extent are the classification patterns of financial ratios for commercial banks belonging to different asset-size classes similar?
    - Do these patterns exhibit the same level of stability over a short period?

3. What are the classification patterns of financial ratios for savings banks?
    - To what extent are these patterns stable over a short period?
    - To what extent are these patterns similar to the patterns of commercial banks?

4. What are the classification patterns of financial ratios for the De Novo commercial banks in the first year of their operation?
    - Are these patterns similar to those for the incumbent commercial banks?
    - If the answer to the previous question is no, in which year after starting their operations are the ratio classification patterns for the De Novo commercial banks analogous to their counterparts, the incumbent commercial banks?

1.3 Content and scope of the study

In the light of the past research briefly reviewed in Section 1.2, and the research questions constructed from the literature, this study focuses, in general terms, on the classification patterns of financial ratios for U.S. banks, together with the stability of these patterns over the period between 2001 and 2005. The general interest of the study is to produce a contribution to the literature on ratio classification by expanding the understanding of researchers and practitioners who use bank financial ratios in regard to the dimensions of performance for: commercial and savings banks; commercial banks of different classes of asset size; and the newly chartered commercial banks.

This research is novel in its attempt to classify bank financial ratios by applying new extensions to the statistical applications commonly used to identify ratio patterns and to assess their stability over time. This study uses Principal Component Analysis (PCA) as the sole technique to uncover the empirical patterns of ratios. Also, for the first time in the ratio classification literature, the study uses Parallel Analysis (PA) to decide on the number of ratio patterns. However, for comparison purposes, the study reports on the number of patterns suggested by the two most conservative and widely used methods: 'eigenvalue greater than unity' and Cattell's scree plot. This can be considered as a merit of this study, since none of the related previous studies have undertaken a comparison of the results of the different methods. Also, this study applies the arcsinh transformation to enhance the distributional properties of the data. There is no consensus in the ratio classification literature on whether or not to transform data prior to performing PCA/FA (Ezzamel et al., 1987a). In the studies that favour using enhanced distributed data, a logarithmic transformation is the preferred method [Pinches et al. (1973, 1975), Johnson (1978, 1979), amongst others]. By using the arcsinh transformation method, not used in previous literature, this study provides a novel contribution to the literature on ratio classification. Furthermore, this study uses a variety of methods to compare the patterns of ratios over time; between commercial and savings banks; and between banks of different size groups. These methods are: visual comparisons, correlation and congruency coefficients, and transformation analysis. As mentioned earlier in Section 1.2, the use of transformation analysis to compare the patterns of ratios has been monopolised by Finnish researchers; this study could be considered as the first attempt to spread the use of this technique outside of Scandinavia. Not only this, but the study extends this factor comparison technique by proposing a significance test for the outputs of the transformation analysis.

The main source of the data on which this study is based is the Uniform Bank Performance Report (UBPR); this is provided by the U.S. Federal Financial Institutions Examinations Council (FFIEC). The UBPR contains data in the form of ratios, percentages and compositions that enable bankers and examiners to evaluate the performance of banks. Banks covered by the reports include U.S. insured commercial and savings banks. This study uses 56 ratios, carefully chosen from the UBPR; they appeal to examiners and researchers. These ratios cover the main aspects of performance from the UBPR: earnings and profitability, margin analysis, liquidity, capitalisation and growth rates. For every year between 2001 and 2005, the study uses large samples of over 5,000 commercial banks, over 200 savings banks, and around 100 De Novo commercial banks. It is worth mentioning that the UBPR data used in this study are those for the fourth quarter of the calendar year. However, ratios of the fourth quarter are calculated in a way that is believed to reflect the activity of the bank for the whole year.

1.4 Significance of the study

This study has emerged from the lack of research into the classification of bank financial ratios. It is the first to investigate, on a large scale, the classification patterns of bank financial ratios and makes the following contributions for practitioners and researchers.

The study provides practitioners (i.e. bank examiners, investors, analysts and others who are interested in evaluating the performance of banks) with a parsimonious set of financial ratios sufficient to capture all the dimensions of performance of the banks, both commercial and savings. The study also points out the ratios and/or the dimensions of performance that are most stable and relevant when banks of a specific size range or age are analysed. Also, given that this study is based on UBPR data, the results are of particular significance to users of UBPR and to regulatory bodies involved in the uniform report.

The study is also of use to researchers who use bank ratios as inputs into advanced statistical models, used to predict specific events such as bankruptcy, mergers and acquisitions, or to build early warning systems to assess the financial soundness of banks. These statistical models place great emphasis on the input variables, which should have low inter-correlations amongst each other, in order to achieve better estimates. To aid researchers making their selection of ratios, the study uses an appropriate methodology that results in identifying patterns of ratios that are independent of each other. Therefore, researchers can choose one ratio to represent each of the identified patterns and use these ratios as inputs in their empirical work.

A further contribution is a methodological one. This study is the first to report the results of using different methods to decide on the number of dimensions or patterns existing in a set of ratios. Although the study relies solely on Parallel Analysis (PA) in this regard, researchers would be able to assess the impact of different methods on the number; also, they would be able to evaluate the results of the previous studies from this point of view. Similarly, the study uses a variety of methods to assess the time-series and cross-sectional stability of the empirical patterns of bank ratios. The results, in terms of the different levels of stability reported in this study, could help researchers to gain further insight into whether the various methods lead to the same conclusion.

1.5 Organisation of the thesis

The rest of the thesis offers detailed descriptions of what has been introduced in this chapter. Chapter 2 provides a survey of the literature with regard to the classification patterns of financial ratios. It emphasises those studies that have utilised PCA/FA as a means of identifying the empirical groups of financial ratios. Chapter 3 reports on the methodology to be followed in this study in order to answer the research questions posed earlier. This methodology centres on the steps required to perform PCA to classify financial ratios and to test the stability/similarity of the identified ratio groups over time, and across different samples and sub-samples. Chapter 4 introduces the data on which the study is based.

Chapters 5, 6, 7 and 8 form the empirical part of this study. These chapters report the results of performing PCA over the different samples used in this study. Chapter 5 outlines the classification patterns of ratios for U.S. commercial banks; the stability of these patterns over the period between 2001 and 2005 is also assessed. Chapter 6 reports the results concerning the ratio patterns and the short-term stability of these patterns for U.S. commercial banks which are classified into different asset-sized groups. Chapter 7 discusses the classification patterns and their short-term stability for ratios of U.S. savings banks. It also examines similarities between these patterns and those identified for the commercial banks reported in Chapter 5. Last but not least, Chapter 8 reports the results of the exploratory examinations of the ratio patterns for newly charted U.S. commercial banks. Each of Chapters 5-8 is written to stand on its own right to answer the four research questions posed earlier. Chapter 9 concludes the thesis. It summarises the key results, discusses the implications and limitations of the study, and provides suggestions for future research.

Chapter 2 Literature Review

2.1 Introduction

Hundreds of financial ratios can be computed easily using available accounting data and modern computing power. Finding a parsimonious set of financial ratios that represents the different activities of the firm has been a central issue in the financial literature and in practice. This chapter examines the literature relating to classification of financial ratios. The primary emphasis is on studies that utilise the techniques of factor analysis (FA) and principal component analysis (PCA) in identifying ratio patterns.

The rest of the chapter is structured as follows. After the introduction, Section 2.2 introduces the major approaches to classifying financial ratios. Section 2.3 introduces theoretical attempts to classify financial ratios by focusing on the *a priori* classification of ratios. Section 2.4 examines the literature that uses FA or PCA to categorise financial ratios. Related studies are reported under seven subsections. Subsection 2.4.1 is devoted to studies that aim to enhance ratios' usefulness and efficiency through investigating the empirical interrelationships among ratios. Subsection 2.4.2 reports studies that assess the stability of ratio classification over periods of different length. Subsection 2.4.3 evaluates studies that check the stability of the empirical ratio groups across different industries and countries. Subsections 2.4.4 and 2.4.5 review the literature that focuses on ratio classification at the level of single industries and countries, respectively. Subsection 2.4.6 reviews the literature that links empirical classification of ratios to other research areas like cash flow measures, markets, operating cycles, failure prediction, ratio distributions, and the proportionality assumption. Subsection 2.4.7 highlights the use of FA or PCA as a data reduction method in the various predictive studies. Section 2.5 reviews a number of studies that employ methods other than FA or PCA to identify or examine the classification of financial ratios. Subsection 2.6 catalogues the evidence available regarding the empirical classification of bank financial ratios. The chapter concludes with Section 2.7 which summarises the chapter and identifies research gaps in the literature.

2.2 Classification patterns of financial ratios: main approaches

The problem of ratio selection evolves from the fact that a massive number of ratios can be calculated; yet, the question is always which ratios to use. Attempts to answer this question have produced a rapidly growing volume of literature. Rees (1995) and Salmi and Martikainen (1994) outline the general approaches to ratio classification that have been followed in the literature. These are summarised in this section.

Rees (1995)

Rees (1995) explained that two main approaches have been adopted to reduce the dimensionality of a set of financial ratios and thus, to enhance the ratio selection process. The first is the *a priori* approach which has been employed in most accounting textbooks. This approach introduces a simple grouping system that can be used to provide some structure to a set of financial ratios. As an example of this approach, Rees (1995, p. 110) uses the three main categories of ratios outlined in Courtis (1978)[1]; Profitability, Managerial Performance, and Solvency.

The second approach to the selection of appropriate financial ratios is based on empirical analysis (Rees, 1995, pp. 110-112). This approach is achieved through two methodologies. The first methodology involves examining the statistical relationships between the different ratios and then, based on this, developing empirically-based patterns among the ratios. Rees (1995) demonstrated that the interrelationships between different financial ratios have often been examined using the multivariate technique of factor analysis (FA). The second methodology relating to the selection of ratios based on their statistical relationships involves investigating the financial ratios used in predictive models and identifying the ratios that were found as significant variables in the predictive studies.

[1] A full review of Courtis (1978) is provided in Section 2.3.

Although Rees (1995) seems to acknowledge the issue of ratio selection, his description of the two approaches is somewhat vague. The observed ambiguity in the text could have been eliminated if Rees (1995) had given further explanations of the two approaches and supported his descriptions by offering more examples[2].

Salmi and Martikainen (1994)

Nevertheless, the most comprehensive and perhaps the only review of the literature of ratio classification is that carried out by Salmi and Martikainen (1994). In their review, which covered the theoretical and empirical basis of financial ratio analysis, Salmi and Martikainen (1994) classified the studies of ratio classification under four sections[3]. These sections are: pragmatic empiricism, the deductive approach, the inductive approach and finally, the confirmatory approach. Salmi and Martikainen (1994) briefly review the studies associated with each of these approaches.

The pragmatic empiricism[4] approach represents the way in which financial ratios are classified in the major accounting textbooks. Such ratio groupings tend to be subjective as these classifications are based, to a great extent, on the judgement and experience of the authors of such books.

The origin of the deductive approach of classifying ratios can be traced back to the du Pont triangle system[5] that links Profits, Sales and Total Assets (Salmi and Martikainen, 1994). According to Salmi and Martikainen (1994), the du Pont system was utilised in a number of studies (e.g. Courtis, 1978) to build certain classification schemes. In these studies, after expanding the du Pont system, a number of financial ratios were gathered from various sources (previous studies, textbooks and business practices) and then allocated under the different sub-headings of the expanded system. Thus, it can be said that the deductive approach uses logic and judgment to assign a

[2] An earlier edition of this book (Rees, 1990) is slightly more detailed on the issue of ratio selection as it gives a short review of a few classification studies. Other than this, the two editions (Rees 1995 and 1990) seem alike in covering the ratios selection topic.

[3] The first three sections were briefly summarised in an earlier study by Salmi et al. (1990).

[4] This term was first used by Horrigan (1968, p. 288) to describe the reliance on the author's practical experience in financial statement analysis using financial ratios.

[5] See Horrigan (1968, p. 286) for a short review of the du Pont ratio analysis and also for some references concerning this system.

number of ratios under pre-determined themes without giving any consideration to the statistical relationships among the different ratios.

The inductive approach, however, classifies ratios empirically rather than theoretically, based on their statistical relationships. Salmi and Martikainen (1994) underlined the use of FA or PCA to identify the different patterns in a set of financial ratios, ideally without making any prior hypotheses regarding the number of classifications to be derived or the ratios that comprise each group. This approach to ratio classification forms the central part of a growing body of literature on which the current study is focused.

Last but not least is the confirmatory approach. This approach aims at finding empirically whether a group of ratios confirms the *a priori* classifications. These *a priori* classifications might have some theoretical foundations (those schemes in textbooks and in the deductive studies) or some empirical basis (i.e. the schemes developed by inductive studies). The evidence provided by the confirmatory approach is empirical where a range of statistical techniques such as FA and Confirmatory Factor Analysis (CFA), amongst others, can be used.

Salmi and Martikainen (1994) provided a comprehensive review, particularly regarding the literature of classification of financial ratios[6]. The merit of Salmi and Martikainen (1994) lies in the fact that they successfully reported the key studies under the four distinctive approaches to the classification of ratios. The current chapter, however, follows a different approach to review the ratio classification literature. This approach groups the studies based on the techniques they used to identify the patterns regardless of whether the studies are inductive, deductive or confirmatory. The chapter first introduces the *a priori* or theoretical classifications of ratios (Section 2.3), then it provides a comprehensive review of the studies that perform FA or PCA to identify the empirical groups of ratios (Section 2.4); and finally, the chapter briefly highlights the research that used empirical techniques other than FA or PCA in relation to ratio classification (Section 2.5).

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[6] The list of references in Salmi and Martikainen (1994) has been expanded in a follow-up paper by Salmi et al. (2005).

2.3 *A priori* classification of financial ratios

Financial ratios are considered as the main instrument in financial statement analysis. Relevant textbooks (accounting, finance and financial analysis text-books) for either professional or academic purposes are hardly ever without a major chapter devoted to ratio analysis. In these books, financial ratios are often classified under a number of categories. Deciding on how many categories there are, and which ratio should be listed under which category, is often very subjective and based on the experience of the author. The *a priori* categories are also dependent on the orientation of the users of the information which could be financial analysts, bankers, non-specialists, regulators, students, etc. Given this, ratio categories and ratios under each group become as diverse as the personal views of the authors and the wide range of interests of the potential users.

Studies that have promoted the empirical classification of financial ratios have described the *a priori* approach as 'traditional normative' (Rees, 1990, p. 142), 'analytical' (Rees, 1995, p. 110), 'pragmatic empiricism' (Salmi and Martikainen, 1994), 'authoritative'[7] (Salmi et al., 1990), and '*ad hoc*' (Gombola and Ketz, 1983b, p. 45). These studies have often referred to a number of books and other studies as examples of the *a priori* approach to ratio groupings. Amongst these, Horrigan (1967, pp. 34-54), Lev (1974, pp. 11-32), Tamari (1978, pp. 21-46), Weston and Brigham (1979, pp. 20-28)[8] and Foster (1986, pp. 60-70)[9] are most cited. The following paragraphs present a number of *a priori* classifications of financial ratios.

To begin with, Horrigan (1967) derived his *a priori* categories of ratios by obtaining lists of financial ratios that were used by different types of analysts. Then, he grouped ratios in each list based on the type of information anticipated from every ratio. This led to a 'rough outline' of five categories: Short-Term Liquidity, Long-Term Solvency, Operating Margin, Capital Turnover and Return on Investment. In the end,

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[7] Salmi et al. (1990) borrowed this term from Horrigan (1968, p. 288 and p. 294).

[8] An earlier edition of this book was also cited (Weston and Brigham, 1972). Note that there exist several other editions of this book.

[9] An older edition of this book has also been cited: Foster (1978).

Horrigan (1967, p. 53) listed seventeen ratios generally recommended by external users grouped under these five categories[10].

However, Lev (1974, p.12) introduced four categories of financial ratio. These groups were believed to reflect the various economic dimensions of the firm's operations. Lev's (1974) *a priori* classifications included: Profitability, Short-Term Solvency (Liquidity), Long-Term Solvency and, Efficiency (Turnover). Similarly, Weston and Brigham (1979, p. 20) considered four groups of ratios: Liquidity Gearing, Activity and Profitability. Also, Tamari (1978, p. 24) divided ratios into four general groups: Profitability, Liquidity, Gearing and, Performance. Foster (1986, p. 60), however, suggested seven categories of ratios: Cash Position, Liquidity, Working Capital/Cash Flow, Capital Structure, Debt Service Coverage, Profitability and Liquidity. Nevertheless, Foster (1986) emphasised that these categories should be taken as illustrative rather than exhaustive. Likewise, recent textbooks continue to offer the authors' views of the way in which financial ratios can be categorised [see for example: White et al. (2003, pp. 119-139), Soffer and Soffer (2003, pp. 100-105), and Van Horne and Wachowicz (2009, pp. 137-151), amongst others].

Given that the current study has a primary interest in the groupings of bank financial ratios, it is important that we take a look at the *a priori* classifications of bank ratios. In this context, two books were found to be of relevance: Golin (2001) and Palat (1989).

Golin (2001) provides a handbook for bank credit analysis which is prepared for analysts, bankers and investors. The handbook offers perhaps the most comprehensive compendium of bank financial ratios (Golin, 2001, pp. 633-644). It lists over 90 ratios which correspond to each dimension of the CAMEL system[11] used by rating agencies to assess the condition and performance of banks. Based on personal judgement, Golin (2001) arranged the collected ratios under the following four categories: (1) Capital indicators, (2) Asset Quality indicators, (3) Earnings,

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[10] A brief description of this scheme is offered in Horrigan (1965, p. 559).

[11] CAMEL is the abbreviation of the following aspects of a bank's performance: Capital, Asset quality, Management quality, Earnings and Liquidity. Lately, CAMELS was introduced where the letter 'S' represents the Sensitivity to market risk.

Profitability and Efficiency indicators, and finally, (4) Liquidity and Funding indicators. Under each of these categories, Golin (2001) provides lists of key and supplementary ratios.

On a much smaller scale, Palat (1989, pp. 50-78) reports a list of financial ratios that can be used to evaluate banks and other financial institutions. It catalogues these ratios into four groups: Profitability, Liquidity, Asset Quality and Capital Adequacy. Palat (1989, p. 50) briefly mentioned that these four categories correspond to the factors that influence the risk of banks which are: the bank's operating results, its quality of assets, stability of liabilities, the composition of assets and liabilities and shareholders' funds. No further information; however, was provided in Palat (1989) regarding the sources of the ratios listed in the book.

Generally, authors of books on financial ratios do not tend to specify the sources of the ratios they provide, or the basis on which they build on their *a priori* categories. This would certainly reflect the level of subjectivity involved in such *a priori* classifications. This critique of the *a priori* approach for grouping financial ratios has generally served as a good introduction to the studies that adopt an empirical approach to group ratios. Other criticisms of the *ad hoc* approach include the difficulty involved in assigning some ratios to one appropriate group when some ratios show characteristics of more than one group. Also, since each group contains many ratios, there is no rule which allows one to choose amongst these ratios an appropriate ratio for the task in hand. Hence, choosing the ratios that adequately fit the purpose would undoubtedly require skill and even imagination [Gombola and Ketz (1983b, pp. 45-46) and Rees (1995, p.110)].

Courtis (1978)

Probably the best way to conclude this discussion is by highlighting Courtis' (1978) categoric framework of financial ratios. Earlier in Section 2.2, Courtis (1978) was cited as a study that used the du Pont system to build up a model for classifying ratios. This study represents one of the very few examples of the deductive approach that uses logic and judgement to categorise ratios[12]. Courtis' (1978) study has been frequently cited in the classification literature and the following paragraphs explain its main contributions.

Courtis (1978) aimed to develop a scheme of financial ratios that would incorporate a wide collection of ratios and cover all the dimensions of a firm's performance. This framework, it was hoped, would facilitate analysts' task of carrying out financial statement analysis by enabling them to select a comprehensive set of ratios sufficient to make them draw the correct conclusions about a firm's financial position.

Courtis (1978) carried out an extensive survey to gather those ratios that would be incorporated into his framework. In this survey, Courtis (1978) examined 12 important predictive studies (these studies incorporated financial ratios in predictive models and found them to be good indicators of distressed firms), 10 key finance and accounting textbooks, and 4 other sources that included almanacs and the publications of financial bodies (Courtis, 1978, pp. 385-386). This resulted in a total of 79 ratios: 28 ratios from the literature, 34 ratios from the books and 17 other ratios from different sources. Courtis (1978) then defined a categoric model by assigning these 79 ratios to suitable categories.

In order to define the salient groups in his model, Courtis (1978, p. 379) asked the following three questions: is the entity making any money? Is the management any good? And is the entity going to stay in business? These questions are believed to be in the minds of all the parties interested in firms' financial statements. So, the main three dimensions of a company's performance would then be: Profitability, Managerial Performance and Liquidity. Courtis (1978) used the du Pont triangle to break down the Profitability dimension into Profit Margin, Capital Turnover and Return on Investment, as mentioned earlier Section 2.2. In turn, Managerial Performance can be captured using ratios that reflect Credit Policy, Inventory, Administration and Asset-Equity Structure. Lastly, the Solvency category was broken down into Short-Term Solvency, Long-Term Solvency and Cash Flow. Courtis

[12] Salmi and Martikainen (1994) mentioned that the deductive approach of ratio classification was followed by the use of some empirical tests (confirmatory factor analysis and other techniques) which created an intermix between the deductive and confirmatory approaches of ratio classifications.

(1978) then allocated the 79 ratios to these subcategories. Whenever ratios appeared to relate to more than one category, Courtis referred to the relevant literature and classified them under the category most often adopted in that literature.

Courtis (1978) stressed that his categoric model was not exhaustive. He further explained that calculating an entire group of ratios might not be essential in the analysis. This is because of the collinearity that might exist amongst the ratios and of which analysts should be aware. He explained that collinearity, in the narrow sense, is caused by the common components of ratios. Given this, a parsimonious set of ratios, carefully selected from Courtis' framework, might be sufficient to carry out an initial analysis of a firm's performance. Nevertheless, if the analyst detects any worrying signal regarding a specific dimension of performance, an in-depth examination should then be carried out using a larger set of ratios that describe this specific troubled dimension.

Courtis (1978) claimed that he incorporated all the aspects of a firm's performance (those that could be measured by ratios) in his categoric scheme. In other words, he could effectively group 79 useful ratios under meaningful categories. However, he stressed that an overall appraisal of a company's financial position required a small, yet carefully selected set of ratios. Courtis believed that the selection of these ratios would become much easier if the analysts referred to his categoric framework while acknowledging the existence of collinearity amongst the ratios. Thus, selecting a comprehensive and parsimonious set of ratios is the key. A comprehensive selection can be made if a good grouping system exists which incorporates all performance dimensions. A parsimonious set of ratios comprises ratios that provide diverse information and disregards those ratios that do not offer new insights; this would ensure that collinearity amongst the selected ratios is at a minimum.

Judging how successful Courtis was in achieving the goals of his study is not an issue in the current research. However, what is important in the context of the current study is to recognise what was Courtis' (1978) main aim as this is the key to understanding a substantial body of literature. In this literature, researchers attempted to carry out what Courtis aimed to do; however, using different methodologies. In these methodologies, the use of logic and judgement is at a minimum, but reliance on previous literature is allowed in order to ensure the usefulness and practicality of the identified groups of ratios. The use of the multivariate techniques of PCAFA to group financial ratios is at the heart of a substantial part of this literature. This literature is examined in the following section.

2.4 Empirical classification of financial ratios: the use of PCA/FA

Some insights into the empirical classification of financial ratios are offered by correlation analysis. Gombola and Ketz (1983b, p. 46) explained that if two ratios are highly correlated then it is likely that one of them is redundant and thus can be disregarded without much loss of information. Likewise, if two ratios are poorly correlated, it implies that they measure two different aspects of performance and can thus be used accordingly. So, given a large number of ratios in a set, if highly correlated ratios are grouped together, the size of the set can be reduced from the actual number of ratios to a smaller number of distinctive groups. Nevertheless, although correlation analysis has been mentioned as a technique that enables financial ratios to be classified, the author of the current study is not aware of any research that has utilised correlation analysis in this way.

As an alternative to using correlation analysis as a grouping procedure, the multivariate technique of FA has often been utilised as a classification method. Prior to introducing studies under this section, however, a number of points need to be clarified. PCA is taken mistakenly to be one of the techniques of FA. One of the reasons for this could be because, in SPSS and other statistical software packages, PCA is given as an FA procedure (Sharma, 1996, p. 58). However, FA and PCA are not exactly the same. FA incorporates a number of techniques; furthermore, the name of some FA techniques can sometimes be confusing and one should be aware that slightly different names might be used for the same FA technique. Nevertheless, FA methods include principal component factoring (very similar to but not PCA), common factor analysis (also known as principal axis factoring and principal factor analysis), alpha analysis and image analysis. Also, one should be aware that in some textbooks, when FA and PCA are compared, the comparison is actually being made between PCA and common factor analysis, the most common technique of FA.

With regard to the classification literature of financial ratios, it is clear that the terms ‘factors’ and ‘components’ have been interchangeably used; also, the exact method of FA is not specified in the majority of studies. In the current review of the literature, the outputs of the different studies will be referred to as components or factors regardless of the exact method used. This should not cause any confusion given that the differences between FA and PCA are well known and given that PCA can be considered as a ‘cousin’ of FA in many ways.

The current study employs PCA as the main methodology and a full description of this method is given in the following chapter (Chapter 3). Nevertheless, it is helpful here to explain the main ideas behind FA and PCA, and the purpose behind choosing a particular rotation method. The aim is to provide some useful terminology prior to introducing the related literature at a later point in this chapter.

PCA is a multivariate technique that is used for data reduction purposes in which a small number of new variables (called components) are formed by linearly combining the original variables. Initially, the number of extracted components equals the number of variables in the dataset. However, only a small number of components is retained if effective data reduction is to be fulfilled. The number of components retained explains the maximum amount of variability in the data. Like PCA, FA is also a multivariate procedure; however, the objective of FA is to uncover the underlying or latent factors that can explain correlation amongst the variables.

Now, a quick note is necessary here with regard to the issue of rotation. Components in the initial solutions are independent from each other (i.e. orthogonal); however, it is advisable to rotate the solution in order to facilitate the process of interpreting the components. For that reason, a decision needs to be made concerning which rotation method to use: an orthogonal or an oblique method. An orthogonal rotation method is chosen if the factors are required to be uncorrelated, whereas the latter method is selected if the factors can be correlated.

After selecting between orthogonal and non-orthogonal rotation methods, another selection needs to be made: to choose between a number of orthogonal or oblique rotation methods. Although some differences exist amongst these rotation methods, they all aim at reaching a 'simple structure'. A factor solution has a simple structure if every factor is defined by a clear set of variables and each of the variables is attached to only one factor (Spicer, 2005, p. 188). Amongst the orthogonal methods, varimax is the most common rotation procedure and direct oblimin is the most famous of the oblique methods. As mentioned before, detailed explanations of PCA and FA in general, including the choice of rotation methods, are given in Chapter 3. Nevertheless, after highlighting selected points with regard to the use and application of PCA and FA, a review of the relevant literature is resumed in the following paragraphs.

The use of PCA and FA in identifying empirically-based patterns or classifications of ratios has attracted a substantial number of researchers since the 1970s. This area of research was pioneered by Pinches et al. (1973). This study and a subsequent one (Pinches et al., 1975) appear to actuate research into the empirical classifications of financial ratios using the multivariate technique of factor analysis. The two papers have been extensively cited in all the literature that later emerged and also in most of the empirical studies that employ financial ratios as input variables in prediction models[13].

A chronological review of this literature might be seen as an effective approach that would highlight the time-line of contributions to the seminal work in this area. The current study, however, does not follow a chronological approach; instead it reviews the relevant literature after classifying it into a number of themes. These themes were identified based on the main purposes of the studies. For example, a number of studies clearly stated that their aim is to find the classification patterns of ratios, whereas the aim of other studies is to find the dimensions of performance for the type of firms under investigation. Moreover, another group of studies focused on the implications of using different measures of performance on the patterns of ratios.

[13] A detailed review of Pinches et al. (1973, 1975) is provided in Subsection 2.4.2.

Furthermore, a part of the literature was industry-driven as it attempts to identify the dimensions of performance or the patterns of ratios for a specific industry. Similarly, a number of studies were particularly interested in identifying the ratio patterns for firms in a particular country. Also, there have been some studies focusing on assessing the stability of the identified financial patterns either over time or on a cross-sectional basis. These and other related points outline the themes of the literature that follow.

2.4.1 Ratio usefulness and efficiency

The two studies reviewed under this theme are Laurent (1979) and Chen and Shimerda (1981). These studies recognised the important role of ratios in financial analysis and considered how a good empirical classification scheme would facilitate the analysis process. Whether ratios are used to compare performance across firms or over time, or whether they are employed in predictive models, understanding their interrelationships is the key to a robust analysis. The two studies are similar in as much as they link the empirical classifications of ratios to the previous ratio literature which was used as the source for the ratios analysed.

PCA/FA is used to identify the patterns of a large set of variables and, based on the identified patterns, a smaller set of variables can be chosen for further analysis. Thus, the outputs of PCA/FA will definitely be related to the inputs of the analysis. Therefore, for ratio classification studies, the identified patterns will depend on the kind of ratios employed. For example, one would not expect to identify a profitability factor in a set of ratios that does not include any ratio that measures profitability, and so on. Therefore, in order that the identified factors portray all the dimensions of a firm's performance, a comprehensive list of ratios needs to be employed. The selection of these ratios and their sources should reflect the question being investigated by the study. Given this, and since Laurent (1979) and Chen and Shimerda (1981) were interested in improving the efficiency of ratio analysis by uncovering the interrelationships amongst useful ratios, their selection of ratios explicitly reflected their goals of identifying a small number of ratios through which to characterise a firm's financial viability.

The list of ratios in Laurent (1979) was selected after a thorough examination of a number of seminal predictive studies and key textbooks. This gave a total number of 60 unique ratios. Forty-five ratios were chosen from the initial list. The chosen ratios were cited at least twice in the literature and, they collectively covered nine of the ten dimensions of a firm's performance developed by Courtis (1978)[14]. Laurent (1979) did not include the administration dimension in his study because the required data regarding this aspect were not publically disclosed. Laurent (1979) used published annual financial statements for 63 public limited liability companies in Hong Kong. For each of these companies, 45 ratios were calculated using the financial statements for the last year available to the author at that time (the exact year is not mentioned).

PCA with an unspecified rotation method was carried out to identify the empirical classifications of the ratios. PCA initially suggests a number of components that is equal to the number of variables analysed; however only a small number of components are retained and interpreted. To decide on the number of components to keep, Laurent (1979) kept the components that could be assigned meaningful names. This resulted in 10 independent components that accounted for 89.7% of the total variance contained in the original set of ratios. These components were assigned the following names: (1) Return on Investment; (2) Gearing; (3) Working Capital Management; (4) Fixed-Asset Management; (5) Long-Term Solvency; (6) Short-Term Solvency; (7) Inventory Management; (8) Standing Charge Cover; (9) Income Retention Policy; and (10) Credit Policy.

Laurent (1979, p. 409) then checked whether the 10 components identified in his study explicitly cover all the 9 'theoretical' categories of Courtis[15]. Based on the content of each of the components, Laurent was able to allocate all his 10 components under the 9 groupings specified by Courtis. However, some empirical components

[14] Although these dimensions are mentioned earlier in Section 2.3, a reminder of them is given here. Courtis' main dimensions are: first, Profitability which includes: Return on Investment, Profit Margin and Capital Turnover; second, Managerial Performance that includes: Credit Policy, Inventory, Administration (not covered by Laurents, 1978), and Asset-Equity Structure. The third main dimension is Solvency and it is divided into Short-Term Solvency, Long-Term Solvency and Cash Flow (Courtis, 1978, p. 373).

[15] See footnote 14.

were related to more than one theoretical dimension. For example, the first empirical component (Return on Investment) was found to cover three of Courtis' dimensions: Return on Investment, Profit Margin and Cash Flow. Laurent (1978, p. 410) explained that ratios under these three theoretical dimensions were not showing sufficient differences in their behaviour; this is why the three theoretical dimensions were covered by only one empirical component.

However, another conclusion could be drawn here: that is, Courtis' (1979) categoric framework might not provide a distinctive list of dimensions. Recall here that Courtis' categoric framework was initially developed to help analysts select a parsimonious, yet comprehensive, set of ratios that fully covers all dimensions of a firm's performance. However, the empirical results of Laurent (1979) show that at least three of Courtis' (1978) categoric dimensions could be captured by only one component; thus, these three dimensions might actually be only one aspect of firm performance. Nevertheless, since testing Courtis' framework was not the principal aim of Laurent (1979), this suggested conclusion should be interpreted with caution. Add to this, the fairly small sample size used by Laurent (63 companies) and there must be some doubt about the generalisability of his results. This is because a sound application of PCA/FA requires the use of large samples[16].

Lastly, Laurent (1979) explained the need to find surrogate measures for the ten components identified in his study. These surrogates should retain the qualities of the ten components. This means that they should be highly correlated with the components they represent and, given that the ten components are independent from each other, the surrogates will exhibit low intercorrelations. Moreover, the surrogate ratios must be meaningful in an accounting sense and easy to calculate (Laurent 1979, p. 411). Finally, Laurent (1979) concluded by stating that the use of a small set of financial ratios that covers all aspects of a firm's activities would enhance the efficiency and effectiveness of financial ratio analysis. In addition, because ratios in such a small set are independent of each other, they can also be useful in prediction research where multivariate techniques are employed.

[16] Chapter 4 (at the end of Section 4.4) gives a further description of the acceptable sample size for a sound application of PCA/FA.

As mentioned in Chapter 1 (Section 1.1), financial ratios have been extensively used in predictive studies[17]. When ratios are selected as inputs to predictive models, their predictive power could be preferred over their descriptive power (Pinches et al., 1975, p. 304). In this case, researchers and analysts might rely on ratios that have been found useful in previous prediction studies. But the question is '…should the results from one study, the results from a combination of studies, or the results from all studies be used? If only one study is to be used, which one should it be?' (Chen and Shimerda, 1981, p. 51). These questions provoked Chen and Shimerda (1981) to investigate whether ratios that are reported to have high predictive power can be grouped under the empirical components that were identified in earlier studies[18].

First, Chen and Shimerda (1981) noted the diverse results of PCA in the previous literature. The variation of the results was in terms of the number of identified factors and the labels assigned to these factors. Nevertheless, Chen and Shimerda (1981) carefully examined the content of the different factors and found that though these factors had different labels, their contents were very similar. Further, the study argued that the differences in the number of factors can be attributed to the use of different ratio sets by the different studies. Consequently, Chen and Shimerda (1981) were able to reconcile the results of the previous studies under the seven factors identified by Pinches et al. (1973, 1975)[19] which were 'common' among the investigated studies.

In a further step, Chen and Shimerda (1981) thoroughly checked a number of failure prediction studies that utilised financial ratios and reported some of them to be significant in predicting failure. This search produced a list of 34 significant ratios which were then classified using the 7 common factors of Pinches et al. (1973, 1975). While the majority of these ratios could be classified under one of the seven common

[17] A list of these predictive studies is provided in Chen and Shimerda (1981, p. 52).
[18] The earlier studies cited in Chen and Shimerda (1981) included Pinches et al. (1973, 1975) (reviewed in the following subsection), Pinches and Mingo (1973), Stevens (1973) and Libby (1975) (reported in Subsection 2.4.7).
[19] These factors are: 1- Return on Investment, 2- Capital Turnover, 3- Financial Leverage, 4- Short-Term Liquidity, 5- Cash Position, 6- Inventory Turnover, 7- Receivables Turnover.

factors, ten ratios could not be grouped under any factor as they were not amongst the ratios initially used in Pinches et al. (1973, 1975).

In order to uncover the interrelationships these 10 ratios had with the rest of the ratios, Chen and Shimerda (1981) conducted a PCA. For this, they calculated all 34 ratios for 1,053 firms from the COMPUSTAT tape for the year 1977[20]. As a result, all 34 ratios were assigned to one of the seven common groups of ratios. Given that ratios in one group are highly correlated with the other ratios in the group and have low correlations with ratios in other groups, the decision-maker can thus select a representative set of ratios; preferably one ratio to represent each of the seven unique dimensions. Ratios in this set would be uncorrelated with each other and, most importantly, the decision-maker can be assured that these ratios are significant in predicting bankruptcy.

Nevertheless, Chen and Shimerda (1981) further added that it is popular to select ratios with the highest absolute factor loadings; however, this selection is sensitive to the particular sample employed. Thus, while employing this procedure might be adequate for data reduction purposes, this is not the case if the aim is to build a theory or to construct a model. Accordingly, the question of selecting the best representative set of ratios has to be addressed. Chen and Shimerda (1981) explained that every ratio contains common information (shared with other ratios that load onto one factor) and unique information (not shared with other ratios). Thus, Chen and Shimerda (1981) suggested that chosen ratios should capture most of the common information contained in their factors and, as a set, these ratios should contain the highest amount of unique information when compared to any other set. Chen and Shimerda (1981) finally stated that financial ratio analysis and ratio selection for decision making would be undoubtedly enhanced once the type and amount of unique information contained in a ratio could be measured. However, decades after this statement, we are not aware of any study that focuses on the unique information contained in financial ratios.

[20] Chen and Shimerda (1981) did not mention whether they rotated the factor solution or not, nor did they mention the proportion of variance explained by the final solution.

At the end of this subsection it is worth mentioning that both Laurent (1979), and Chen and Shimerda (1981) have been extensively cited in the literature. Both studies conducted a very basic PCA; however, they added new perspectives to the classification patterns of financial ratios through the general methodology they followed. The new perspective in Laurent (1979) was the incorporation of Courtis' theoretically-developed scheme of financial ratios into an empirical analysis of ratios. For Chen and Shimerda (1981), the originality of their study lies in the fact that they used key literature in ratio classification and in failure prediction to produce results that facilitate the process of bankruptcy prediction.

2.4.2 Time stability

Four studies are reviewed in this subsection. The first is a study conducted by Pinches et al. (1973) who investigated the long-term stability of empirically-based financial patterns. This is followed by a review of Pinches et al. (1975) which assessed the short-term stability of financial patterns. Martikainen et al. (1995b), the focus of the third review, studied the stability of ratio patterns for firms over a period of three years prior to failure and the last study is that of Devine and Seaton (1995) which investigated the stability of quarterly financial ratio patterns. Nevertheless, other studies such as those of Ezzamel et al. (1987a), Gombola and Ketz (1983b) and Yli-Olli and Virtanen (1989) also offer some evidence regarding the time stability of ratio patterns although the time stability of the patterns is a secondary subject in such studies. Thus, full reviews of these studies are provided later in the chapter[21].

Pinches et al. (1973) is considered to be one of the pioneering studies in the field of financial ratio classification. The study sought to develop empirically-based classifications of financial ratios for industrial firms and to measure the time stability/change in these classifications over the long term. The dataset in Pinches et al. (1973) comprised 48 financial ratios calculated for 221 COMPUSTAT industrial firms. The study covered the period between 1951 and 1969 and within this period, analysis was performed using data obtained for four years: 1951, 1957, 1963 and

[21] Ezzamel et al. (1987a) is reviewed in Subsection 2.4.4; the other two studies are examined in Subsection 2.4.3.

1969. Pinches et al. (1973) seemed to screen their data; however, they did not mention what type of data screening they carried out. Before running the analysis, they transformed all the financial ratios using a common log transformation. This was carried out to enhance the likelihood of normality in the distribution of ratios, reduce outliers and improve the homoscedasticity of the distributions.

Pinches et al. (1973) used FA to identify the financial patterns of ratios; they rotated the solutions using both oblique and orthogonal methods to facilitate interpretation of the factors. The two rotation methods produced very similar results; nevertheless, the study only reported the outputs of the (biquartimin) oblique rotation. The final solution for each of the four years covered in the study contained only those factors that had an eigenvalue greater than one; however, the results were checked for discontinuity. The final solutions explained between 87% and 92% of the variance in the original data over the four years. The identified factors were labelled as follows: (1) Return on Investment, (2) Capital Intensiveness, (3) Inventory Intensiveness, (4) Financial Leverage, (5) Receivable Intensiveness, (6) Short-Term Liquidity and, (7) Cash Position.

Pinches et al. (1973) first checked for the long-term stability of their factors by carrying out visual examinations of the magnitude of the loadings of each ratio onto the factors over the four years. They found that the ratios loading onto the Financial Leverage factor were the most consistent over the four years; thus, this factor was the most stable. The Cash Position factor, however, had the most inconsistent loadings which implied it was unstable in the long term.

In addition to visual inspections, Pinches et al. (1973) computed the correlation coefficients of the factor loadings for the following pairs of years: 1951-1957, 1957-1963, 1963-1969 and also between the first and the last year in the period 1951-1969. The Financial Leverage factor had the highest correlation coefficients in all the pairs of years, which confirmed that this factor was the most stable. Other factors such as Receivable Intensiveness, Capital Intensiveness and Cash Position had relatively low correlation coefficients over some periods. This indicated that these factors underwent significant changes over the years.

Pinches et al. (1973) also checked whether the industrial firms included in their sample were involved in the stability/change of the factor patterns in the long term. This was carried out using: (1) differential-R factor analysis conducted between the years 1951 and 1969, (2) mean averages of the ratios in each of the four years analysed in the study and, (3) t-test statistics for the differences between the mean averages of the ratios between the years 1951 and 1969. Pinches et al. (1973) did not offer adequate explanations of the differential-R factor analysis; however, a later study by Ezzamel et al. (1987a) provided a description of this technique as they employed it in their own work on financial ratio patterns.

Ezzamel et al. (1987a, p. 529) explained that differential-R factor analysis can be used as a measure of positional change between two time periods. This analysis is carried out using the following two steps: first, the positional change matrix is computed as a standardised difference matrix between the data matrices of the two static time periods chosen; second, FA is performed on this matrix, producing what is called differential factor loadings. When all ratios that belong to a specific factor have high differential factor loadings, this indicates that all firms were involved in the observed change/stability of ratios over the years. When differential factor loadings of the majority of ratios that belong to a factor are low, this indicates that the change/stability in the magnitude of ratios over the years was not exhibited by all the firms used in the sample. The trends in the magnitude of ratios can be observed by comparing the mean values of ratios over the period and also by testing the statistical significance of the differences in the mean values of ratios between the first and last year of the period examined.

By carrying out the steps mentioned above, Pinches et al. (1973) found that Return on Investment and Cash Position exhibited some downward trends and that all the industrial firms in the sample were involved in these observed trends. Also, Financial Leverage exhibited some upward shifts which also occurred for all the industrial firms between 1951 and 1969. Capital Intensiveness generally showed an upward trend although this did not appear to occur for all industrial firms. Finally, nearly all the industrial firms were involved in the moderate changes observed over the period in Inventory Intensiveness, Receivable Intensiveness and Short-term Liquidity.

Pinches et al. (1973) showed that it is possible to classify the financial ratios of industrial firms into empirically-based groups. The composition of these patterns appeared to be fairly stable over the longer term although the magnitude of the financial ratios underwent moderate changes.

Without doubt, Pinches et al. (1973) was an original and unique study but it was soon criticised by Douglas (1973). Douglas (1973) criticised Pinches et al. (1973) for failing to report the types of data screening they carried out and pointed out that this might have some effect on the validity of their results. Douglas (1973) argued that the outputs of FA might be influenced by the screening process employed. Since no relevant screening details were reported in Pinches et al. (1973), the factor results might not be superior to the *ad hoc* classification of ratios. Douglas' (1973) view, regarding the failure to report what data screening had been used seems valid and it can also be added that Pinches et al. (1973) did not justify the choice of the list of ratios employed in their study. Stating the ground on which they based their selection of ratios would have enabled readers to make a better assessment of the credibility of their study.

Following on from Pinches et al. (1973), a study by Pinches et al. (1975) had several aims; the first was to examine the stability of empirically-based financial ratio groups over a short period while the second was to determine the hierarchical relationships amongst the ratio groups. The third aim was to integrate the latest empirical findings on the predictive significance of individual financial ratios with the empirically-based patterns identified in the study.

The study commenced by identifying the empirically-based financial patterns for a set of 48 ratios chosen after a thorough review of previous literature. Each of these ratios was obtained for 221 industrial firms in each year over the period between 1966 and 1969. The study also followed that of Pinches et al. (1973) by applying a common log transformation to all 48 ratios over all years. Pinches et al. (1975) performed FA with a (biquartimin) oblique rotation in order to identify the financial patterns[22]. By retaining all the factors with an eigenvalue in excess of unity, the 48 ratios were classified into seven groups. A seven-factor solution was found in each year of the study and these solutions accounted for 92%-93% of the variance in the data over the years. The seven patterns were given names similar to those identified by Pinches et al. (1973). Some of these empirical patterns were not expected based on previous research and *a priori* groupings. For example, traditional financial theory suggests that there would be a profit margin group but empirical results failed to distinguish this group from two other components: Return on Investment and Capital Turnover. Short-term stability of the financial patterns was assessed by making a visual comparison and by carrying out correlation analysis. The results indicated that the patterns were reasonably stable over the short term.

In order to assess the similarity between the seven financial patterns that were identified, Pinches et al. (1975) performed a higher-order or hierarchical factor analysis of the first-order factor groups. In hierarchical factor analysis, FA with an orthogonal rotation is performed over a correlation matrix of the first-order factors. So, the correlation matrix of seven factors was subjected to another FA in order to identify relationships between the different groups. This analysis was conducted for every year over the period between 1966 and 1969. In every year, the study found three higher-order factors and named them as follows: Return on Invested Capital, Overall Liquidity, and Short-Term Capital Turnover. However, some instability was observed in the contents of these higher-order factors over the short term. The instability was caused by one of the first-order factors (the Cash Position factor) which appeared to join different higher-order groups in different years. However, Pinches et al. (1975) doubted the importance of the Cash Position group as this group had the least theoretical underpinning and empirical significance amongst all first-order factors.

In the last part of the study, Pinches et al. (1975) related their results to the findings of the latest prediction studies at that time. Financial ratios have been found to be

[22] Pinches et al. (1975, footnote 9) explained that it was necessary to use an oblique rotation method in order to carry out the hierarchical factor analysis in the second phase of the study. Nevertheless, an orthogonal rotation was also performed and returned similar results to those for the oblique rotation.

significant predictors in prediction studies so Pinches et al. (1975) examined a number of predictive studies (particularity those which predicted bond ratings, bankruptcy and mergers) and obtained a list of ratios that were found to have high predictive power. This list contained ratios that belonged to four of the empirical classifications they identified: Return on Investment, Capital Turnover, Inventory Turnover and Financial Leverage. Other ratios with high predictive power were included in their study; however, these ratios failed to load significantly onto any of the seven empirical groups. Also, a number of ratios with high predictive power were not amongst the 48 ratios used by Pinches et al. (1975).

Finally, Pinches et al. (1975) highlighted the importance of selecting financial ratios based on their predictive and descriptive power. By the term descriptive power they meant that the chosen ratios should represent all the different empirical dimensions of performance. Thus, by providing evidence regarding interrelationships amongst the different ratios and the extent of their short-term stability, Pinches et al. (1975) hoped that their study would eventually facilitate the process of selecting ratios for further predictive research.

Martikainen et al. (1995b) were also interested in measuring the time series stability of financial patterns; however, they followed a slightly different methodology from Pinches et al. (1973, 1975). Martikainen et al. (1995b) noted the extensive use of industry-relative financial ratios (IRRs) in bankruptcy prediction models when different industries were analysed[23]. This led Martikainen et al. (1995b) to question whether the interrelationships of IRRs were different from those amongst ratios in their traditional form. They also questioned whether the patterns of IRRs were stable over time. If the use of ratios in an industry-relative form changed the interrelationships amongst ratios, then the accuracy of multivariate prediction models that employed these ratios would be problematic.

The sample used by Martikainen et al. (1995b) consisted of 148 small- and medium-sized Finnish firms. These firms came from three different industries: metal, textile,

[23] An IRR is the ratio of a firm's financial ratio relative to the mean value for that ratio in the firm's industry at a given point in time (Martikainen et al. 1995b, p. 1703).

and trading and service. Half of the firms in the sample were failed firms and the other half were non-failed. The failed firms were matched in terms of size and industry to their non-failed counterparts. Failed firms were included in the sample because IRRs have been used in failure prediction models and also because prior research found that financial patterns of ratios become highly unstable for firms before they fail[24]. The study used 16 ratios to represent Lev's (1974) four dimensions of performance as well as other dimensions found in the literature which included cash flow position, working capital position, growth, and operating leverage.

Martikainen et al. (1995b) performed PCA for failed and non-failed firms separately using financial ratios in the industry-relative form first, then in their traditional form. This analysis was performed for the first, second and third year prior to failure. Identifying financial patterns was not the main focus of the study; the focus was rather on the time stability of these patterns. Therefore, the study did not report many details with regard to extracting factors, nor the labels that were assigned to these factors. The study only mentioned that four components were derived in every analysis. The cumulative amount of variance explained by the patterns of IRRs was always smaller than the amount explained by the patterns of traditional ratios. This indicated that using IRRs appeared to distort some of the correlations amongst these ratios.

In the central part of the study, Martikainen et al. (1995b) used transformation analysis to measure the stability of the identified patterns over the three-year period prior to failure. Then, they compared the stability level exhibited by IRRs and traditional financial ratios. Transformation analysis checks whether two factor solutions are similar and, more importantly, it uncovers the source of any dissimilarity between the solutions[25]. The results of transformation analysis showed that the amount of instability was higher for the IRR patterns compared to the traditional financial ratio patterns. To explain this in a different way, the industry effects seemed to stabilise the fluctuation of ratios over time. Thus, when these effects were removed by using the IRRs, the patterns of ratios exhibited greater instability. Certainly the

[24] Martikainen et al. (1995b) particularly cited the study by Martikainen and Ankelo (1991) which is reviewed later in Subsection 2.4.6.
[25] Chapter 3 (Subsection 3.4.4) gives further details about transformation analysis.

instability increased as the failure year grew closer and was higher for failed firms compared to their non-failed counterparts.

Martikainen et al. (1995b) provided evidence that using IRRs alters the interrelationships between the ratios and increases their instability over time. Thus, interpreting the results of multivariate failure prediction models that employ IRRs should be conducted with caution.

Annual data were employed in most of the studies that aimed to identify the empirical classifications of financial ratios and to assess their time series stability. Little research, however, has focused on quarterly financial data. A useful study in this area is that of Devine and Seaton (1995) which focused on deriving ratio patterns using quarterly financial information. This study also compared the quarterly patterns that were identified with the patterns of annual financial ratios. The stability and quality of quarterly financial information were questioned in prior research for a number of reasons. Firstly, there are limited organisational resources that provide information concerning interim reporting. Secondly, the quality of quarterly reporting is somewhat questionable given that less auditing control is involved in preparing these reports when compared to annual reports. Thirdly, there might be incentives for management to produce interim reports that reflect the most favourable position for the firm. Therefore, Devine and Seaton (1995) investigated whether the possible lack of quality in quarterly financial information reported in previous studies affect the empirical patterns of this information.

Devine and Seaton (1995) used 44 ratios for 328 COMPUSTAT industrial firms. These 44 ratios were also used in Pinches et al. (1973, 1975)[26]. The 44 ratios were available for the firms in each quarter over a six-year period between 1985 and 1990. Devine and Seaton (1995) followed what might be considered a conservative approach to identify the financial patterns for quarterly and annual data and to compare them. Similar to previous studies, Devine and Seaton (1995) used PCA with

[26] Devine and Seaton (1995, endnote 2) noted that Pinches et al. (1973, 1975) stated that they used 48 ratios whereas their published results only included 44 ratios. These were the 44 ratios used by Devine and Seaton (1995). Nevertheless, Pinches et al. (1973, 1975) did actually use 48 ratios; however, they only reported the ratios that had significant loadings in any of the years covered in their study.

an oblique rotation (orthoblique method). However, what was different with this study was the way in which Devine and Seaton (1995) arranged their samples. The study calculated the 44 ratios for the 328 firms on a yearly basis for six years and combined the observations to form one 'combined annual' sample. Similarly, they combined the observations of every quarter for every year and obtained one 'combined quarterly' sample. Finally, the observations of each quarter for every year were combined to form four samples, each representing a quarter.

Devine and Seaton (1995) identified 12 dimensions for each of these samples[27]. The solutions explained 88.1% of the variance in the combined annual sample, 84.6% in the combined quarterly sample, and between 87.5% and 89.5% in the quarterly samples. The 12 dimensions in the combined quarterly sample were labelled as follows: 1-Leverage, 2-Current Asset Turnover, 3-Return on Sales, 4-Return on Equity, 5-Fixed Asset Turnover, 6-Return on Assets, 7-Inventory Turnover, 8-Working Capital Turnover, 9-Inventory Intensity, 10-Debt Ratio, 11-Cash Turnover, and 12-Sales Velocity. Similar labels were given to the 12 components identified for the combined annual sample except for component nine which was labelled as Capital Ratio. Components 9 and 12 of the combined quarterly sample could not be identified in the samples of the different quarters. However, three new components were identified in some of these quarters: Working Capital Intensity, Current Ratio and Liquidity.

Devine and Seaton (1995) carried out a comprehensive visual check to compare the contents of the different dimensions. They first compared the underlying dimensions in combined quarterly and annual data. The results indicated that there were potentially considerable differences in the information included in quarterly and annual financial statements. When the consistency of the dimensions was compared across the different quarters, the study noted some variations amongst these dimensions. However, some quarterly dimensions exhibited an acceptable level of stability across the quarters. Furthermore, Devine and Seaton (1995) extended the

[27] The study initially adopted the method of 'eigenvalue >1' to decide on the number of components to keep. This suggested keeping a number between 11 and 13 components across all the samples. However, after assessing the significance of the eigenvalues, it was decided to extract 12 components in all the samples.

analysis by computing the congruency coefficients between the factors in the different samples[28]. The findings regarding congruency coefficients confirmed the results of the visual examinations.

Devine and Seaton (1995) also offered some additional findings. As mentioned earlier, their study used the same ratios as Pinches et al. (1973, 1975) for COMPUSTAT industrial firms. Devine and Seaton (1995) identified 12 underlying dimensions in the annual data whereas only 7 dimensions were uncovered in Pinches et al. (1973, 1975). Devine and Seaton (1995) recalled that a log transformation was applied to the data in the two previous studies; this meant that firms with non-positive ratios had to be eliminated from the samples. Thus, Devine and Seaton (1995) excluded firms with non-positive ratios and performed the analysis using the remaining firms after using the log transformation. This resulted in 7 dimensions similar to those reported in the previous studies. Interestingly, the analysis was performed again without transforming the data and it also resulted in 7 dimensions – again, similar to those in the previous literature. According to Devine and Seaton (1995), this was consistent with previous research that suggested that PCA, amongst other interdependence methods, is robust with respect to non-normality; i.e. it gives similar results for normally and non-normally distributed data. More importantly, Devine and Seaton (1995) showed that the information in annual financial statements had 12 underlying dimensions, not 7 as previous empirical work had suggested.

Devine and Seaton (1995) identified underlying dimensions in quarterly data and compared them across quarters and with those from annual information; this seemed to be a valid approach. Although the study appeared to follow closely the design of previous relevant literature, it adopted some crucially different sampling procedures. Here it should be recalled that the quarterly and annual financial information was combined over a six-year period. This implied that the patterns of ratios, whether quarterly or annual, were assumed to be stable over the period and this permitted the yearly observations to be combined. However, unless there is clear evidence to

[28] Similar to a correlation coefficient, congruency coefficient is widely used in the classification literature to check for similarity in the contents of two factors. A congruency coefficient can have a value between 0 and ± 1; the closer the coefficient to unity, the higher the similarity between the two factors. Chapter 3 (Subsection 3.4.3) offers further details regarding the congruency coefficient.

support this assumption, pooling data from different years into one sample is questionable. Furthermore, this procedure was not common in the relevant literature which mainly identified the financial patterns on a yearly basis. For these reasons, all the conclusions drawn by Devine and Seaton (1995) should be viewed with some scepticism.

This subsection has reviewed a number of studies that focused on assessing the stability of empirical financial patterns over time. Pinches et al. (1973) assessed the stability of financial patterns over a long period. In doing this, they used visual comparison and correlation coefficients. They also employed differential-R factor analysis to measure the degree of involvement of the firms in changes of the magnitude of ratios over time. The study concluded that the identified patterns were fairly stable over the period. Visual comparison and correlation coefficients were also used by Pinches et al. (1975) to assess the short-term stability of financial patterns. Their study concluded that the patterns were stable in the short period. Markitainen et al. (1995b), on the other hand, used transformation analysis to check the similarities in financial patterns of industry-relative and traditional financial ratios for firms prior to failure. They found that the use of IRR caused some instability in financial patterns. Finally, Devine and Seaton (1995) carried out extensive visual comparisons, in addition to computing congruency coefficients, to compare the patterns of annual and quarterly data. They found that quarterly financial patterns were inconsistent over the quarters; they also differed from their counterpart annual patterns.

In addition to time stability, researchers were also interested in assessing the cross-sectional stability of patterns. The key studies in this area are reviewed in the following subsection.

2.4.3 Cross-sectional stability

Time series stability and cross-sectional stability have received much the same amount of attention by researchers. This subsection reviews evidence concerning the stability of financial ratio patterns across different industries and different countries. The retail and manufacturing industries appear to receive most attention in the literature. These two types of firm were investigated in Johnson (1978, 1979), and by Gombola and Ketz (1983b). The financial patterns for several other industries were compared in Ketz et al. (1990) and in Martikainen et al. (1994). On the other hand, the US and Finland were the only two countries for which financial patterns were compared in a study by Yli-Olli and Virtanen (1989).

2.4.3.1 Across industries

This subsection commences by examining Johnson's study (1978) which had the following three purposes: (1) to develop empirically-based patterns of financial ratios for primary manufacturing and retail firms, (2) to examine the cross-sectional stability of the identified patterns between the two types of firm and, (3) to verify the explanatory efficiency of two subsets of ratios when compared with the entire set under investigation. Manufacturing and retail firms were chosen in particular because they represent the extremes in terms of capital as opposed to labour intensiveness (Johnson, 1978, note 1).

Johnson (1978) extracted his sample from the COMPUSTAT data tapes for the year 1972. The sample comprised 465 firms from two industries: 306 primary manufacturing firms and 159 retail firms. For every firm, 61 ratios were calculated. Some of these ratios were transformed using the log transformation to improve the approximation to normality of the distribution of ratios, improve homoscedasticity, and to reduce outliers. Separate PCA's with an (unspecified) orthogonal rotation were performed over the datasets of the two industries. Johnson (1978) kept all components with an eigenvalue greater than one; he also checked the results for discontinuities.

Nine components were identified for each of the two industries. The nine-factor solutions accounted for 86% and 87% of the variance for manufacturing and retail firms, respectively. The components were assigned the following names: 1-Return on Investment; 2-Financial Leverage; 3-Capital Intensiveness; 4-Inventory Intensiveness; 5-Cash Position; 6-Receivable Intensiveness; 7-Short-Term Liquidity; 8-Decomposition Measures and; 9-Loose Ends. Amongst these, component 8 was of some interest as the study included some decomposition measures which successfully loaded heavily onto this component for the two types of firm.

Johnson (1978) visually compared the ratios related to the nine components and the size of their loadings for the manufacturing and retail firms. The contents of the first eight components were generally consistent for the two types of firm. However, the instability of component 9 was apparent as ratios that loaded highly onto this factor for one type of firm, had near-zero loadings for the other type of firm. Also, this component explained a trivial amount of variance for both types of firm (less than 4%). Factor solutions for manufacturing and retail firms were further compared using congruency coefficients. These coefficients were of a significant size for the first eight components, amongst which Financial Leverage was the most similar, and Inventory and Capital Intensiveness were the least similar for the two types of firm. Component 9, not surprisingly, had a relatively small congruency coefficient which confirmed the visual observations concerning the dissimilarity of this factor across the two industry groups.

In the last part of the study, Johnson (1978) used multiple regression analysis to further assess the similarity between the financial patterns of manufacturing and retail firms. For each industry group, Johnson (1978) constructed a regression equation using the ratios with the highest loadings onto the components as predictor variables. Johnson (1978, p. 210) briefly explained that stable factor patterns are indicated if the percentage of variation explained by the validation and cross-validation phases are approximately equal and approach unity. Johnson (1978) used two sets of nine ratios to construct a regression equation, one for each group of firms. His main findings were as follows: the nine ratios for the retail firms could explain 78% of variations in the retail group while, for manufacturing firms, the set of nine ratios explained 79% of the variation in that group. The cross-validation results indicated that the nine ratios for the retail firms could explain 65% of the variation in the manufacturing group. The nine ratios for the manufacturing firms, however, could explain 77% of the variation in the retail group. Thus, Johnson (1978) stated that rather than using all 61 ratios, the set of nine ratios for manufacturing firms could be used for both industries without much loss of information.

Johnson (1978, p. 213) concluded his study by stating that the number of identified factors and the composition of these factors were 'remarkably' consistent with the findings of Pinches et al. (1973). The two studies proved that it was feasible to identify meaningful empirically-based financial patterns for industrial firms and that these patterns were stable over time; the patterns were also reasonably consistent across different industries.

Here it is important to note, however, that Johnson (1978) appeared to generalise the results of his study without obtaining sufficient support for the conclusions he reached. It may be recalled here that Johnson (1978) did not initially propose to back up or rebut the findings of Pinches et al (1973). For example, Johnson (1978) did not justify his selection of 61 ratios, nor did he mention whether any of the 48 ratios used in Pinches et al. (1973) were amongst his list of ratios. Also, he did not appear to investigate whether the two types of firm he studied were amongst the firms studied by Pinches et al. (1973). Furthermore, the single year covered by Johnson (1978) fell outside the period covered in Pinches et al. (1973) which was between 1951 and 1969. While the two studies identified a different number of factors: seven in Pinches et al. (1973) and nine in Johnson (1978), Johnson (1978) stated that the number and content of the patterns in the two studies were 'remarkably' consistent. In fact, Johnson (1978) did not carry out any examination to check whether the patterns of the two studies were indeed similar.

In a subsequent study, Johnson (1979) carried out fairly similar research to that of Johnson (1978) to assess the cross-sectional stability of financial ratios. However, Johnson's (1979) paper appears to be more structured than his previous study and this could explain the widespread citation of this study compared to Johnson (1978). Surprisingly, the older study was not cited in Johnson (1979).

Johnson (1979, p. 1036) clearly stated that one purpose of his study was to refute or confirm the main findings of Pinches et al. (1973, 1975) using a larger set of variables. Another purpose was to compare the financial patterns for samples of retailers and primary manufacturers. Johnson (1979) used 61 ratios similar to

Johnson (1978), adding that 40 of these ratios were common to Pinches et al. (1973, 1975). As with Johnson (1978), his list of ratios comprised a number of financial decomposition measures. The 61 ratios were calculated for 306 primary manufacturers and 159 retailers for two years: 1972 and 1974.

Johnson (1979) commenced the analysis by performing univariate and multivariate t-tests for the ratios of the two groups of firms. The mean values of ratios were significantly different between primary manufacturers and retailers. This could indicate the existence of considerable differences in the empirical classifications of these ratios between the two types of firm. To investigate this matter, Johnson (1979) used PCA with a varimax rotation to derive the financial patterns. Four separate analyses were performed for the two types of firm in the years 1972 and 1974. First, however, the common log transformation was applied to some of the ratios in order to achieve better distributional properties prior to performing PCA. Johnson (1979) kept the components which had an eigenvalue in excess of unity and explained individually a substantial proportion of the variance (a minimum of 5%). He also checked the results for discontinuities; this resulted in eight components. The previous study, however, identified nine components where component 9 (Loose Ends) did not explain a substantial amount of variance; also, its content was inconsistent between the two groups. For similar reasons, Johnson (1979, footnote 4) decided to discard this component and keep only 8 components for each of the datasets[29]. The final solutions (based on 8 factors) explained at least 80% of the variance in the datasets. The eight dimensions were given the same labels as components 1 to 8 in Johnson (1978).

Johnson (1979) found that all 40 of the ratios used in Pinches et al. (1973, 1975) loaded onto the first seven components. Only a few ratios, however, were slightly inconsistent in their loadings or did not load onto the same factors as found in Pinches et al. (1973, 1975). The eighth component identified in Johnson (1979), Decomposition Measures, was not amongst the components of Pinches et al. (1973, 1975). This component emerged because Johnson (1979) included decomposition

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[29] Note here that Johnson (1979) gave his reasons to discard component 9 without any reference to Johnson (1978).

measures in his list of variables. Having these measures loading together onto a single component indicated that these measures represent an aspect of a firm's performance that is not captured by the traditionally used financial ratios.

Johnson (1979) examined the cross-sectional stability of the factor patterns between the two types of firm using visual comparison, congruency coefficients and canonical analysis. These are the same techniques he used in his earlier study; however, Johnson (1979) used the term 'canonical analysis' to describe the multiple regression procedures that were explained in the previous study. Firstly, visual comparisons between the patterns of the two industries pointed to a high degree of cross-sectional stability in the two years in term of the consistency of the factor loadings across the two types of firm. The congruency coefficients were large enough to consider the patterns as stable between the two industries. Finally, canonical analysis showed that approximately 90% of the variance in the factor loadings was common for the two types of firm in the two years considered in the study. This indicated that the composition of each ratio group, and the relative importance of individual ratios to a particular group, were largely stable across retailers and primary manufacturers.

Hence, as well as the time series stability of the empirically-based financial patterns reported in earlier studies, Johnson (1979) added strong evidence that these patterns were stable across the two types of firm he investigated. Although this conclusion is not different from the conclusion of Johnson (1978), the older study lacked adequate explanations and empirical work to support such a conclusion. Johnson (1979), however, seemed to overcome this criticism and offered a conclusion that reflected, to a reasonable extent, the actual empirical analysis carried out. Nevertheless, the fact that Johnson (1979) failed to report or cite any inconsistencies with his earlier study can be considered as misleading although this comment is not intended to undermine the evidence provided by the two studies.

The ratio patterns for manufacturing and retail industries were further investigated by Gombola and Ketz (1983b)[30]. In their study, Gombola and Ketz (1983b) examined

[30] Gombola and Ketz (1983b, pp. 46-47) explained that the two industries lie at the opposite ends of the spectrum given their fundamentally different financial characteristics. Thus, if the study found that the

the cross-sectional stability of financial patterns for the two industries. Also, they assessed the long-term stability of the patterns of each industry and compared the results. Gombola and Ketz (1983b) had another particular interest: this was to check the impact of the definition of cash flow and defensive interval measures on the financial patterns of the two industries. They noted that previous research [Pinches et al. (1973) and Johnson (1979)] used net income plus depreciation as a proxy for cash flow, and operating expenses as a proxy for cash expenditures. Unlike these studies, Gombola and Ketz (1983b) used different definitions to calculate cash flow by adjusting net income plus depreciation for all accruals and deferrals. Similarly, they calculated cash expenditure ratios on a cash basis as well as on an accrual basis.

The sample used in Gombola and Ketz (1983b) comprised 783 manufacturing firms and 88 retail firms obtained from the COMUPSTAT annual file for the period between 1971 and 1980. For each of the firms, they calculated a list of 58 ratios. This list contained all the 48 ratios used in Pinches et al. (1973) in addition to a number of new ratios. Four of these ratios had working capital from operations in the numerator; another four ratios had cash flow in the numerator. Gombola and Ketz (1983b) used the definitions they proposed for cash flow and fund expenditure whenever necessary in calculating the ratios.

Initial inspections of the mean values of the 58 ratios revealed that there were some cross-sectional differences between manufacturing and retail firms. For example, turnover ratios for retail firms were higher than the corresponding ratios for manufacturing firms. These differences were expected to reflect in the classification patterns of ratios for the two industries.

Gombola and Ketz (1983b) used FA (the exact method is not specified) with a varimax rotation to identify the financial patterns for the two samples for each year between 1971 and 1980. They kept all factors with an eigenvalue greater that one; they also computed congruency coefficients to assess the cross-sectional and time series stability of the identified patterns.

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financial patterns of the two industries were similar, it would be reasonable to expect to identify similar ratio patterns for other organisations with financial characteristics lying between manufacturing and retail firms.

Given the results for all the years for the two industries, manufacturing and retail firms appeared to have several factors in common. These included Return on Investment, Cash Position, Financial Leverage, Receivables Intensiveness, Debt Structure, Short-Term Liquidity, Cash Flow and Cash Expenditures. The last two factors emerged as a result of employing different definitions for cash flow and defensive interval measures[31]. Given that these definitions led to the identification of two new dimensions, Gombola and Ketz (1983b) warned against using simple proxies for cash flow, and against using the accrual concept of expenses as a proxy for the cash concept of expenditures. Also, some factors were identified for one type of firm in some of the years. The most important of these was the Return on Sales factor which was found for the retail group only. In some years, where this factor could not be identified separately, return on sales ratios loaded together with inventory intensiveness and asset turnover ratios and formed a factor that was unique to retail firms; this was called Turnover. The counterpart to Turnover is Inventory Intensiveness which was identified for manufacturing firms. Nevertheless, Gombola and Ketz (1983b) found that seven of the financial patterns for the manufacturing group were very similar to the seven patterns found by Pinches et al. (1973).

The stability results showed that further differences existed between the ratio classifications for manufacturing and retail organisations. Financial patterns for the retail group exhibited a higher level of stability over the long term compared to those for manufacturing firms. Yet, the patterns identified for both types of firm were evidently more stable over time than across the two industries. Thus, the overall results of Gombola and Ketz (1983b) implied that analysing the financial performance of different industries, particularly the retail and manufacturing industries, might require the use of different sets of financial ratios.

Overall, Gombola and Ketz (1983b) followed a fairly similar approach to earlier studies but used longer time periods. Although extensive comparisons between the two types of firm were conducted, Gombola and Ketz (1983b) seemed to miss some

[31] The Cash Expenditures factor was identified for the two industries in every year, as was the Cash Flow factor for the retail group. Cash Flow, however, was found for the manufacturing group in seven of the ten years covered in the study.

important issues. For example, they did not report some specific statistics relating to FA. These include the percentage of variance explained by the solutions, the criteria used to decide on the number of factors, the precise number of factors derived for the two industries, and the factoring method they employed. Reporting this information would have made it easier for readers to assess the credibility of the results they reported.

Martikainen et al. (1994) investigated the industry effects on the interrelationships between financial ratios using factor analysis and transformation analysis. Their sample consisted of small- and medium-sized Finnish firms representing three industries: metal (66 firms), textile (26 firms), and trade and service (56 firms). Half of the firms in each industry were failed firms of a similar size to the non-failed firms that comprised the other half of the sample. The data were analysed annually for three years prior to failure. Martikainen et al. (1994) justified the use of the two types of firm by referring to the extensive use of financial ratios in failure prediction studies. Thus, analysing the interrelationships of ratios for failed and non-failed firms would undoubtedly facilitate research into bankruptcy prediction. The study employed 16 ratios commonly used by creditors in decision making and in the previous literature. These ratios were carefully chosen to represent many dimensions of a firm's performance[32]. PCA with a varimax rotation was performed for each of the industries for every year over a three-year period prior to failure. Cattell's scree plot[33] indicated that retaining four components would be enough to describe the dimensions for each industry in every year. The four-factor solutions explained between 71.8% and 78.0% of the variance in the data.

Assigning meaningful labels to the four components appeared irrelevant in Martikainen et al.'s (1994) study given that their central focus concerned assessing the similarity of these patterns across the different industries using transformation analysis. The results of transformation analysis indicated the existence of considerable industry effects on the interrelationships of financial ratios. These

[32] The data set used in this study appears similar to that used in Martikanen et al. (1995b) which was reviewed earlier in Subsection 2.4.1.
[33] This is one of the methods used to decide on the number of factors to retain. This method is described in Chapter 3 (Subsection 3.3.2).

effects need to be dealt with appropriately when ratios are analysed in cross-industry samples. For this, Martikainen et al. (1994, p. 65) suggested using samples that cover only one industry, or using appropriate dummy variables or industry-relative ratios[34].

Overall, there are some concerns with Martikainen et al.'s (1994) study. First, including non-failed firms in the samples is likely to limit the relevance of the study for those interested in bankruptcy prediction. Secondly, it would have been helpful if the study had provided the labels of the extracted components as this could make researchers aware of the dimensions of the industry that are of interest to them. It could also help to include these dimensions in their models by selecting a set of ratios that represents each of these dimensions. Another concern relates to the rather small sample size used in Martikainen et al. (1994). The study classified a set of only 16 ratios, adding that one of the industries (textiles) was represented by only 26 firms. As mentioned earlier in this, and in the following chapter, the larger the sample used in FA or PCA, the more generalisable the results. Although using a parsimonious set of ratios is preferable in FA, high cases-per-variable ratios should always be employed. Clearly, the ratio of firms-per-ratio for the textile industry was far below the minimum of 5-to-1 suggested in most textbooks (for example, Hair et al., 1998, pp. 98-99). Failing to meet the minimum size requirements in FA can cause the results to be sample-specific. Unfortunately, this might be the case for Martikainen et al. (1994)[35].

Ketz et al. (1990) carried out a comprehensive cross-industry analysis of financial ratios. The book can be characterised by the following two points. First, it identified the financial patterns which are specific to different industries, checked their time series stability, and compared them to financial patterns for the economy (excluding the industry under investigation). The aim was to help practitioners and researchers in choosing a parsimonious set of ratios when conducting a cross-industry analysis or the analysis of a single industry. The second interesting point regarding this book is that it expanded the relevant literature on the classification of financial ratios. This is because it employed a number of factoring and rotation techniques and compared

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[34] A related study reviewed earlier (Martikainen et al., 1995b), showed that the use of IRR appeared to add to the instability of factors over time.
[35] This also applies to Martikainen et al. (1995b) which was reviewed earlier.

their outputs. There is some redundancy in the book as the analysis was reported separately for every industry (Ketz et al., 1990, p. 15). Therefore, rather than meticulously reviewing the analyses and results of Ketz et al. (1990), this section of the literature review gives a general description of the book. This includes reviewing the design of the study, summarising the data and methodology, and highlighting some key findings.

Ketz et al. (1990) commenced their analysis by identifying the classification patterns for the whole economy and investigating their stability over the period between 1978 and 1987[36]. Then, Ketz et al. (1990) identified the financial patterns for every industry, examined their time stability, and compared them to those for the rest of the economy.

In all the analyses that were conducted, Ketz et al. (1990) used 32 financial ratios chosen for their popularity and common use in previous literature. Initially, the study considered all the non-banks and non-utility firms on the COMPUSTAT Annual Industrial file. Only firms with enough information to calculate the 32 ratios were included. This resulted in 476 firms being used in the economy analysis. For the analysis on an industry level, this sample was divided into seven subsamples: (1) automobile and aerospace; (2) chemical, rubber and oil; (3) electronics; (4) food; (5) retail; (6) steel and (7) textile. For an industry to be represented in a sample on its own it had to have more than 32 firms[37]. Since the number of firms operating in some industries was less than 32, such industries had to be combined with others with similar characteristics[38]. The number of firms included in the industry samples ranged between 33 (food) and 97 (chemical, rubber and oil). Also, 96 companies were not operating under any of the seven industries. These companies comprised part of the economy sample.

[36] Firms on the COMPUSTAT annual industrial file, excluding banks and utility firms were considered as a surrogate for the entire U.S economy (Ketz et al., 1990, p. 193).
[37] Ketz et al. (1990, p.21) suggested that the minimal requirement is one firm for every ratio. This is, however, far less than the usual minimum requirement of 5-to-1 cases-per-variable ratio suggested in many textbooks. Chapter 4 (at the end of Section 4.4.) gives more details on this issue.
[38] Firms were allocated to their industries based on how they were classified by COMPUSTAT (i.e. the authors did not change the COMPUSTAT classifications). However, firms which operated in more than one industry were assigned by the authors to the industry in which they had the largest segment of business (Ketz et al., 1990, p. 21).

All the analyses were initiated by testing whether the mean and the variance for every ratio in the different industry samples were significantly different from those for the economy as a whole and over time. Classification schemes were then developed using common factor analysis as the principal technique. Also, other techniques were explored to check whether the outputs were sensitive to the method being used. The other techniques included: iterated principal factor analysis, maximum likelihood factor analysis, Harris component analysis, alpha factor analysis, and image factor analysis. The outputs of all these methods were similar to those of common factor analysis except for the maximum likelihood method. To decide on the number of factors in the final solution, the study utilised three methods: eigenvalue greater than unity, Cattell's scree plot and the interpretability of the factors. Interestingly, the three stopping rules pointed to the same number of factors. Furthermore, Ketz et al. (1990) used three orthogonal rotation methods: varimax, quartimax and equamax; and two oblique methods: orthoblique and promax. The orthogonal rotation methods generally yielded the same answers, and the answers for the two oblique methods were also similar. However, some differences were observed between the orthogonal and oblique methods. The similarity between industry factor patterns and those of the whole economy was measured using congruency coefficients. Congruency coefficients were also computed between all possible pairs of years to measure the time series stability of factor patterns for the different industries and for the economy analysis.

Given the detailed descriptions of the results reported in Ketz et al. (1990), summarising the findings would be monotonous rather than relevant here. Therefore, we briefly mention that the study identified seven factors for the whole economy which explained over 90% of variability in the data. These factors were labelled as follows: Return, Cash Flow, Cash Position, Inventory, Sales, Liquidity and Debt. These factors exhibited a good level of stability over the ten-year period. Likewise, seven classification schemes were identified for almost every industry in the economy for most of the ten years. The only major exception to this was the retail industry which showed two Return factors: Return on Sales and Return on Assets.

Interestingly, the industry classification schemes also appeared stable across the different periods.

Finally, Ketz et al. (1990) highlighted some potential limitations in their study. Data inadequacies were pointed out as one of the limitations. The potential shortfall of the data arose because COMPUSTAT, the main source of the data, is known to have survivor and size biases: i.e. COMPUSTAT tends to offer data for large firms which have been in business for a long time. However, Ketz et al. (1990) did not consider this to have a significant impact on their results as the central purpose of the study was to show the usefulness of factor analysis methods in developing taxonomies and in uncovering the interrelationships amongst ratios. The other potential limitation related to the possibility of misclassifying a firm and failing to place it in the right industry group. This was, nevertheless, unavoidable given the nature of the publicly available data on which the study was based.

In his review of Ketz et al. (1990), Mensah (1991) pointed out that the study replicated, to a large extent, the approach followed in pioneering studies in the field (e.g. Pinches et al., 1973). However, in spite of this, Mensah (1991) is of the view that Ketz et al. (1990) make a significant contribution to the literature. Ketz et al. (1990) added to the literature when they explored the use of different factoring and rotation techniques and compared their outputs. Also, Ketz et al. (1990) carried out a comprehensive analysis of seven industries over a period of time beginning with high inflation followed by a deflationary environment, and then a deep recession followed by strong economic expansion. Nevertheless, given the diversity of the period, Mensah (1991) criticised Ketz et al. (1990) for failing to offer theoretical explanations for the changes observed over time or for the inter-industry differences they observed. In other words, Mensah (1991) thought that Ketz et al. (1990) offered only a partial explanation of their findings.

Ketz et al. (1990) made a significant effort to develop taxonomies of financial ratios for seven industries and to examine their similarity to patterns for the rest of the economy. For this, they employed a number of factor analyses and rotation techniques and covered a long period of time. All this resulted in a large amount of output. However, reporting the findings of nearly every method they employed appeared to divert attention from the main aims of the study. Overall, it was left to readers to work through the extensive details and draw their own conclusions regarding the results for any specific industry. Another note can be also added here regarding the rather small sample size used to represent some industries (the food industry was represented by just 33 firms) although it is understandable that the authors of the book tried to make the most of what the database (COMPUSTAT) offered. Regrettably though, they did not appear to study the sample size requirements necessary to achieve a sound application of factor analysis.

2.4.3.2 Across countries

Our review of the literature to date shows that the stability of financial patterns has been investigated extensively over periods of different lengths and across different industries. However, evidence provided by these studies is mainly based on two countries: the US and Finland. Evidence from both countries was brought together in a study by Yli-Olli and Virtanen (1989) which sought, amongst other purposes, to explore the cross-country stability of financial patterns for the US and Finland[39].

In addition to measuring the cross-country invariance of the ratio patterns, Yli-Olli and Virtanen's (1989) other purposes included: checking the impact of different aggregation methods on the ratio patterns, and measuring the long-term stability of these patterns. Yli-Olli and Virtanen (1989) used a set of 12 financial ratios which represented the following four *a priori* measures of a firm's performance: short-term solvency, long-term solvency, profitability, and efficiency. These ratios were calculated for U.S. and Finnish firms for every year in the periods 1947-1975 and 1974-1984, respectively. U.S. firms that had the same year-end (31 December) were chosen from the COMPUSTAT annual industrial tape. According to Yli-Olli and Virtanen (1989), including firms with the same year-end would offer a clear picture of the different phases of economic cycles compared to using firms with different year-ends. The U.S. sample consisted of 450 firms in 1947, and the number of firms

[39] It is worth mentioning that Yli-Olli and Virtanen (1989) and a subsequent study by Yli-Olli and Virtanen (1990) are identical. Neither of the two studies cited the other. Also, a substantial part of these two studies was identical to Yli-Olli and Virtanen (1985). Nevertheless, the two studies (1989 and 1990) cited Yli-Olli and Virtanen (1985) which covered only U.S. data.

included in the sample increases gradually throughout the years until it reaches around 1,500 firms in 1975. The Finnish sample consisted of 42 firms; these were all the firms quoted on the Helsinki Stock Exchange (excluding banks and insurance companies) during the period between 1974 and 1984.

Yli-Olli and Virtanen (1989) used PCA with a varimax rotation to extract factor patterns. The number of factors employed was based on the interpretability of the factors, and also on *a priori* knowledge of the number of dimensions represented by the employed ratios (as mentioned earlier, the employed ratios came from four *a priori* classifications). The resulting factor solutions were compared over time and between the two countries using transformation analysis. Thus, the approach followed by Yli-Olli and Virtanen (1989) to extract the factors and to check for their stability over time and across countries was based on a widely used methodology. However, the study is distinguished from previous literature since it was based on multivariate time series data. So, rather than analysing the data on a yearly basis and comparing the resulting patterns over the years and between the two countries, Yli-Olli and Virtanen (1989) arranged their data matrices differently. For each of the two countries, the rows of the data matrix represented the years (1947 to 1975 and 1974 to 1984 for the US and Finland, respectively) and the variables (columns) were the mean values of each of the 12 ratios over the firms[40]. The mean values for every ratio were calculated using two aggregation methods: the arithmetic average (called the equal-weighted average) and the value-weighted average[41]. In addition, the results of this study were based on data in first difference form rather than levels form. This is because, after performing PCA using data in the value- and equal-weighted indices of ratios, the extracted factors could not be interpreted easily; also, results were significantly different according to the averaging method used. Given that time-series data were used, this problem might have been caused by the highly correlated ratios over time; thus, first difference of the ratios was used to deal with trends in the time series. Accordingly, data in the original level values were discarded.

[40] See Yli-Olli and Virtanen (1990, Appendix 2) for the U.S. and Finnish data matrices.

[41] See Yli-Olli and Virtanen (1985, pp. 18-21) for calculations and further explanations of these two aggregation methods.

Yli-Olli and Virtanen (1989) started off by analysing U.S. data in first difference form using both value- and equal-weighted indices. They extracted four factors in both cases which accounted for 87.8% and 86.4% of the variance in the value- and equal-weighted ratios, respectively. The identified factors were not fully correspondent to the *a priori* classifications. For example, factors identified using the value-weighted averages were given the following labels: Solvency, Profitability, Efficiency, and Dynamic Liquidity. Interestingly, the short-term and long-term solvency *a priori* classifications were actually represented by only one empirical factor.

The long-term stability of the U.S. factors was then examined. For this, Yli-Olli and Virtanen (1989) divided the period into two sub-periods; each covered the same number of years (1947-1961 and 1962-1975); they then applied PCA to the data in the two sub-periods (data were in first difference form for both value- and equal-weighted ratios). Using transformation analysis, the identified patterns in the two sub-periods were compared to each other and further, to those identified for the whole period. The results showed that U.S. financial patterns calculated using value-weighted averages were generally stable over time. However, financial patterns based on equal-weighted averages of ratios were unstable over time.

In a further step, Yli-Olli and Virtanen (1989) identified the financial patterns in the Finnish data using the two aggregation methods. Then, they used transformation analysis to check for the structural invariance between U.S. and Finnish financial patterns. Different results were reported for the two different aggregation methods. When value-weighted averages were used, the patterns in the two countries showed strong structural invariance whereas a slight structural invariance was found between the patterns when equal-weighted averages were used.

To sum up, Yli-Olli and Virtanen (1989) found that the identified factor patterns, based on the value-weighted aggregation method, showed both time-series stability and strong structural invariance between the U.S. and the Finnish data. However, when equal-weighted averages were used, unstable financial patterns and a slight structural invariance were reported. Thus, Yli-Olli and Virtanen (1989) recommended the use of value-weighted indices as against equal-weighted indices in ratio analysis on an aggregate level. Furthermore, after carrying out a brief examination, equal-weighted indices appeared particularly sensitive to outliers and to heterogeneity in the data. Finally, Yli-Olli and Virtanen (1989) stated that the best set of financial ratios should represent all the different dimensions of a firm's performance and that it is important that these dimensions are stable across the different countries and over time.

In summary, Subsection 2.4.3 focused on the literature dealing with cross-sectional stability of the financial patterns. Financial patterns were compared, using different methods, across different industries and different countries. The comparison methods employed for checking cross-sectional stability were no different from those used in measuring the time series stability of the classifications. These methods included visual comparison, congruency and correlation coefficients, and the more complicated technique of transformation analysis in the most recent studies. These techniques were also used by the studies reported in the following subsections. Similarly, the methodology followed in the studies reviewed in the following subsections is similar to the methodology used by the previously reviewed studies: i.e. they all used PCA/FA to derive the empirical classifications of ratios. Subsection 2.4.4 reports evidence from several other countries while Subsection 2.4.5 reviews studies conducted in different industries. Subsection 2.4.6 covers the studies which are not listed under any of the categories mentioned above, and finally, Subsection 2.4.7 provides a brief description of the way in which PCA/FA was utilised as a data reduction technique in prediction studies. The forthcoming subsection reviews studies conducted in three countries: UK (Ezzamel et al., 1987a), New Zealand (Mear and Firth, 1986) and India (Pandey and Bhat, 1988).

2.4.4 Ratio patterns on a country level

The majority of studies reviewed so far in this chapter reported U.S. and Finnish evidence regarding the empirical classification of financial ratios. A study by Ezzamel et al. (1987a) contributed to the literature by adding evidence from the UK. Ezzamel et al. (1987a) noted a disparity in the results of previous studies regarding the identified factors and their time series stability; they thus realised the importance of extending the research to cover UK data. Ezzamel et al. (1987a) sought to investigate the patterns of financial ratios in the UK and to assess the stability of the identified patterns over the period between 1973 and 1981. Rather than simply replicating the research design of Pinches et al. (1973), Ezzamel et al. (1987a) followed different sampling procedures and utilised some statistical tests that were not used by Pinches et al. (1973).

Ezzamel et al. (1987a) examined two sample populations; the first sample consisted of all UK manufacturing firms on the EXSTAT database for which the complete list of variables was available in any of the years 1973, 1977 and 1981[42]. This was different from the sampling procedure used in Pinches et al. (1973) which included only firms that were available in all the years of the study; this made the sample in Pinches et al. (1973) more homogenous. However, according to Ezzamel et al. (1987a, p. 523), a survival bias was introduced by the sample in Pinches et al. (1973) which caused their results to be inapplicable to all the U.S. manufacturing firms. Thus, Ezzamel et al. (1987a) sought to avoid these problems by following a different sampling procedure in their first phase of the analysis. Nonetheless, in order to check whether sampling procedures could influence the results of FA; Ezzamel et al. (1987a) used a second sample population that only contained firms that were available in all three years covered in the study. The results of the two populations were then compared. The size of the first sample ranged between 1,115 (1973) and 1,434 (1981) manufacturing firms whereas the second sample consisted of 842 firms. For each firm in the two samples, 53 ratios were calculated. Ezzamel et al. (1987a) initially obtained a long list of 152 ratios based on the popularity and usefulness of the ratios in the literature. However, the long list of variables was subjected to a number of screening techniques which resulted in 53 ratios remaining for analysis.

Using the first sample, Ezzamel et al. (1987a) employed FA with both orthogonal and oblique rotations. Although the results of the two rotation methods were similar, the oblique method produced a better clustering of variables; thus the orthogonal results were not reported in their study. The 'eigenvalue greater than unity' criterion pointed

[42] Only UK firms were included in the sample; these belonged to 53 manufacturing classifications irrespective of the end of their financial year.

to 11 factors in 1973, 15 factors in 1977 and 10 factors in 1981. However, to facilitate comparisons with year 1981, Ezzamel et al. (1987a) kept only 10 factors in 1973 and 1977. The 10-factor solutions accounted for 73%, 66% and 75.9% of the variance in the data in the three years, respectively. The ten financial patterns of the UK manufacturing companies were labelled as follows: 1-Capital Intensiveness; 2-Profitability; 3-Working Capital; 4-Liquidity; 5-Long-Term Debt; 6-Asset Turnover; 7-Profitability II; 8-Inventory; 9-Asset Turnover II; and, 10-Liquidity II. These factors, to some extent, seemed different from the factors identified in previous studies. Ezzamel et al. (1987a, p. 527) attributed these differences to the use of different sample sizes, different sets of ratios and different time periods. Also, whether the analysed ratios were transformed or left in their raw form might also cause some differences in the results. Nevertheless, the results reported above were based on raw ratios as Ezzamel et al. (1987a, p. 527) agreed that it is often not possible to decide on the right transformation method to be used.

Using the factor results of the raw data, Ezzamel et al. (1987a) visually checked the consistency of ratio loadings onto the identified factors in the three years covered in the study. This revealed that the most stable factors over the period were Long-Term Debt, Working Capital and Inventory while the most unstable factors were Asset Turnover II and Capital Intensiveness. To gain more insight into the extent of the stability of the identified patterns in the long term, Ezzamel et al. (1987a) used the same methods as those employed by Pinches et al. (1973). These included calculating correlation coefficients, performing differential-R factor analysis, comparing mean averages of ratios over the years, and testing the significance of the differences of ratio means between the start and end of the period (i.e. years 1973 and 1981). Furthermore, Ezzamel et al. (1987a, p. 528) noted that the correlation coefficients between factor loadings over time measured the extent of time series stability in the interrelationships; nonetheless, these correlations did not measure changes in the magnitude of loadings over time. In order to measure this, for each pair of years, Ezzamel et al. (1987a) calculated the percentage of the absolute deviation between the ratio loadings onto a factor in the two years to the ratio loadings onto the factor in the earlier year.

Unlike the conclusion made by Pinches et al. (1973), by considering the results of all the methods mentioned above, Ezzamel et al. (1987a) concluded that the identified financial patterns were unstable over time. Ezzamel et al. (1987a, pp. 531-532) attributed the inconsistency in the stability results between their study and that of Pinches et al. (1973) to one the following reasons: (1) the differences in time periods covered by the two studies; (2) differences in the institutional and economic conditions of firms in the UK and US; (3) the presence of more outliers in UK data in Ezzamel et al. (1987a) compared to data used in Pinches et al. (1973); (4) the issue of data transformation, and/or (5) the use of different sampling procedures. While the possible effects of the first three methods were not checked by Ezzamel et al. (1987a), they again defended their decision to use untransformed data by stating that researchers and decision makers rely on ratios in raw rather than transformed form, as well as citing the current state of disagreement regarding the choice of correct transformation method. This means that Ezzamel et al. (1987a) were only able to check whether the use of a different sampling procedure had an effect on the results they reported.

To check whether sampling procedures had an impact on the results, Ezzamel et al. (1987a) performed FA using the second sample that contained firms with complete observations in all three years of the study (842 firms). The analysis was performed on a yearly basis and resulted in 11 factors that accounted for over 80% of the variance in the data. However, to compare the results with those of the first population, Ezzamel et al. (1987a) extracted only 10 factors which accounted on average for 78% of the variance in the data. This was higher than the percentage of variance accounted for by the factors of the first population which allowed the sample size to vary over the years; nonetheless, the extracted factors were very similar. Interestingly, the patterns identified using the second population showed higher time series stability compared to the sample with variable number of firms (the first population). However, the stability level displayed by the factors of the UK constant sample (the second population) was still lower than that reported for the U.S. data in Pinches et al. (1973). Thus, according to Ezzamil et al. (1987a), the extent of the time stability of the classifications appeared to be dependent on the exact population of the sample analysed.

Some of the implications of Ezzamel et al. (1987a) were similar to those found in previous studies in the sense that they addressed the existence of different financial dimensions in a set of ratios that, once identified, could be utilised by the different parties interested in firms' performance. Also, by carefully choosing some ratios to represent each financial dimension, there is the possibility to reduce data without much loss of information. Yet, given the results of analysing a UK sample over different time periods, Ezzamel et al. (1987a) suggested that extending these results over different time periods and in different countries would not be a simple task.

Mear and Firth (1986) identified financial patterns using a number of accounting variables and ratios for a heterogeneous sample of listed companies in New Zealand. Interestingly, their study included the growth rates of some accounting figures rarely examined in the earlier literature; it also included a number of size variables, though these variables were not in the form of ratios. Mear and Firth (1986) chose their variables and ratios based on previous classification studies and on a review of variables used by the financial community in New Zealand; this resulted in 44 variables and ratios. These were calculated for a sample of 135 companies[43] using data for the last year available to the authors at the time (i.e. 1 November 1983)[44]. A common log transformation was applied to a number of variables to improve the distributional properties of the data; this required the elimination of firms with negative values from the sample. Consequently, the study was finally based on 114 firms.

Mear and Frith (1986) performed both FA and PCA and the results were similar so they only reported the outputs of FA[45]. Also, they used different rotation methods: varimax and quartimax orthogonal rotation methods and the promax oblique method. These methods produced very similar results so the study only reported the varimax rotated solution. Furthermore, unlike the studies reviewed so far in this chapter, Mear

[43] The sample initially included all companies listed on the New Zealand Stock Exchange whose primary activities were not in finance, the property sectors or mining.

[44] The exact year covered by the study was not explicitly mentioned but the growth rates were calculated over the four years prior to 1983.

[45] Mear and Firth did not report the particular method of FA they performed.

and Firth (1986) examined the adequacy of the FA model and reported some relevant results[46].

Mear and Firth (1986) grouped the 44 variables into seven factors that accounted for 82% of the variance in the original data[47]. The labels assigned to these factors were as follows: Profitability, Size, Activity, Solvency, Liquidity, Growth in Size, and Growth in Profits/Profitability. Amongst these factors, Mear and Firth (1986) focussed attention on the two growth factors: Growth in Size and Growth in Profits/Profitability.

This subsection is concluded with further evidence at a country level based on the paper by Pandey and Bhat (1988) using Indian data. Pandey and Bhat's study (1988) used a large sample of 612 Indian companies operating in a number of processing and manufacturing industries. Pandey and Bhat (1988) identified eleven factors: 1- Return on Investment, 2- Sales Efficiency, 3- Equity Intensiveness, 4- Short-Term Liquidity, 5- Current Asset Intensiveness, 6- Cash Position, 7- Activity, 8- Earnings Appropriation, 9- Financial Structure, 10- Interest Coverage and, 11- Long-Term Capitalisation. Furthermore, the study seemed to use some of the techniques employed by Pinches et al. (1973) and Ezzamel et al. (1987a) as it used differential-R factor analysis to assess the stability of the patterns over a long period of 20 years; it also calculated the correlation coefficients and the percentage of the absolute deviations in factor loadings over the years. The results of these methods showed that Indian financial patterns were reasonably stable in the long term.

To sum up, Ezzamel et al. (1987a), Mear and Firth (1986) and, Pandey and Bhat (1988) identified financial patterns for UK, New Zealand and Indian firms, respectively. These studies followed fairly conservative methodologies to extract factors and in time series and cross-section comparisons. Interestingly, Ezzamel et al.

[46] Checking the appropriateness of data to FA is covered in almost all the relevant text books. However, most researchers seem to take no notice of this step in the relevant classification literature. Chapter 3 (Subsection 3.3.1) gives further details in regard to this issue.

[47] Mear and Firth (1986) did not explicitly state the criterion/criteria used in deciding on the number of factors they extracted. The only statement they made in this regard was as follows (p. 50): 'An inspection of the initial factor solutions, using squared multiple correlations of the prior communality estimates, resulted in the identification of seven common factors.'

(1987a) investigated the impact of different sampling procedures on the patterns of ratios for UK firms, and they found that UK manufacturing financial patterns were unstable over time. Mear and Firth (1986) used size and growth variables and these newly-studied variables resulted in new factors being identified for a sample of New Zealand companies. Finally, Pandey and Bhat (1988) showed that financial patterns for Indian manufacturing companies appear to be stable over the long term. The review of the classification literature is continued in the following subsection which introduces studies that were conducted at a single industry level.

2.4.5 Ratio patterns on an industry level

Most of the studies that developed financial ratio patterns and measured their time series stability utilised heterogeneous samples from different industries (e.g. Pinches et al., 1973; Johnson, 1979; and Ezzamel et al., 1987a, amongst others). Manufacturing firms particularly have attracted the attention of most researchers in the classification field. It is questionable, however, whether the results of such studies can be generalised to the level of single homogeneous industries. It was showed earlier in this chapter (Subsection 2.4.3.1) that Ketz et al. (1990) looked closely at the financial patterns of seven different industries, assessed their stability in the long term, and compared them to the patterns for the whole economy excluding the industry under investigation. However, Ketz et al. (1990) did not particularly question the existence of distinctive and stable financial patterns for a homogeneous industry although the various analyses they performed could have enabled them to address this issue. Nevertheless, the question of whether distinctive stable financial patterns can be derived for a homogenous sample was addressed in the study by Cowen and Hoffer (1982).

Cowen and Hoffer (1982) extended the work of Pinches et al. (1973, 1975) in addressing the nature and stability of ratio groupings in the context of a single homogeneous industry. The crude-oil industry was chosen by the study as one in which an adequate number of firms were operating; also this industry was considered to have a high degree of homogeneity. Using Standard & Poor's COMPUSTAT tapes, Cowen and Hoffer (1982) retrieved data for 72 companies for every year between 1966 and 1975. For each of these companies in every year, 14 variables were utilised, amongst which were 13 ratios[48]. These ratios were chosen to represent the following four groups: profitability, liquidity, leverage and turnover. Cowen and Hoffer (1982) performed PCA with a varimax rotation for every year in the period, and also for a sample that combined the companies in all the years. The number of factors extracted ranged between four and five. However, Cowen and Hoffer (1982) did not report this explicitly[49], nor did they mention the criteria they used to decide on the number of factors or the amount of variance explained by the solutions. Furthermore, Cowen and Hoffer (1982) did not label the factors they identified; rather they reported the ratios with the highest loadings onto each of the factors over the years.

Cowen and Hoffer (1982) carried out a visual check of the results over the years which revealed that there was little time series stability in the factor patterns as well as some inconsistency in the loading of ratios within the factors. Furthermore, ratios did not appear to be clustered into the four pre-determined categories based on which ratios were selected. In addition, the solutions did not correspond to the seven groups identified in Pinches et al. (1973, 1975). Nevertheless, Cowen and Hoffer (1982, p. 109) noted that certain groups of ratios appeared to move together (for example: liquidity and turnover ratios, and profitability and leverage ratios); this was consistent with one finding of Pinches et al. (1975). Overall, Cowen and Hoffer (1982) noted that the financial patterns for a single, relatively homogenous industry and their time series stability did not appear to be consistent with the findings of Pinches et al. (1973, 1975), nor did the patterns correspond to the predetermined groups of ratios.

Since non-normally distributed data might have affected the outputs of PCA, Cowen and Hoffer (1982) repeated the analysis after transforming their data using a log transformation. The transformation approach they followed was formed in such a way that normalised all values as positive and reduced the effects of outliers while the relative positions of firm ratios remained unchanged. Factor loadings resulting from using transformed data showed more consistency during some particular sub-periods;

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[48] The variable list consisted of 13 Dunn and Bradstreet ratios in addition to the Total Assets figure which was included in the data as a size variable (Cowen and Hoffer, 1982, pp. 106-107).
[49] This was noted after looking at the table of results in the study (Cowen and Hoffer, 1982, p. 108).

however, instability was still evident for all the years. In addition, results from the transformed data did not support the existence of the four pre-determined ratio groups. The time series stability of the factor patterns was also checked by assessing the size of the correlation coefficients between the factors in the adjacent years for the two datasets, raw and transformed. The results of this step supported the findings of the visual analysis.

Cowen and Hoffer (1982) also performed cluster analysis in order to determine whether consistent and stable industry subgroups exist. In cluster analysis, industry subgroups are identified based on a number of ratios so that firms in a subgroup have similar ratios while firms in other subgroups have differing ratios. Cowen and Hoffer (1982) performed the analysis using eight carefully selected ratios based on the outputs of the PCA they carried out in the first phase of the study. The transformed ratios used in cluster analysis were those that had the highest loadings onto the factors in all the years of the study and, as a set, had insignificant interrelationships amongst each other. The results showed that there were no consistent statistical groupings of firms across all the years or even within specific sub-periods. Thus, as consistent industry subgroups did not appear to exist, Cowen and Hoffer's (1982) results cast doubt on the validity of previous findings which favoured the use of industry subgroup averages when evaluating firms' performances against the use of the whole industry averages.

Overall, the findings of Cowen and Hoffer (1982) cast doubt on the validity of identifying ratio classifications on a micro basis. Their study showed that it could not be assumed that ratio groups were consistent or stable over time. Additionally, the results of cluster analysis implied that the use of industry subgroup averages as standards to which a firm's performance should be assessed were invalid and ineffective. Consequently, Cowen and Hoffer (1982) highlighted the need for more research at the industry level.

In the context of the current chapter, Cowen and Hoffer (1982) can be summarised in the two following points. First, Cowen and Hoffer's work (1982) was the first, and probably the only, study that noted the possible effect of the homogeneity of data on the outputs of FA and the stability of factors over time. Second, Cowen and Hoffer followed a conservative approach to derive their patterns; however, some reservations can be made as they failed to report the criteria they used in deciding on the number of factors to be kept. Also, they skipped the step of labelling factors, rather they carried out all the analyses by referring to these factors using the initial category of ratios that loaded onto them.

The issues raised in Cowen and Hoffer (1982) regarding the consistency and stability of financial ratio patterns at a micro industry level did not seem to attract the attention of other researchers, who carried on adding further evidence to different industry levels, with hospitals seeming to be one of the most investigated industries. These studies include: Counte et al. (1988), Cleverly and Rohleder (1985), Chu et al. (1991), Zeller et al. (1996), Zeller et al. (1997), and Watkins (2000). Also, a number of studies focused on the empirical groups of ratios for the U.S. defence industry; amongst these are Moses (1995) and a number of Master's dissertations: Bowden (1998), White (1994), and Katz (1995). Financial patterns of ratios for the Turkish construction sector were investigated by Emin Öcal et al. (2007), while financial ratios for commercial airline companies were empirically classified by Ali and Charbaji (1994). All these studies are given as examples of relevant research that has been carried out at a single industry level. We need to emphasis that the literature survey given here is not intended to be comprehensive. Rather we provide a few important facts about particular industries only[50]. For this reason, the selected studies are not reviewed in detail; however, a summary of each is given in Appendix 2.1. The following paragraphs, nevertheless, highlight some important points for each of the industries reported in Appendix 2.1.

Hospitals. Given the differences between industries, the use of specific industry financial ratios has been emphasised, especially for studies using hospital data. For example, Cleverly and Rohleder (1985), Chu et al. (1991), Zeller et al. (1996), and Watkins (2000) all used specific hospital ratios. Furthermore, some studies using hospital ratios assumed that the financial characteristics/dimensions of hospitals (i.e.

[50] Studies carried out within the banking industry are reviewed in a separate section (Subsection 2.6) given their significance to the current study.

the ratio factors or components) were either correlated or non-correlated. For instance, Cleverly and Rohleder (1985) assumed the dimensions to be uncorrelated whereas Counte et al. (1988) and Zeller et al. (1996) assumed them to be correlated. Based on the assumption of correlated or non-correlated characteristics, the appropriate rotation method (orthogonal or oblique) was chosen. Such an assumption was not normally made by the studies reviewed earlier in this chapter; the focus in these studies was simply on the rotation method used without much attention being paid to whether the dimensions were believed to be independent or dependent. Furthermore, the ownership type of hospitals, hospitals' mission and location were all taken into account when the financial patterns of hospital ratios were identified in Zeller et al. (1996). This is an interesting point as Zeller et al. (1996) appeared to be probably the only study that considered the impact of these traits upon the patterns of ratios. Another point, which can be added here with regard to Zeller et al. (1996), is that this study checked the consistency of loadings of the different ratios across the different categories of hospitals using correlation coefficients. Zeller et al. (1996) computed the correlation coefficients between the ratios (not the factors) using ratio loadings onto the factors in the different hospital categories. This is different from previous studies which assessed the stability of factors by calculating the correlation coefficients between the factors using loadings of all variables (see Pinches et al., 1975, p. 300 as an example). Another point, which can be added here relating to Zeller et al. (1996), is that the researchers appeared to mistake factor scores for factor loadings[51]. Last but not least, Watkins (2000) analysed non-accounting information besides financial ratios in order to study the characteristics of hospitals' performance. Similar research does not seem to have been carried out for any other industry.

Defence industry. Two main points can be made with regard to studies conducted on the defence industry. Firstly, Moses (1995, p. 11) and Bowden (1998, p. 31) used rank transformation as a means to deal with skewness and extreme values in the datasets. In rank transformation, ratio values were set in an ascending order and given scales starting at 1 for the smallest value; the ordinal ranks were then normalised.

[51] Factor scores are different from factor loadings. A variable loading onto a factor is the correlation between this variable and the factor. However, the factor score is calculated for every case/company and results from multiplying the loadings of each variable by the value of this variable for that company and adding up the results.

Thus, the initial relative order for values was maintained; also, extreme values were dealt with without having to remove any value. However, White (1994, p. 25) chose to eliminate some outlying values rather than to transform the data. Secondly, most of these studies seemed to combine the observations into one sample over the given period of time. It also appeared to be usual in these studies to divide the period into sub-periods and compare the results in order to check for time series stability in the identified patterns. A similar approach was used by Yli-Olli and Virtanen (1989), and Devine and Seaton (1995), as mentioned in Subsection 2.4.2. Also, some studies used first differences in ratio values in order to measure the primary dimensions of change in financial conditions [see Yli-Olli and Virtanen (1989) in Subsection 2.4.3.2 which also used first differences in the data.]

Construction. Emin Öcal et al. (2007) utilised factor scores, averaged over all companies, to check for time series stability of each group of ratios. In previous literature, however, the time series stability of financial patterns and the trends of ratios were investigated using correlation and congruency coefficients of factor loadings, and transformation analysis (Subsection 2.4.2).

Commercial airlines. Ali and Charbaji (1994) followed a fairly conservative approach to identify the classifications of ratios for commercial airline companies. They successfully uncovered differences between patterns for airline firms and for manufacturing and retail firms. Also, their results provided further evidence concerning differences between the *ad hoc* and empirical classifications of ratios.

To sum up, the results of Cowen and Hoffer (1982) cast doubt on the existence and stability of financial patterns of ratios for a single industry. Although exhaustive research has been conducted to identify the empirical groups of ratios for many single industries (Appendix 2.1), none of these studies actually attempted to test whether the findings of Cowen and Hoffer (1982) can be generalised. These studies, however, seemed to investigate which financial patterns can characterise an industry rather than questioning the existence and consistency of these patterns at the level of a homogeneous industry. Nevertheless, more questions regarding the classification patterns of ratios were raised by other studies; these are reviewed in the following subsection.

2.4.6 Classification patterns of ratios identified in conjunction with different research issues

Categorising financial ratios and checking the cross-sectional and time series stability of the identified groups forms only a part of the relevant literature. Besides this 'classical' literature, a number of studies have raised issues in regard to classification patterns of ratios. For example, a number of studies added new ratios to the 'typical' sets of ratios used in empirical work and also considered whether new classifications could be identified. Amongst these, the study of Gombola and Ketz (1983a) examined the impact of new definitions of cash flows on the classifications of ratios while Zeller and Stanko (1994) were interested in cash flow ratio groupings for retail firms. Add to this is Salmi et al. (1990), which included a number of market-based variables in their dataset. Also, the literature was extended by Short (1980) who checked whether price-level adjusted ratios could be grouped in a similar manner to historical cost based ratios. Moreover, a number of studies considered the classification patterns of ratios in conjunction with other research issues such as the length of operating cycles, failure prediction, ratio distribution, proportionality assumption, and stock returns. These studies are: Jensen and Ketz (1987), Martikainen (1991), Martikainen et al. (1995a), Kallunki et al. (1996) and, Martikainen (1993), respectively.

Price-level adjusted ratios

Short (1980) questioned whether the use of alternatives to historical cost accounting might cause a change in the classification of ratios[52]. Therefore, Short (1980) identified the financial patterns for a set of 36 ratios in terms of historical and price-level adjusted cost. He used a sample of 259 COMPUSTAT firms in the year 1972.

[52] Note that a substantial part of Short (1980) is reported in an earlier study by Short (1978); nevertheless, Short (1980) appears more relevant to the purposes of the current chapter. Short (1978) performed FA using 'historical' and 'price-level' ratios. One ratio was selected to represent each of the identified factors; these ratios were then used as inputs to regression models built to investigate the relationship between market risk and accounting data. Also, Short (1978) computed factor scores and used them in his regression models.

The ratios were subjected to natural log and square root transformation to improve the approximation to normality. He then carried out the analyses using both transformed and untransformed data: all yielded similar results. FA was performed using both orthogonal and oblique rotation methods; both methods resulted in essentially the same factor solutions. By retaining factors whose eigenvalue was greater than unity, seven factors were kept for both historical and price-level data. These were: (1) Return, (2) Capital Intensiveness, (3) Asset Turnover, (4) Financing Policy, (5) Inventory Turnover, (6) Working Capital, (7) Current Position (for historical cost ratios)/ Cash position (for price-level adjusted data).

Short (1980) found that the groupings of ratios for the historical and price-level data were similar. This conclusion was reached after conducting visual comparisons and also by studying the residual matrix which was calculated using the Schonoemann and Carroll technique. Short (1980, p. 379 and p. 388) briefly explained that the price-level factor solution was rotated until it became as similar as possible to the historical cost accounting factor solution. The two factor matrices were then subtracted from each other resulting in the residual matrix. By assessing the size of the elements of the residual matrix, it was possible to identify the ratios that caused a change in the factor structure. The Schonoemann and Carroll technique is very similar to the more traditionally used transformation analysis; yet, Short (1980) is probably the only study which has utilised this method. Based on Short's (1980) sample, inflation adjustments did not seem to cause a change to the classification of ratios; this meant that the interrelationships amongst ratios did not change when price-level adjusted data were employed. Nevertheless, Short (1980) suggested his analysis should be replicated for periods with higher inflation rates as this could alter the results. In particular, the Return factor is probably the most affected by higher rates of inflation.

Cash flow ratios

An extension of Short (1980) was offered by Gombola and Ketz (1983a). This extension was two-fold as Gombola and Ketz (1983a) covered many years with varying inflation rates, as well as employing differently defined cash flow ratios. Gombola and Ketz (1983a) noted that previous literature (mainly Pinches et al., 1973 and Johnson, 1978) defined cash flow as net income plus depreciation and found cash flow ratios to be associated with return/profitability ratios. Thus, in their study, Gombola and Ketz (1983a) employed a different measurement of cash flow by adjusting net income for all accruals and deferrals. They also checked whether this would result in a further cash flow factor besides the seven factors identified in earlier studies.

Gombola and Ketz (1983a) used every industrial company on the COMPUSTAT tape and this provided enough data to compute 40 ratios on three levels: historical cost (HC), general price level (GPL) with purchasing power gains and losses not included in income, and GPL with purchasing power gains and losses included in income. The results were based on 119 firms. For every year between 1962 and 1980, FA with a varimax rotation was performed using ratios computed on the three levels and this resulted in a total of 57 analyses. The results of these analyses were compared cross-sectionally between HC and GPL solutions, and over time. To aid the comparison, congruency coefficients were calculated and assessed.

By keeping factors with eigenvalues greater than unity, Gombola and Ketz (1983a) extracted eight factors in the majority of the years using HC and GPL data. Seven of these factors were similar to those found by Pinches et al. (1973), Johnson (1979) and Short (1978)[53]. The eighth factor was formed by cash flow ratios which did not associate with profitability ratios. Very similar results were also obtained using GPL ratios whether or not gains and losses from changes in purchasing power were included in the calculation of income.

It was noted that Gombola and Ketz (1983a), as with Gombola and Ketz (1983b) reviewed in Subsection 2.4.3.1, did not report certain statistics relevant to the application of FA. The focus in Gombola and Ketz (1983a) was rather on whether cash flow ratios would cluster together separate from other ratios and whether this would hold over time, and for both GPL and HC data.

[53] See footnote 52.

Length of operating cycles

Following Gombola and Ketz (1983a, 1983b) who analysed a number of cash flow ratios, Jensen and Ketz (1987) observed that the length of the operating cycles, which might have an effect on the classification of cash flow ratios, was not considered in these two studies. Thus, Jensen and Ketz (1987) questioned whether asset flow measures could be grouped in a similar manner for firms with short and long operating cycles[54]. They used seven asset flow measures[55] normalised by sales, common equity and total assets. These formed 21 ratios, all of which were available for 674 industrial firms on the COMPUSTAT file for every year in the period between 1974 and 1981. Operating cycles were calculated for all firms and two subsamples were extracted from the major sample: one contained firms with the shortest operating cycles and the other subsample included firms with the longest operating cycles. For every year in the period, Jenson and Ketz (1987) performed FA with a varimax rotation using the full sample and the two subsamples with different operating cycles.

For all the years covered by Jensen and Ketz (1987), asset flow measures for the all-firm sample were grouped into four factors; this was consistent with the findings of Gombola and Ketz (1983a, 1983b). These factors were: Asset Flow measure to Sales, Return on Assets, Return on Common Equity, and Cash Flow. The results for firms with the long operating cycles were similar to these which meant that cash flow measures for these firms were distinct from other dimensions. However, for the sample of firms with short operating cycles, a separate Cash Flow factor was found for only half of the years studied. The final finding implied that the interrelationships amongst asset flow measures were unstable for the short operating cycle group. Nevertheless, given the findings of Jenson and Ketz (1987), both Return and Cash Flows should be investigated for firms with short operating cycles, even though this could be redundant in some years as the study showed.

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[54] Operating cycle is obtained by adding up the number of days to sell inventory (which equals 360 days divided by average inventory turnover) and the days sales in receivables (which equals 360 days divided by the average accounts receivable turnover), (Jensen and Ketz, 1987, p. 3).

[55] These measures were: net income, net income plus depreciation, operating net income, operating net income plus depreciation, working capital from operations, quick flow from operations, and cash flow from operations (Gombola and Ketz, 1983b, p. 2).

Ratio classifications and cash flow literature were further enriched by a study carried out by Zeller and Stanko (1994). Their study targeted retail firms and was mainly interested in whether operating cash flow ratios measure a distinct or redundant dimension of a retail firm's performance. By addressing this question, financial analysts could be advised on whether or not to include cash flow ratios besides accrual-based ratios when analysing the performance of retail firms.

Zeller and Stanko (1994) used a list of 34 ratios, the majority of which were drawn from Ketz et al. (1990). Most importantly, the list contained a number of 'newly-derived' operating cash flow ratios besides what were described as the 'traditional' operating cash flow ratios. The list of ratios was calculated for over 200 retail firms on the COMPUSTAT file for every year in the period 1988-1991. FA with a promax rotation[56] was performed on a yearly-basis, and three criteria were used to decide on the number of factors to retain: eigenvalue greater than unity, scree plot and the interpretability of factors. Given the results of the yearly analyses, the operating cash flow ratios appeared to measure a unique and stable dimension of retail firms' performance. This dimension represented the firms' 'ability to pay' and should not be ignored when retail firms' performance is analysed.

Markets

Whilst relatively little evidence has been assembled on the classification of cash flow ratios, Salmi et al. (1990) noted that market-based ratios had not yet been investigated in the context of ratio classifications. Given this, Salmi et al. (1990) examined the classification patterns for three types of ratio: accrual, cash flow and market-based ratios. Their sample consisted of 32 publicly traded Finnish companies for the period 1974-1984. For each of these firms in every year, 28 carefully selected ratios were calculated. Equal-weighted averages were calculated for each ratio in each year. To identify the factors, Salmi et al. (1990) performed PCA with a varimax rotation and decided on the number of factors by examining the scree plot. This resulted in their retaining 10 factors. To examine the stability of these factors over the period, the

[56] Promax rotation was performed because Zeller and Stanki (1994, p. 7) believed that firms' characteristics are not independent of each other.

analysis was repeated for two sub-periods: 1974-1978 and 1979-1984. Transformation analysis was performed between the resulting solutions.

By following a hypothesis-testing methodology, the overall results of Salmi et al. (1990) can be reported as follows. Firstly, Salmi et al. (1990) hypothesised that market-based ratios would load onto a factor accounting for return and riskiness. The results did not support this hypothesis as market-based ratios loaded broadly onto different factors and not onto a distinct factor. Interestingly, however, the size variable and market-based beta together formed a stable factor which, according to Salmi et al. (1990), was consistent with earlier research that suggested the interdependence of firm size and security betas. Secondly, the profitability and operational leverage factors were amongst the accrual-related stable factors. This, to some extent, confirmed the second hypothesis that a firm's activities can be characterised by two dimensions: dynamic performance and static financial standing. Thirdly, cash flow ratios loaded, as hypothesised, onto a stable factor of their own. Finally, Salmi et al. (1990) hypothesised the existence of factors that represent the four traditional classifications of ratios: solvency, profitability, liquidity and turnover. However, empirical results did not fully support this hypothesis. Last but not least, the content of the dynamic liquidity factor was of some interest as it was formed by the defensive interval measure and accounts receivable. Also, the significance of growth estimates in financial analysis was emphasised by the fact that growth and operating margin formed a distinct stable factor in Salmi et al.'s (1990) empirical analysis.

Market variables were also of some interest to Martikainen (1993) who noted that studies that investigated the empirical classification of financial ratios were not linked to stock markets. Given this, Martikainen (1993) investigated the relationship between the empirical classifications of firm-specific financial variables and stock returns. Eleven ratios were chosen for the study which came from four traditional categories of a firm's performance: profitability, financial leverage, operating leverage and corporate growth. Previous research had linked each of these categories individually with stock market-based variables. Martikainen's (1993) sample consisted of 28 firms which had their common (ordinary) shares listed in the Helsinki

Stock Exchange for the period between 1975 and 1986. To enhance normality in the distributions of the ratios, outliers were identified and deleted; also, a square root transformation was applied to some ratios. Stock returns were determined as changes in the logarithmic price indices.

The whole period covered in Martikainen (1993) was divided into four sub-periods of similar length: 1975-1977, 1978-1980, 1981-1983 and 1984-1986. For each of these periods, a separate PCA with a varimax rotation was performed; a promax oblique rotation was also performed and similar results were obtained. Based on the interpretability of factors, Martikainen (1993) kept three factors for each of the sub-periods: Profitability, Leverage (operating and financial), and Growth. Transformation analysis was then performed to measure similarity in the identified factors over the sub-periods. Following this, and to establish the link between firms' financial characteristics and stock returns, Martikainen (1993) computed the factor scores for each of the four sub-periods and calculated the correlation coefficients between factor scores and stock returns. The highest correlation coefficients were found between factor scores of Leverage and stock returns, which meant that this factor appeared to be the most important one in explaining stock returns. Then, Martikainen (1993) checked whether any single ratio had incremental information content in explaining stock returns. This was implemented using regression analysis in which the most important factor in explaining stock returns was used and the resulting residual term represents the amount of stock return not explained by the significant factor. This error term was then correlated with each of the financial ratios in the sub-periods in order to assess which ratio could explain this part of the return. However, none of the ratios were found to have significant correlations with the residuals.

Furthermore, Martikainen (1993) repeated the analysis after removing trading and transport firms from the sample, thereby keeping only industrial firms. Correlation coefficients between factor scores and stock returns indicated the importance of the Profitability factor in explaining stock returns whereas the Leverage factor appeared to be less important. Also, none of the ratios appeared to have incremental information that could explain the part of the stock returns that was not explained by the most significant factor.

Failed firms

The majority of studies reviewed so far in this chapter identified the classification patterns of ratios using data from healthy firms. However, in previous subsections (2.4.2 and 2.4.3), two studies by Martikainen et al. (1995b, 1994) used samples that combined data for failed and non-failed firms. The two studies, however, did not intend to compare the patterns between failed and non-failed companies. Rather, they investigated other issues loosely related to bankruptcy prediction such as the use of industry relative ratios (IRRs) and the effects of industry on the patterns of ratios. Nevertheless, Martikainen and Ankelo (1991), based on previous relevant literature, assumed the financial patterns for failed firms to be unstable in the period prior to failure and so sought to provide empirical evidence in this regard.

Martikainen and Ankelo (1991) used data from 40 small- and medium-sized Finnish firms divided into two samples of similar size: one consisted of failed firms and the other of non-failed firms. The two types of firm were matched in terms of size and industry. Also, the study used 12 ratios representing the four *a priori* classifications of Lev (1974): profitability, liquidity, financial leverage and efficiency. These ratios were calculated for each of the two samples for every year in a five-year period prior to failure. PCA with a varimax rotation was performed on a yearly basis for the two samples. Martikainen and Ankelo (1991) extracted four-factor solutions for each of the analyses based on *a priori* knowledge of the dimensions that existed in the data, and on the eigenvalue criterion. Then, they performed transformation analysis to assess the stability of the solutions for each sample over the five-year period; the stability level was compared between failed and non-failed firms.

Martikainen and Ankelo (1991) reported clear evidence of the instability of the classification of ratios for firms prior to failure when compared to non-failed firms. In other words, their results indicated that the level of change in the empirical interpretation of ratios was higher for failed firms compared to their non-failed counterparts. Thus, Martikainen and Ankelo (1991) recommended that these findings should be taken into account in future research when building bankruptcy prediction models using financial ratios for failed firms since the interpretation of these ratios becomes problematic as failure approaches. However, the sample in Martikainen and Ankelo (1991) was probably the smallest sample used in the literature concerning the classification patterns of ratios. Using a significant sample size in order to obtain results that are not sample specific is emphasised in many books on factor analysis. Given this, the findings of Martikainen and Ankelo (1991) should thus be viewed with caution until the analysis has been repeated using a larger dataset.

The last two papers reviewed in this subsection deal with two properties of financial ratios namely: ratio distributions and the proportionality assumption.

Distributional properties

Many researchers in the field of the classification of financial ratios are apprehensive about using data which deviate from the normal distribution. For this reason, they normally employ different transformation methods to help with convergence towards the normal distribution. Some such studies are Pinches et al. (1973, 1975), Jonson (1978, 1979), and Mear and Firth (1986), amongst others. On the other hand, some researchers are comfortable when using non-normally distributed data. This is either because there is no consensus regarding the most appropriate transformation method (Ezzamil et al., 1987a) or because they believe that FA is robust with regard to non-normally distributed data (Devine and Seaton, 1995). Until Martikainen et al.'s (1995a) study, the literature lacked a study that investigated the importance of this issue in determining financial ratio classification patterns.

Martikainen et al. (1995a) investigated the impact of the distributional irregularities of financial ratios on the empirical classifications of ratios. They used 10 ratios generated from five categories: profitability, financial leverage, liquidity, working capital and cash-flow. These ratios were calculated for all firms continuously listed on the Helsinki Stock Exchange for the period between 1974 and 1987; this resulted in 34 firms being available for the analysis. Martikainen et al. (1995a) carried out the empirical analysis in two stages. First, the distributional properties of financial ratios were investigated using the Shapiro-Wilk test for normality; a high level of non-normality in the distributions was reported for most of ratios. For these ratios, normality was restored, either by identifying and deleting outliers, or by applying a square root transformation. In the second stage, PCA was carried out for each year over the period using ratios in transformed and raw forms. Then, transformation analysis was performed to investigate the cross-sectional similarity between the factors of transformed and raw ratios and their stability over the period.

By adopting the 'eigenvalue greater than unity' criterion, Martikainen et al. (1995a) identified four factors for both forms of ratio in every year covered by the study. A visual inspection showed some difference in the way in which raw and transformed ratios were classified; the results of transformation analysis confirmed this. Thus, distributional irregularities were found to have a significant impact on the classification patterns of financial ratios. Furthermore, these distributional irregularities appeared to be behind the instability of the financial patterns for the raw ratios. Thus, when transformed ratios were used, a noticeable decrease in the time series instability of the patterns was reported. Nevertheless, the relatively small sample size used in the study has to be acknowledged; for this reason, Martikainen et al. (1995a) suggested repeating the analysis using bigger samples.

The proportionality assumption

This subsection concludes with a consideration of the work of Kallunki et al. (1996) who integrated tests of the proportionality assumption with research based on the classifications of financial ratios[57]. The key concern of the paper was to check whether a departure from proportionality lead to considerably different classifications of financial ratios. Kallunki et al. (1996) studied 10 financial ratios representing the following five categories: profitability, financial leverage, liquidity, working capital

[57] When financial items are divided by common bases like firms' sales and total assets, comparisons over time or across firms can be made as financial ratios will then control for the effects of size. However, this requires that the proportionality assumption holds. A ratio is proportional when the relationship between its components (i.e. numerator and denominator) is linear and the constant term is zero (Kallunki et al., 1996, p. 535). The literature of financial ratios includes a number of studies which are devoted to the proportionality assumption: for example, Lev and Sunder (1979), Fieldsend et al. (1987), Trigueiros (1997), Sundarsanam and Taffler (1995), and others. Discussions on ratio proportionality raised the issue of the validity of the ratio method; this led some researchers to debate whether regression analysis, as compared with ratio analysis, could provide more powerful results. Amongst these studies are: Whittington (1980), McDonald and Morris (1984, 1985), Barnes (1986), and Berry and Nix (1991).

and cash flow. These ratios were calculated for a sample of 34 listed Finnish companies for every year in the period 1980 to 1987.

The empirical work was carried out in two stages: first, Kallunki et al. (1996) tested whether the proportionality assumption held for these ratios for every year over the period. This was done by estimating two regression models: one used financial items whilst the other used these items but in a ratio form. With some exceptions, Kallunki et al. (1996) found that the proportionality assumption held well for the model that used ratios. Given these exceptions, they then checked whether the observed deviation from proportionality would lead to different patterns of ratios. So, in the second stage, Kallunki et al. (1996) employed unrotated PCA on a yearly basis to derive the factor patterns of financial ratios, and of the residuals of the regression model that used ratios. Using the eigenvalue criterion, solutions of four factors were extracted for both ratios and residuals; these solutions accounted for very high percentages of the variance in the data. In order to check the similarity of these solutions, transformation analysis was then performed. The empirical classification results were very similar for the patterns of ratios and residuals. Thus, according to Kallunki et al. (1996), decision makers would reach similar conclusions concerning the financial patterns of firms irrespective of whether they used ratios or regression techniques. Given the simplicity of the ratio method, Kallunki et al. (1996) favoured this approach. However, they counselled that the validity of the ratio method might differ between ratios given that the proportionality assumption might not hold well for certain ratios.

In summary, this subsection reviewed studies that examined different issues in the context of ratio classification patterns. As shown above, Short (1980) found that using ratios adjusted for inflation did not have much of an impact on the ratio characteristics of a firm. These results were then confirmed by Gombola and Ketz (1983a) who added further evidence regarding the existence of a cash flow dimension of performance. Jensen and Ketz (1987) found that this cash flow factor might not be separate from profitability ratios for firms with short operating cycles. Zeller and Stanko (1994) were interested in cash flow ratio classifications for retail firms and found that these ratios formed a unique dimension for retail firms which described the retail firms' 'ability to pay'. Furthermore, Salmi et al. (1990) investigated the classifications of market-based ratios; unexpectedly though, these ratios did not form a unique factor. Regarding the relationships between ratio classifications and stock returns, Martikainen (1993) found that the Leverage factor was very significant in predicting stock returns for a cross-industry sample; yet, for a less heterogeneous sample, the Profitability factor was more significant in relation to stock returns. In regard to the stability of financial patterns for failed firms, Martikainen and Ankelo (1991) found these patterns to be highly unstable compared to the patterns of non-failed firms. The subsection also presented the study of Martikainen et al. (1995a) which found that ratio distributional irregularities were behind the instability of ratio patterns. When normality was restored to the distributions, a stable solution was reported. Finally, Kallunki et al. (1996) found that residuals of a regression model that used financial ratios were classified in a similar manner to financial ratios. Yet, Kallunki et al. (1996) were in favour of the use of the ratio method approach compared to the regression analysis approach because of its simplicity.

Studies reviewed in the chapter so far have demonstrated how financial ratios would be classified and how certain issues would affect these classifications. The issues covered included the impact of time, industry, country and new definitions of ratios, amongst other issues. Most of the research reviewed above was driven by one objective: to summarise a large number of ratios by using a smaller, manageable set of factors or ratios without losing much of the information provided in the original set of ratios. The following subsection illustrates a selection of broad applications of factor analysis as a data reduction technique in finance-related research.

2.4.7 The use of factor analysis in different research areas in finance

The studies reviewed so far in this chapter employed FA as a technique to achieve an empirical classification of financial ratios. In line with these studies, a substantial volume of finance literature has utilised FA regarding financial ratios as an intermediary procedure to screen data prior to performing further analysis. Further analysis in this sense has often included event prediction, such as bankruptcy/distress, merger and acquisition, bond ratings, and credit scoring. It has also included analysing firms' characteristics and performance, and assessing market risk.

This subsection aims to address and evaluate the approach used in a number of studies in which the technique of FA was utilised as a part of, but not as the ultimate, methodology. To represent this literature, 24 studies in the field of finance were selected from different publications over a time span from 1973 until recently. The list of the chosen studies is not comprehensive as the purpose is to acknowledge this part of the literature rather than to conduct an exhaustive survey. The selected 24 studies and their particular research area are as follows. From the bankruptcy prediction literature, the following studies were chosen: Libby (1975), Taffler (1981, 1982 and 1983), Richardson and Davidson (1984), Laitinen (1991), Ganesalingam and Kumar (2001), Skogsvik (1990), Gombola et al. (1987), El Hennawy and Morris (1983), and Mensah (1983). The literature that evaluates firms' performance and characteristics is represented by the following studies: Taffler and Sudarsanam (1980), Schatzberg and Weeks (2004), Meric and Meric (1994), Hutchinson et al. (1988) and, Ritchie and Kolodinsky (2003). Market risk literature is represented by Elgers (1980) and Melicher (1974) while corporate acquisition literature is exemplified by: Stevens (1973), Barnes (1990), Zankis and Zopounidis (1997) and Sorensen (2000). Last but not least, literature concerning prediction of bond rating and credit scoring is represented by Pinches and Mingo (1973) and Emel et al. (2003), respectively.

Relevant details regarding the application of FA in these studies are summarised in Appendix 2.2. The following paragraphs, however, summarise a number of key issues extracted from Appendix 2.2.

As mentioned earlier, a number of research issues were investigated in the 24 studies summarised in Appendix 2.2. However, these studies appear to use similar statistical techniques to answer the research questions of interest. Amongst these techniques, multiple discriminant analysis (MDA) was often utilised given its popularity and usefulness in event prediction research. Amongst the studies that used MDA are Taffler (1981), El Hennawy and Morris (1983), Richardson and Davidson (1984), Barnes (1990), Pinches and Mingo (1973), and Stevens (1973). Logistic regression analysis (logit) was also utilised in a number of prediction studies, amongst which are: Mensah (1983), Schatzberg and Weeks (2004), and Sorensen (2000). Univariate and multivariate analysis of variance (ANOVA) was used to compare the characteristics of firms in Meric and Meric (1994), Sorensen (2000), and Hutchinson et al. (1988). Also, it can be seen from Appendix 2.2 that two studies only, those of Taffler and Sudarsanam (1980) and Ritchie and Kolodinsky (2003), performed FA as the sole technique to answer their research question: to identify the important characteristics of a particular type of firm.

As is known, multicollinearity among variables can cause serious problems in regression approaches so reducing the degree of multicollinearity appears to be the main reason for using FA in the prediction studies summarised in Appendix 2.2. As a means of dealing with the problem of collinearity, either factor scores were calculated and used as inputs to the advanced statistical techniques, or, representative ratios, often those with the highest factor loadings, were chosen from each of the identified factors and used to carry out the empirical analysis. For example, Laitinen (1991), and Schatzberg and Weeks (2004) were amongst the studies that used factor scores, whereas the studies of Gombola et al. (1987), Barnes (1990), and Pinches and Mingo (1973) utilised the results of FA to select a parsimonious set of ratios on which they based their empirical work. So, the widespread use of FA in the finance literature can be generally attributed to the effectiveness of this multivariate technique in dealing with the problem of multicollinearity amongst financial variables. What is of further interest to this chapter, however, is the way in which FA has been applied in finance and whether this differs in any sense from the application of FA as a classification technique when compared to the studies reviewed earlier in this section. This can be answered by shedding light on the third and fourth columns in Appendix 2.2; these describe the data, application and results of FA in the 24 studies.

First, with regard to the samples used in the different studies in Appendix 2.2, the selection of ratios to be factor analysed was based on, either some *a priori* classifications [El Hennawy and Morris (1983) and Elgers (1980), amongst others], or on previous related literature (Gombola et al., 1987), or on popularity in the field

(Schatzberg and Weeks, 2004). Also, in a number of studies, the financial ratios were subjected to some type of data transformation and outliers were treated as attempts to improve the distributional properties of the ratios prior to performing FA and other statistical techniques. Amongst these studies are: El Hennawy and Morris (1983), and Taffler and Sudarsanam (1980). Furthermore, it is apparent from Appendix 2.2 that the number of ratios used to perform FA varied vastly amongst the 24 studies. Whilst only 5 ratios were used in Rinchardson and Davidson (1984), other studies, such as those of Taffler (1981, 1982, 1983), used much larger sets of 80 ratios on which they ran FA.

With regard to whether FA was performed based on cross-sectional or time series data, it can be noticed that most of the studies reported in Appendix 2.2 obtained data for different years and combined them into one sample on which they performed FA. In other words, data were often retrieved for a period of time that exceeded one year; this period generally commenced a couple of years prior to the event under investigation [see, for example, Huchinson et al. (1988), and Zankis and Zopounidis (1997), amongst others]. However, a smaller number of studies in Appendix 2.2 performed FA on a yearly basis and assessed the yearly results to use them in further empirical work [e.g. Gombola et al. (1987), El Hennawy and Morris (1983), and Richardson and Davidson (1984)].

Studies summarised in Appendix 2.2 generally focused on industrial firms[58] and used samples of different sizes. In most of the studies, a sufficient number of firms were used for every ratio which was employed; this satisfied the sample size requirement in FA (a minimum of 5 firms for every ratio used, according to Hair et al., 1998, pp. 98-99). However, it can be noted in Appendix 2.2 that studies which aimed to predict a particular event, tended to combine different types of firm into the sample subjected to FA, such as acquired and acquiring firms (Zankis and Zopounidis, 1997), or failed and non-failed firms (Ganesalingam and Kumar, 2001). However, in studies interested in identifying the characteristics of firms, the samples used included firms representing the particular population of interest to these studies [Taffler and Sunarsanam (1980) and Meric and Meric (1994)].

[58] Studies that used banking samples are introduced separately in Section 2.6.

Furthermore, the terms FA and PCA were often interchangeably used in the studies reported in Appendix 2.2. Also, the number of factors retained for further analysis in these studies was often decided using the criterion of eigenvalue in excess of unity (some studies referred to this criterion as Kaiser's rule). Varimax orthogonal rotation appeared to be the preferred method of rotation, especially when FA was performed to reduce multicollinearity amongst the chosen financial ratios. This is because, as mentioned earlier, orthogonal rotations produce uncorrelated factors or factors that are independent of each other. Thus, when these factors are used in further statistical analysis (either in the form of factor scores, or when a parsimonious set of ratios with the highest loadings onto each of the factors are used), the correlation amongst these variables is expected to be at a minimum; thus, the multicollinearity problem is, hopefully, resolved.

Last but not least, Appendix 2.2 shows that different factor solutions covering various aspects of firm operation were identified; in the majority of the studies, these factors were assigned suitable names. However, factors identified in one study are not expected to resemble the factors found in others reported in this or in the previous subsections. This is because, giving definite assessments regarding the similarity among the different studies of the derived factors would require detailed investigations of the ratio contents of the factors amongst other issues, which is beyond the scope of our study. A final note to add with regard to the studies summarised in Appendix 2.2 is that the majority of these studies did not report the percentage of variance explained by the identified factor solutions. This, however, appeared to be of greater importance in the studies reviewed in the previous subsections which tended to report the percentage of variance accounted for by derived factor solutions as a way to show how effective these solutions were in summarising data without much loss of information contained in the initial larger dataset.

To sum up, this subsection briefly highlighted the application of FA in a selected group of studies in finance for purposes other than finding the empirical classifications of financial ratios and testing their stability. The paragraphs above showed that FA was the preferred technique for addressing the multicollinearity problem amongst financial ratios, either by utilising factor scores or by using only ratios with the highest factor loadings in further empirical analysis. The studies summarised in Appendix 2.2 used different sets of ratios, covered different periods, and included various sample sizes. These studies largely used the eigenvalue criterion and the varimax rotation method to achieve final factor solutions. The results produced different numbers of factors and thus, vastly different factor labels and different factor contents were not unusual in these studies. In short, the summary of the empirical literature given here appears to be in line with the findings of studies reported earlier in this chapter.

Summary of Section 2.4

Section 2.4 is one of the core sections in the proposed study. This section summarised the most important studies that used PCA/FA as a means to develop empirical classifications of financial ratios. This literature was grouped under a number of sub-headings, such as ratio usefulness and efficiency, time stability, cross-sectional stability, ratio classifications on a country level, ratio classifications on an industry level, ratio classifications in conjunction with other research areas, and finally, the use of ratio classifications identified by PCA/FA as a data screening procedure prior to performing other statistical techniques. Section 2.5 considers a number of ratio classification studies that have used techniques other than PCA/FA, whereas Section 2.6 offers empirical evidence regarding the classifications of banks' financial ratios.

2.5 Empirical classification of financial ratios: the use of techniques other than PCA/FA

The studies reviewed under this section employed techniques other than PCA/FA to investigate the patterns or sets of financial ratios. Amongst these are some multivariate statistical techniques, such as canonical analysis used in Polhman and Hollinger (1981), and confirmatory factor analysis (CFA) employed by Kanto and Martikainen (1990, 1992), Martikainen et al. (1997), Chen and Olinsky (2006) and Raymond and St-Pierre (2007). Also, some studies used questionnaires to explore certain related issues, amongst which are Gibson (1982) and Shivaswamy et al. (1993).

Studies into the classification patterns of financial ratios were all driven by the objective of identifying a parsimonious set of ratios sufficient to account for much of the information offered by a large set of ratios. However, the question is: to what extent does each of the ratio groups contain unique information that is not provided by the other groups? Answering this question was the aim of Polhman and Hollinger (1981) who used canonical correlation analysis and redundancy indices. Canonical analysis was used as it is the most appropriate technique to find overlapping information in two sets of variables. Polhman and Hollinger (1981) then used the outputs of the canonical analysis to calculate the redundancy indices that show the amount of information redundant in one set of variables given the information provided by another set. Using COMPUSTAT data for 384 firms, Polhman and Hollinger (1981) tested two classification schemes: the traditional one that groups ratios into four categories: liquidity, leverage, activity and profitability; and the empirical scheme identified in Pinches et al. (1975) that grouped ratios into seven groups[59]. Polhman and Hollinger's (1981) results indicated that Pinches' (1975) dimensions were not in fact seven 'distinct' sets of information. In other words, the information provided by one group was not necessarily restricted to this group; some redundancy was evident. The results of testing the traditional four groups of ratios also revealed some redundancy in the information provided by each of these groups. In other words, Polhman and Hollinger (1981) found that a group of ratios that measures a particular aspect of performance does not only contain unique information regarding this aspect but also contains information about other aspects. Thus, financial analysts cannot really rely on one category of ratios to cover a certain aspect of performance as this set of ratios would not provide all the information needed regarding this aspect; thus, this would lead them to draw wrong conclusions.

The ratio classification literature has been further extended by a number of relatively recent studies that have utilised the technique of CFA[60]. Rather than trying to find the

[59] Pinches et al. (1975) is reviewed in Subsection 2.4.2.
[60] Chapter 3 (Subsection 3.2.2.4) summarises the main differences between PCA/FA and CFA.

empirical patterns of ratios, studies that used CFA aimed to test the empirical validity of existing (theoretical or empirical) classification schemes and to check whether such schemes could provide a good fit to the empirical data. Most of the attention was given to Lev's (1974) traditional scheme that groups ratios under four categories: liquidity, profitability, leverage and efficiency. Amongst the studies that tested this scheme using CFA are Kanto and Martikainen (1990, 1992) which used U.S. and Finnish data, respectively. In each of the two studies, a set of 12 ratios was used: three ratios from each of the four traditional dimensions. The results of the two studies were fairly similar as they both found that the categories of ratios were interrelated; thus, both studies concluded that Lev's (1974) categorisation of ratios was poor. These results were consistent with the previous literature that suggested that the *a priori* or traditional categorisations of ratios are inadequate [Pinches et al. (1973, 1975), amongst others].

Lev's (1974) categorisation scheme was further tested in Chen and Olinsky (2006), also using CFA. Chen and Olinsky (2006) also compared Lev's (1974) scheme to another theoretical scheme developed by Koh and Killough (1990) which categorised ratios into five groups: liquidity, profitability, financial leverage, activity, and returns and market[61]. Chen and Olinsky's (2006) study used data from different industries and various measures of goodness of fit to check which of the two ratio schemes provided better levels of fit to the data. The results indicated that Koh and Killough's (1990) scheme had higher goodness of fit levels compared to Lev's (1974) scheme. Moreover, Chen and Olinsky's (2006) results were in line with previous evidence concerning the existence of different classification patterns for different industries.

Furthermore, in a recent study, Raymond and St-Pierre (2007) used data for small- and medium-sized Canadian manufacturers to test and validate an *a priori* classification scheme of financial ratios. The scheme was developed by the authors and consisted of 24 indicators, 19 of which were financial ratios and 5 were subjective indicators[62]. The 24 indicators were grouped under 5 *a priori* dimensions: growth,

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[61] Note that the main purpose in Koh and Killough (1990) is not relevant to our study; therefore, Koh and Killough's (1990) study is not reviewed here.
[62] One subjective or perceptual indicator was included under each of the a priori dimensions to strengthen the model where SMEs' chief executives provided their subjective assessments of their

profitability, liquidity, gearing, and efficiency. Raymond and St-Pierre (2007) used CFA to validate this scheme and their results indicated that three dimensions: liquidity, profitability and gearing were somewhat interrelated and appeared to reflect the 'financial' position of an SME. Besides these three dimensions, considering the growth and efficiency dimensions can help to achieve a complete, strategic and integrated picture of the SME.

Last but not least, CFA was also used to test Lev's (1974) classification scheme in Martikainen et al. (1997). However, Martikainen et al. (1997) did not use CFA to test the empirical validity of Lev's (1974) scheme; rather, they used it as a novel technique to measure the time-series stability of the traditional categories and provide a description of the possible causes of the instability of these categories over time. Martikainen et al.'s (1997) results indicated that all Lev's (1974) categories, apart from the profitability group, were reasonably time-invariant. However, the study found that the accuracy or the reliability of the ratios as measures of these dimensions changed over time. According to Martikainen et al. (1997), the time variant reliability of financial ratios as measures of the underlying dimensions could possibly be behind the instability evidence of the financial patterns reported in previous studies.

In addition to the use of multivariate techniques in investigating the classification of ratios, some researchers sought a better understanding of financial ratios using the survey approach. Amongst such studies are those of Gibson (1982) and Shivaswamy et al. (1993). Gibson (1982) asked financial executives to assign 20 ratios selected from various sources (textbooks, interviews with financial executives, and annual reports) to one of the following categories: liquidity, long-term debt paying ability, profitability, or others. Overall, the results of Gibson (1982) indicated that there was some consensus amongst financial executives on the primary dimension measured by each of the investigated ratios. On the other hand, Shivaswamy et al. (1993) surveyed banks officers who were involved in originating loans and commercial lending. The officers were asked to choose from amongst 43 ratios the ratios they thought were useful when making lending decisions with regard to manufacturers and retailers. The

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enterprise's growth, profitability, liquidity and gearing. Also, efficiency was judged using the information provided by SMEs' product managers (Raymond and St-Pierre, 2007, p. 37).

results showed that 19 ratios were important in evaluating manufacturers' financial viability whereas 14 ratios were important with regard to retailers. Also, the sets of ratios considered important to appraise manufacturers and retailers were different. While profitability and leverage ratios were of more importance with regard to manufacturers, liquidity and activity ratios appeared more significant in the case of retailers. This indicated that the industry differences should be accounted for in ratio analysis. Furthermore, Shivaswamy et al. (1993) compared the behaviourally important ratios described above to those found to be statistically significant in 13 bankruptcy prediction studies. They found that the important ratios in the two approaches (behavioural and statistical) did not appear to be closely related.

Summary of Section 2.5

This section presented the research that was carried out in relation to financial ratio classifications which did not utilise the technique of PCA/FA. The application of CFA appeared to be a relatively new trend in the classification literature. However, only a small number of studies utilised this approach compared to the more widespread approach of PCA. A substantial part of the research reported in this section was conducted to test what is considered as the '*ad hoc*' or 'traditional' ratio classification scheme introduced by Lev (1974). The section also highlighted the use of the survey research method to assign ratios to groups, and also to find sets of ratios that were useful in analysing different industries. Finally, the section brought to light the evidence reported with regard to the extent to which both the traditional and empirical groups of ratios contained redundant information: this evidence was found via the use of canonical analysis.

So far, this chapter has reported the current evidence that is available in relation to the classification patterns of financial ratios for almost all areas, but not for the banking industry. Given that the current study primarily aims to investigate the classification patterns of banks' financial ratios, the relevant banking evidence is gathered and presented separately in the section that follows.

2.6 Classification patterns of bank financial ratios

The classification patterns of financial ratios have been identified for many different industries, as demonstrated in previous sections, yet the banking industry appears to be the least studied. A thorough survey of the ratio classification literature failed to find any study that was aimed primarily at identifying the empirical patterns of bank financial ratios. However, it appeared that banking research conducted in other financial areas has relied heavily on PCA/FA as one of a range of methodologies followed. Amongst the studies that applied FA to bank financial ratios, 15 studies were chosen; these are presented in this section[63]. However, given that investigating the financial patterns of bank ratios was not the principal aim in any of these studies, a detailed review of them is not undertaken here. Rather, the current section focuses only on the practical issues that are related to the application of PCA/FA in the selected 15 studies. Appendix 2.3 summarises these issues in the same manner as that used in Appendix 2.2, and the following paragraphs address a number of important issues relating to these studies, such as: the way in which PCA/FA has been utilised in banking research, the banking data used, the empirical steps leading to the identification of factors, and the available evidence regarding the classification of bank financial ratios.

To begin with, the objectives and the core techniques used in the 15 studies summarised in Appendix 2.3, were as follows. Saunders (1969)[64] and Jackson (1974) identified the dimensions or characteristics of a set of banking variables; they used PCA as the key technique. Meric et al. (1991) and Johnson and Meinster (1975) investigated the characteristics of banks involved in acquisition activities: the two studies used MANOVA and MDA, respectively. Whalen and Thomson (1988) and Poon et al. (1999) used logit models to predict bank ratings (CAMEL and Moody's

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[63] The survey conducted was not conclusive but it is not claimed in any way that these studies are the only ones available. However, these 15 studies were readily available to the author at the time when this chapter was being written and are good examples of the research conducted in the area.

[64] Saunders (1969) is one of the earliest applications of PCA in finance. Saunders' (1969) study, however, seemed under-cited in the classification literature. This could be due to the fact that the study did not aim primarily at classifying ratios into empirical groups and the inclusion of some economic variables besides the ratios used. The purpose of the study, however, was to group a number of banking variables, which were popular inputs into regression analysis in the banking area, into distinct groups. The study recommended using only one variable from each of the identified groups as inputs into regression models. The study was heavily criticised by Chiattello (1974) for not applying any rotation method to the solutions.

financial strength ratings, respectively). West (1985) and Canbas et al. (2005) developed early warning systems to identify distressed banks; logit analysis was used in the two studies. Besides this, discriminant and probit analysis was used in Canbas et al. (2005). Ali et al. (1995) and Charbaji (2001) classified banks into groups based on a number of performance measures; they used cluster analysis and MDA. Zopounidis et al. (1995) used ordinal regression models to evaluate banks' performance whereas Shih et al. (2007) only used the technique of PCA and compared performance amongst banks in different ownership groups. Cheng and Ariff (2007) investigated the relationship between banks' risk and abnormal returns using regression analysis whereas Yeh (1996) investigated the relationship between banks' efficiency scores produced by Data Envelopment Analysis (DEA) and banks' financial characteristics. Last but not least, Haslem et al. (1986) used PCA to investigate profitability in international banking activities and compared it to the profitability of domestic banking activities.

For most of the studies summarised in Appendix 2.3, PCA was performed as an intermediary step prior to performing further statistical analysis. Nevertheless, in studies like those of Saunders (1969), Jackson (1974), Shih et al. (2007) and Haslem et al. (1986), PCA was the sole analytic technique used. The purpose in these studies, however, was not to develop empirical classifications of financial ratios. Similar to the studies reported in Subsection 2.4.7, the main reason behind performing PCA in banking research has been to reduce multicollinearity amongst the variables. In this sense, Saunders (1969) and Jackson (1974) suggested that choosing only one variable from each of the identified dimensions is sufficient to represent this dimension in further analysis. Charbaji (2001) and Zopounidis et al. (1995) were the only two studies in which a set of variables was selected to represent the different dimensions; this set was then used in the analysis conducted by the two studies. The majority of the studies summarised in Appendix 2.3, however, calculated factor scores and utilised them in the empirical work.

To evaluate the results of the 15 studies concerning the application of PCA/FA, a close look is taken here at the banking samples used in these studies. As can be seen from the third column in Appendix 2.3 that describes the samples in the 15 studies, a number of banking variables were included besides financial ratios in some of the studies. These are: Saunders (1969), Jackson (1974), Poon et al. (1999), West (1985) and Meric et al. (1991). Furthermore, the number of variables (in ratio and non-ratio form) varied broadly across the different studies. For example, Shih et al. (2007) used only 10 ratios while Poon et al. (1999) used 100 variables. However, the number of variables used by a substantial number of the studies was of the order of 20 ratios [see, for example, West (1985) and Whalen and Thomson (1988), amongst others]. Furthermore, a log transformation of the variables was used in only two studies to improve the normality in the distributions: Ali et al. (1995) and Charbaji (2001).

The studies summarised in Appendix 2.3 were conducted using data from different countries. However, the majority of the studies were based on U.S. data [amongst which are Meric et al. (1991) and West (1985)]. Also, it is worth mentioning that some studies combined banks from different phases into one sample, such as failed and non-failed banks in Canbas (2005), and acquired and acquiring banks in Johnson and Meinster (1975) and Meric et al. (1991). Also, it should be noted that in the above studies, and also in other studies such as Yeh (1996) and Cheng and Ariff (2007), data from different periods were combined into one sample on which PCA/FA was based. Thus, PCA/FA was not performed on a yearly basis in the majority of the studies summarised in Appendix 2.3. Exceptions to this are the studies of Ali et al. (1995), Charbaji (2001), Poon et al. (1999) and Shih (2007) who based their studies on a one-year sample. Also, the studies of West (1998) and Zopounidis et al. (1995) stood out as the only studies that ran PCA/FA on a yearly basis and utilised the results of the different years collectively in the further empirical work they conducted.

Last but not least in regard to the samples used by the selected studies to represent the banking research summarised in Appendix 2.3, it is noted that the number of banks used was fairly small for most of the studies reported (the samples consisted of fewer than 50 banks in nearly half of the studies that were reviewed). Also, given that the number of variables employed in these studies was generally around 20, it can be concluded that the minimum requirement of five banks for every variable employed, as suggested by most textbooks (see, for example, Hair et al., 1998, pp. 98-99), has not been taken into account. However, in two of the studies that used U.S. data, West (1985) and Jackson (1974), large samples were used (1,000+ banks).

With regard to the practical steps taken to perform FA in the banking research, the fourth column in Appendix 2.3 shows that PCA was the preferred technique in most of these studies. However, the studies of Whalen and Thomson (1988) and West (1985) were the only two to use Principal Axis Factor Analysis[65]. The number of factors extracted in most of the 15 studies was solely decided using the eigenvalue greater than unity criterion; in the rest of the studies no stopping rule was reported. Also, most of the studies used the varimax (orthogonal) rotation method. A few studies, however, did not report any rotation [for example, Zopounidis et al. (1995)] whereas other studies utilised oblique or uncorrelated factors [for example, Ali et al. (1995)].

The results of performing PCA/FA generally as a screening procedure in the different studies summarised in Appendix 2.3, appear divergent given the differences in the samples used. As demonstrated in previous paragraphs, a number of non-ratio variables were used besides ratios in some studies. Also, different sets of variables were used to serve the various objectives of the studies. These studies were conducted using different approaches for banks in different countries and over different periods. Therefore, checking for consistency amongst the results of PCA/FA in these studies would be a meaningless procedure and thus, it is not undertaken here. However, it is noted that the number of factors identified in the majority of the studies bordered between 3 and 4, regardless of the differences in the number of variables used. Also, the 3- and 4-factor solutions appeared to account for a percentage of variance that varied massively across the studies [for example, 4-factor solutions accounted for over 88% of the variance in Yeh (1996) and for less than 65% in Shih et al. (2007)]. A few studies, however, identified 6 to 8 components [West (1985) and Meric et al. (1991)], whilst two others found 13 [Jackson (1974) and Haslem (1986)].

[65] Yeh (1996, p. 985) mentioned that Principal Factor Analysis was performed. However, it can be understood from the context of Yeh (1996) that the study was actually referring to PCA.

Summary of Section 2.6

Section 2.6 reported the little evidence available regarding the classification patterns or empirical groups of bank financial ratios. The section briefly reviewed a selection of the studies that utilised PCA/FA for bank ratios, alongside which a number of other non-ratio variables were analysed. Similar to Subsection 2.4.7, ratios were factor analysed, mainly for data reduction purposes, to help deal with multicollinearity amongst the variables prior to using them as inputs to multivariate statistical models. What made the classification evidence provided by these studies incomplete is the fact that none of these studies were aimed primarily at investigating the empirical patterns of bank financial ratios. Thus, the financial ratios that were analysed and the sample banks used in these studies were selected only to meet the main purpose of the studies, which apparently was not to develop the empirical patterns of bank financial ratios. Also, the samples used in some of these studies combined banks in different phases and also for different periods. All of the above points were normally avoided in the 'classic' classification studies that were reviewed earlier in this chapter, amongst which were mentioned Pinches et al. (1973 and 1975), Ezzamel et al. (1987a) and Gombola and Ketz (1983b).

All the points made above lead to the identification of a large gap in the classification literature since it clearly lacks research into the financial patterns or the empirical groups of financial ratios within the context of the banking industry. Answering the question of how many empirical groups of bank ratios are there, and studying the consistency of these groups over time and across different phases of banks, would definitely help in bridging the identified gap. Researchers and practitioners who use financial ratios in their models to study banks' performance or measure their sustainability would then certainly gain more understanding into the characteristics of the ratios they use. This is exactly what the proposed study offers, as the following chapters elaborate.

2.7 Conclusion

The preceding sections have reviewed and synthesised the literature on the classification patterns of financial ratios. Particular attention was paid to studies that employed the technique of principal component analysis / factor analysis to uncover the interrelationships amongst ratios. At the centre of the enormous research conducted in this area since the 1970's have been attempts to answer the following questions: Given a large set of ratios, what are the key ratios that represent the different dimensions of performance without incurring the loss of much information? Are the classifications of ratios stable over short and long periods? Are the ratio patterns similar across different industries? Finding answers to these (and other) questions would, it is hoped, enhance research in the different fields that use financial ratios and also help decision-makers in different disciplines who rely heavily on ratio analysis.

The core part of this chapter reviewed studies that used PCA/FA as a means of classifying financial ratios. These studies were driven by many motives, amongst which the chapter included discussions under the following headings: improving the usefulness and efficiency of ratios; investigating the time series stability of ratio patterns; exploring the cross-sectional stability of the classifications across industries and countries; and identifying ratio patterns on the level of single countries and industries. Moreover, ratio classifications were viewed in the context of different research issues, such as the use of different sets of ratios, the length of operating cycles, stock market research, bankruptcy research, distributional properties, and the proportionality assumption. The chapter also presented research that performed PCA/FA over financial ratios as a preliminary step to further statistical analyses. Research into bankruptcy prediction, takeovers, mergers and acquisitions, firms' characteristics and performance, markets, bond ratings and credit scoring have utilised PCA/FA primarily as a data reduction technique. A separate section was devoted to the studies conducted within the banking industry.

The comprehensive literature survey carried out in this chapter identified the following gaps. Firstly, despite the extensive studies of financial ratio patterns in many industries, the banking industry has not received a great deal of attention. Evidence on the empirical classifications of bank financial ratios is scanty; indeed almost non-existent. Secondly, the current body of literature is lacking research that explores the effects of the size of firms on the classification of ratios. Although many issues have been explored within the context of empirical ratio classifications, none of the previous studies has investigated whether the interrelationships amongst ratios for firms of different size are similar. Thirdly, the literature survey shows that firms with differing characteristics have been investigated (failed, healthy, acquiring, acquired, merging firms, etc). However, there is no evidence concerning the classification of ratios for De Novo firms; in other words, the effect of the age of firms on the classification of ratios has not yet been explored. Lastly, in terms of methodological issues, it was shown that little has been done to refine the methodology for identifying the empirical groups of ratios and measuring their similarity over different samples. Although PCA/FA remains the favourite technique in this sense, none of the recent studies has actually incorporated certain new applications in FA which have been made accessible through the recent advances in programming and statistical software. The eigenvalue criterion has been used extensively to decide on the number of underlying patterns in the set of financial ratios but new, improved and more accurate techniques, such as parallel analysis, have not yet been exploited in the field. Similarly, the review above showed that the use of transformation analysis appeared to be monopolised by Finnish researchers who have access to innovative software packages. Researchers worldwide, however, have heavily utilised the conservative, straightforward techniques of visual comparisons, correlation and congruency analysis in measuring the stability of ratio patterns. Given all the gaps identified above, the current study provides a novel contribution to the literature regarding ratio classification patterns.

In accordance with the above issues and concerning the gaps found in the literature, the proposed research focuses on studying the classification patterns of financial ratios for commercial and savings banks, and on checking their stability over time. Also, this study aims to explore the effects of size and age of banks on the empirical classifications of ratios. Drawing on the literature, this study employs principal component analysis to identify the ratio patterns and uses various methods to measure the cross-sectional and time series stability of the derived patterns. These methods include visual comparisons, correlation and congruency coefficients, and transformation analysis. Besides using large samples, this research contributes to the existing literature by virtue of the following points: firstly, by using the arcsinh transformation method to improve the approximation of ratio distributions to normality; secondly, by employing parallel analysis to decide on the number of components in the factor solutions; and thirdly, by developing a significance test to be used along with transformation analysis. The next chapter, Chapter 3, presents the methodology of the study.

Chapter 3 Methodology

3.1 Introduction

The aim of this chapter is to introduce the methodology to be followed in order to answer the primary and secondary research questions posed earlier (Chapter 1, Section 1.2). Answering these different research questions simply requires the following two steps: first, identifying the ratio patterns for the different samples of banks (commercial, savings, commercial banks in different size classes, and De Novo commercial banks) and time periods (years 2001-2005); second, assessing the time-series and cross-sectional stability of these patterns. This study uses Principal Component Analysis (PCA) as the chief technique. Performing this technique requires following a number of steps and taking certain decisions which all lead to identifying the empirical patterns of ratios. These patterns are then compared using various factor comparison methods which include: visual comparison, correlation and congruency coefficients, and transformation analysis. These are the major points that are discussed in this chapter. The chapter also emphasises the improvements that can be made to the conservative methodologies followed in previous studies.

The rest of the chapter is structured as follows. The first part of Section 3.2 gives a brief summary of the use of PCA in the previous literature. The second part of this section justifies the choice of PCA as the main technique used in this study; it gives general descriptions of PCA, the use of PCA, the differences between PCA and Factor Analysis (FA) and between Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). Section 3.3 details the steps that lead to identifying the components; particularly, it focuses on the factorability tests, the methods used to decide on the number of components and the interpretation step. Section 3.4 discusses the methods used to compare the different factor solutions. These include visual comparison, correlation and congruency coefficients and transformation analysis. This section also describes a significance test proposed by the current study as an extension to transformation analysis. Section 3.5 concludes the chapter by giving a summary of the chapter's content and introduces the chapter that follows.

3.2 Deriving the patterns: PCA

Previous chapters highlighted how PCA has been widely used in the ratio classification literature and also as a data reduction technique in many areas in finance. In the current study, PCA was chosen as the main technique to be used to identify the financial patterns of banks' ratios. This section justifies the choice of this particular multivariate technique by briefly revisiting the relevant classification literature. It also explains the ideas behind this technique and how it can be used, highlights the differences between PCA and FA and underlines the exploratory aspect of this technique as opposed to Confirmatory Factor Analysis (CFA).

3.2.1 Literature revisited

In Chapter 2, a detailed review was carried out in regard to the ratio classification literature. This literature was initiated by the point that, given the massive number of ratios that can be easily computed from financial figures, there is an overlap in information content reported by these ratios; in other words, there is redundancy. This provoked research into how to choose a small set of ratios without losing much of the information. The literature focused on grouping together ratios that report on the same dimension. Then, a small set of ratios, chosen to represent all of the identified groups, should be sufficient to account for most of the information that exists in the larger set. Also, using such a small set of ratios would reduce the amount of effort required to analyse the ratios without compromising the information content. So, the question that has evolved is how to classify financial ratios. A substantial part of the classification literature has focused on grouping ratios empirically. In doing this, the multivariate techniques of PCA and FA have proved popular and useful. Moreover, research into other areas in finance, particularly event prediction, has been noticeably influenced by the classification literature as it adopted these techniques for data reduction purposes prior to performing more advanced statistical analysis.

To aid in justifying the choice of PCA as a classification technique in this study, Appendix 3.1 lists 17 studies that relied on either PCA or FA to identify ratio patterns. These 17 studies were selected from Section 2.4 in Chapter 2 which surveyed what is considered to be the 'classic' ratio classification literature. The different columns in Appendix 3.1 will be referred to whenever necessary in this and in the following chapter.

To begin with, both PCA and FA have been widely used to identify the empirical patterns of financial ratios [see the method of extraction in Appendix 3.1: for example, Johnson (1979) and Chen and Shimerda (1981) used PCA; while Pinches et al. (1973, 1975), and Ezzamel et al. (1987a) used FA]. As briefly mentioned in Chapter 2 (Section 2.4), PCA and FA are not the same technique as some important differences exist between them. However, these differences are rarely discussed in the classification literature. The only exception to this are the studies of Pinches et al. (1975, endnote 4), Johnson (1979, footnote 3) and Mear and Firth (1986, footnote 2). These studies briefly highlighted that PCA assumes that all the variance for the variables/ratios is common amongst the variables in the dataset. FA, however, divides this variance for each variable into a common variance (shared by all variables), and a unique variance and an error variance which are not shared; and it only analyses the common variance. Also, Pinches et al. (1975) and Johnson (1979) added that differences also lie in the existence of a second rotation for FA but not for PCA. All the same, it is important to point out that none of the studies justified their use of either method.

Furthermore, a typical classification study uses either PCA or FA, but not both, to identify the patterns. Mear and Firth (1986), however, was the only exception to this as they performed both FA and PCA over their data; both methods gave similar results in their study although they only reported the outcomes of FA (Mear and Firth, 1986, footnote 2).

While PCA and FA have been rarely utilised in the same study, the extensive study of Ketz et al. (1990) provides the only evidence regarding the similarities and differences in the results from using different FA methods. As mentioned in Chapter 2 (Section 2.4), factors in FA can be extracted using different extraction methods; i.e. FA is not one technique, it is actually the general name for a number of methods such as common factor analysis and alpha factoring, amongst others. However, most classification studies that used FA seem not to report the specific method they used in FA. Amongst these studies are Pinches et al. (1973, 1975), Short (1980) and Gombola and Ketz (1983b). This fact leaves readers who have a fairly good grasp of FA asking why the exact method is not stated in most studies.

Moreover, the terms ‘components’ and ‘factors’ seem to be interchangeably used in the literature. Furthermore, some studies were not precise when stating the type of analysis that was carried out. Chen and Shimerda (1981, p. 53), for example, cited the studies of Pinches et al. (1973, 1975) amongst those that used PCA whereas both studies in fact used FA. Although a great deal of confusion between PCA and FA is evident in the literature, this study recognises the differences between the two methods and provides further technical explanations in the following subsection. However, it is crucial to state that although our study only performs PCA, it follows the practice of using the terms components and factors interchangeably throughout the chapters as this helps the flow of the text.

Previous paragraphs will have definitely raised many questions: for example, why does the current study pay attention to whether PCA or FA has been used in the literature and why has it chosen PCA and not FA as the main method for identifying the patterns of ratios? These questions and others are answered in the following subsection.

3.2.2 Why PCA?

PCA is a multivariate technique in which new variables are formed as linear composites of the original variables where the new variables are not correlated with each other. In other words, PCA transforms a set of correlated variables into a smaller set of uncorrelated variables, called components (Stevens, 2002, p. 387). Thus, PCA is considered as a data reduction technique.

3.2.2.1 What is PCA?

The mathematics behind PCA (and FA) can be complicated[66]; the following paragraphs, however, provide non-mathematical explanations of this technique. Helpful textbooks in this regard are Stevens (2002, pp. 386-387), Hair et al. (1998, pp. 100-103), and Sharma (1996, pp. 125-128).

PCA starts with a fairly large set of correlated variables (i.e. ratios in the case of the current study) measured for a sample of cases (i.e. banks in this case)[67]. Then it divides the total variance in the data (which equals the sum of the variances for all the variables) to give the first principal component that accounts for the maximum proportion of the variance in the data. The second component is then extracted; this accounts for the maximum proportion of the variance that is left in the data after taking away the proportion of the variance accounted for by the first component. In the same manner, the third component accounts for the maximum proportion of the variance left in the data after extracting the first and second components; the same pattern is followed with later components. So, each of the components is formed by linear combinations of all the variables in the data. The coefficients of a principal component are called 'loadings'; these describe the importance of variables to the component. In other words, these loadings are the correlations between the variables and the components. Furthermore, the components are initially extracted in such a way that the correlation coefficient between each pair of components is equal to zero; in other words the components are uncorrelated with each other. Also, initially, PCA extracts as many components as there are variables in the data; and each component accounts for a smaller and smaller proportion of the total variance. Therefore, it is often the case that a few components (smaller than the number of variables) account for most of the variance (or information) that exists in the original variables. It is here that PCA is most useful as a data reduction method.

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[66] Jolliffe (2002) covers all the mathematical aspects of PCA. Specialised books on FA also provide a good deal of mathematical explanation: e.g. Harman (1967), Rummel (1970), Cattell (1978) and Gorsuch (1983).

[67] When the purpose is to group the variables, this mode of FA is called R-factor analysis. However, when the aim is to group the cases, this mode is called Q-factor analysis. The latter mode is less popular as there are more appropriate clustering techniques to carry out this work (Hair et al., 1998, p. 97).

3.2.2.2 The use of PCA

PCA is used when the purpose is to summarise data into a smaller set of variables without losing much of the information in the original variables. The data reduction can be achieved by following one of the following two options (Hair et al., 1998, pp. 116-120). The first option is to select the variables that have the highest loadings onto each of the identified components; these variables can then be called 'surrogate variables'. The second option is to create a small number of new variables that replace the large number of original variables in any further multivariate statistical analysis. These new variables are formed by linear combinations of the original variables which can be in the form of 'factor scores' or 'summated scales'[68]. In the case of factor scores, all the original variables are considered in the linear combination whereas for summated scales, only those variables that have significant loadings onto the component are included when either the total or the average score of these variables is computed. Each of these data reduction options has its advantages and disadvantages. Hair et al. (1998, pp. 116-120) provide simple explanations on how to choose between these options.

The use of components as a variable reduction scheme is further highlighted by Stevens (2002, pp. 388-89). PCA is used to determine the number of underlying constructs or dimensions that accounts for high percentages of variance in the data. Stevens (2002) further explains that in the context of multiple regressions, performing PCA on the predictors solves the multicollinearity problem; also, PCA can be used to reduce the number of predictors. Similarly, working with a smaller number of variables sounds appealing in other types of analysis. In MANOVA, for instance, it is advisable to apply PCA to reduce the number of criterion variables before carrying out the analysis. Examples of studies that use PCA in the way outlined by Stevens (2002) were given in Chapter 2, particularly in Subsection 2.4.7 and Section 2.6.

[68] Choosing surrogate variables and computing factor scores has been behind the use of PCA in the majority of the studies in finance and banking (see Appendix 2.2 and 2.3). Summated scales, however, have been shown to be of less use in the relevant literature.

3.2.2.3 PCA vs. FA

As mentioned earlier, PCA is often mistakenly thought to be one of the techniques of FA. Most popular statistical software packages (like SPSS) contribute to the confusion here as they list PCA as a FA method (Sharma, 1996, p. 58). A number of textbooks do the same [for example, Hair et al. (1998, Chapter 3) and Stevens (2002, Chapter 11), amongst others]. Other textbooks, however, devote two separate chapters to cover the two types of analysis [for example, Sharma (1996, Chapters 3 and 4), amongst others].

Nevertheless, both PCA and FA have been widely used in the literature relating to financial ratios as data reduction and classification techniques. The literature, however, does not explicitly differentiate between the purposes of the two methods. These are generally more emphasised in textbooks where PCA is often introduced as a data reduction technique while FA is seen as the most appropriate method to use when the purpose is to uncover the structure or the latent dimensions underlying the data. In other words, PCA is used as a data reduction method while FA is used as a classification method.

To differentiate between PCA and FA, the way in which the two techniques treat the specific and error terms in the variance needs to be understood. PCA treats any variance in the data as shared between all the variables whereas FA considers two types of variance for every variable: one is shared or common amongst the variables and another (also divided into two types) a unique or specific variance to the variable, and a variance caused by measurement error. Based on this, PCA is recommended if the aim is to account for the maximum variance in the data and prior knowledge exists that the specific and error terms are small. FA, on the other hand, is recommended if the amount of error and specific variance is known so it can be excluded in order that only the common or shared variance will be considered. In practical terms, the diagonal elements of the correlation matrix are all unity if PCA is used (see Section 3.3 for more details). However, if FA is carried out, the unit diagonal elements are replaced by the estimated common variance shared by the variables (this is called communality) and the correlation matrix is thus called the reduced correlation matrix.

The differences between PCA and FA are well explained in Sharma (1996, p. 128) as PCA emphasises maximising the explained variance whereas the emphasis in FA is on explaining the inter-correlations amongst the variables. Also, the components in PCA can be viewed as formative indicators in the sense that they are formed by linear combinations of all the variables. On the other hand, the variables in FA can be viewed as reflective indicators since every one of these variables is a function of latent factors and unique or specific factors: that is, these variables reflect the presence of hidden factors.

Furthermore, it is worth mentioning that extracting the factors in FA can be carried out using many methods; the most common is common factor analysis (also called principal axis factoring or principal factor analysis). In fact, when FA is compared to PCA, the comparison is often conducted between common factor analysis and PCA [for example: Hair et al. (1998, pp. 100-103)]. Other techniques of FA include: alpha factoring, principal component factoring, image snalysis, maximum likelihood factor analysis, unweighted least squares factoring and generalised (weighted) least squares factoring.

When faced with the choice between PCA and FA, it was decided that PCA would be the most appropriate technique for our study; the following points justify this choice. First, the application of PCA is more popular than FA in the ratio classification literature as well as in many other areas in the financial and banking literature (see Appendix 3.1 and refer to Chapter 2). Second, although FA might appear appealing, given that it uncovers the dimensions that exist in the dataset, it involves some complications which have, to an extent, contributed to the popularity of PCA (Hair et al., 1998, pp. 102-103). Third, PCA is more appropriate given that the study is more driven by data reduction than by the purpose of uncovering the latent dimensions in the data. Thus, there is a better chance that the results of this study can be utilised by researchers who seek to choose bank ratios as inputs for their statistical models. By choosing one ratio to represent each of the identified components, researchers can be assured that they have covered all the dimensions that exist in the larger set of bank ratios; and also that the amount of multicollinearity amongst the chosen ratios is reduced. Fourth, PCA and FA may arrive at the same results provided that the number of variables to be analysed is in excess of 30 or that the estimated shared variance for most variables (i.e. communalities) is greater than .60 (Hair et al., 1998, p. 103). Given this, and since our study uses 56 bank ratios[69], it is expected that there will be no significant differences between the results of both methods. This point is also confirmed by Mear and Firth (1986), the only ratio classification study that uses both PCA and FA. Mear and Firth (1986, footnote 2) found the results of the two techniques to be very similar. Taking these four points into account shows PCA to be more relevant to the current study than FA.

3.2.2.4 EFA vs. CFA

FA in general terms has two main classes: Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA); choosing which class to use is one of the early decisions that face the researcher. All the methods that have been reported in the previous subsection are considered to be an EFA method. Loosely speaking, PCA can be also considered as an EFA technique. Now, it is important to note some differences between EFA and CFA. The reason why these differences are highlighted here is that a number of recent studies in the ratio classification literature have performed CFA; some of these studies were reviewed in Section 2.5 in Chapter 2. Such studies tested whether a set of financial ratios corresponds empirically to some traditional grouping schemes.

Choosing between EFA and CFA generally depends on whether the researcher has a specific theory regarding the structure of the data. In general, EFA is considered to be more of a theory-generating than a theory-testing technique which is the case with CFA (Stevens, 2002, p. 411).

A theory-generating procedure starts with little or no knowledge about the structure of the data; this includes having little or no knowledge of the following (Sharma, 1996, p. 128): a) the number of factors or dimensions; b) whether these dimensions are orthogonal or oblique (i.e. correlated or not correlated); c) the number of variables associated with each factor; and finally d) which variables represent which factor.

[69] Chapter 4 (Section 4.4) provides all the relevant details in regard to the ratios used in this study.

Hence, the aim is to explore or search for a factor structure or theory that can explain the collinearity amongst the variables. This involves finding answers for the questions a-d; and this is what EFA seeks to do.

Contrary to EFA, in CFA the factor structure is hypothesised *a priori* as in terms of the number of factors, whether these factors are correlated or orthogonal, and which variables will load onto which factors; all these are specified in advance (Stevens, 2002, p. 411). Therefore, the aim in CFA is to test the fit of the *a priori* factor model.

Since the current study uses bank financial ratios, and given the absence of a strong theory or empirical base on which to build hypotheses in regard to these ratios, CFA is clearly not an adequate method to pursue. Hence, EFA is the most appropriate procedure since its aim is to explore the dimensions of a set of bank financial ratios for data reduction purposes.

In summary, PCA which as previously noted as an EFA technique has been extensively used in the ratio classification literature. Also, this technique has been widely performed in many financial areas as a preliminary step for data reduction purposes prior to performing more advanced statistical techniques. PCA is a data reduction technique in which a small number of new variables are formed; these account for a large proportion of the variance in the dataset. This technique was chosen over FA techniques as the aim of our study is to replace a large set of bank financial ratios by a smaller set without suffering a significant loss in information. By choosing one ratio to represent each of the identified components (i.e. surrogate ratios), researchers in the banking field who use financial ratios can benefit from this study when selecting, from amongst the large number of available ratios, a small set of ratios that can be used as inputs to their statistical models. Performing PCA involves a sequence of decisions; these are explained in the following section.

3.3 Deriving the patterns: practical steps of PCA

This section discusses the practical steps that lead to identifying the components of a PCA; these steps have to be repeated for every PCA conducted in this study[70]. Performing PCA requires making decisions regarding a number of points. The points explained in this study include: the factorability of the data, deciding on the number of components, choosing a rotation method, and interpreting the solution. These points were gathered from different sources and have been presented in the study in whatever place best serves the flow of the text. Also, it is worth mentioning that these steps are emphasised more in textbooks than in the literature where the stopping rule and the rotation method are the only two steps generally reported (see Appendix 3.1).

3.3.1 Factorability

Assessing the factorability of the data means checking whether they are appropriate for PCA. For this, a number of methods exist and are emphasised in textbooks. The relevant literature, however, does not seem to cover this point except for the studies of Mear and Firth (1986) in the classification literature[71]; and Cheng and Ariff (2007) and Canbas et al. (2005) from the banking studies that used PCA[72]. Bartlett's Test of Sphericity (BTS), in addition to the Kaiser-Meyer-Olkin (KMO) measure of sample adequacy (MSA), were generally the preferred tests in these studies. In addition to these methods, some textbooks suggest visual inspection of the correlation matrix or using the anti-image correlation matrix [Hair et al. (1998, pp. 99-100) and Sharma (1996, p. 116)]. All the factorability tests are based on the correlation matrix, the starting point in PCA, and aim to check whether the variables in the data exhibit enough intercorrelations to justify performing the analysis.

To begin with, if the correlation matrix contains a substantial number of sizeable correlations [i.e. correlation coefficients >.30 according to Hair et al. (1998, p. 99)] the data are then appropriate for PCA. Sizeable correlations indicate that the variables have something in common or that they are measuring the same dimension; these

[70] Similar steps, more or less, must be performed to implement FA.
[71] See Appendix 3.1.
[72] See Appendix 2.3 and Chapter 2 (Section 2.6).

dimensions can be uncovered by performing PCA. On the other hand, small correlations signify that the variables do not share much in common and that they are merely a group of heterogeneous variables; PCA in such cases is not recommended (Sharma, 1996, p. 116).

Furthermore, partial correlations can also be used to check the suitability of the data for PCA. Partial correlations measure the correlation between variables when all the other variables are taken into account. If some underlying factors (or dimensions) exist in the data, the partial correlation would then be small because variables in this case can be explained by the underlying dimensions (Hair et al., 1998, p. 99). High partial correlations indicate that such dimensions do not exist in the data. The negative value of the partial correlation is often used in this sense and is called the 'anti-image correlation matrix'; high anti-image or partial correlations signify that PCA is unsuitable for the data [for example, Hair et al. (1998, p. 99) and Sharma (1996, p. 116)].

Also, there exist two popular diagnostic measures of the factorability of the correlation matrix. These are: Bartlett's Test of Sphericity (BTS) and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (MSA) (also called Kaiser's measure). Bartlett's Test of Sphericity (BTS) provides the statistical probability that the correlation matrix has significant correlations among at least some of the variables[73]; the KMO test, however, measures the degree of common variance among the variables (Hair et al. 1998, pp. 99-100). The value in the latter measure ranges between 0 and 1, and it can be interpreted using the guidelines given in Kaiser and Rice (1974), cited in Sharma (1996, p. 116). Following these, a KMO statistic of .90 or above is regarded as 'marvellous', .80 or above is 'meritorious'; .70 or above is 'middling'; .60 or above is 'mediocre'; .50 or above is 'miserable'; and below .50 is 'unacceptable'.

[73] Sharme (1996, p. 76) mentioned that BTS, although popular, is not that helpful as it is sensitive to sample size in a way that even small correlations are significant for large samples; this makes it less helpful in a practical sense. Hair et al., (1998, p. 99) has the same view regarding this point.

This study uses the two measures of BTS and KMO to quantify the extent of intercorrelations in the data: i.e. whether it is appropriate to apply PCA. A quick visual inspection of the correlation matrix is also carried out although the correlation matrices could not be reported in this thesis because of space limitations. Unlike in most of the ratio classification literature, this study reports the results of these factorability tests because of their significance in the textbooks of the area; also, it is believed that reporting such results reveals some of the data characteristics with regard to PCA.

Now, if the factorability measures give satisfactory results, PCA is then resumed. Using this method of extraction, the number of components initially extracted will be equal to the number of variables. The total variance accounted for by all these components also will be equal to the total number of variables; this is because each variable is standardised to have a mean of zero and a standard deviation of one and given that PCA assumes that each variable shares all its variance across all other variables. As mentioned earlier, the first component accounts for the largest proportion of the variance, the second component accounts for the largest proportion of the variance left in the data after extracting the first component, and so on for the rest of the components. Thus, the first few components account for the majority of variance; only these few components should be retained and interpreted particularly if the analysis is driven by data reduction purposes. Nevertheless, deciding on how many components to retain is a controversial topic to which the following subsection is devoted.

3.3.2 Deciding on the number of components

The number of components to be retained and interpreted in this study is solely decided by Parallel Analysis (PA). Nevertheless, the number of components suggested by two commonly used methods, the eigenvalue criterion and Cattell's scree plot, is also reported for comparison purposes. The following paragraphs give explanations of these methods.

The eigenvalue criterion (also called the latent root criterion and Kaiser's rule). This is the most common stopping rule and it is the default retention criterion in many statistical software packages. Using this criterion, only components with eigenvalues that exceed unity are retained and interpreted. Components with an eigenvalue of less than unity contribute less to the cumulative variance; and thus, should be discarded.

The eigenvalue criterion gives a better estimate of the correct number of components under certain circumstances. Stevens (2002, p. 390) gives some of these circumstances: when the number of variables exceeds 30 and the communalities are over .70; or, when the sample size is over 250 and the mean communality equals or exceeds .60. Furthermore, Hair et al. (1998, pp. 103-106) states that the latent root method is most reliable when the number of variables ranges between 20 and 50; this method tends to extract too few components for samples with less than 20 variables while it suggests too many factors for over 50 variables. This stopping rule has been widely used in the ratio classification literature. Amongst the studies that mainly used the latent root method are: Short (1980) and Gombola and Ketz (1983b), as Appendix 3.1 demonstrates.

Cattell's scree plot. This method is also widely cited in the relevant textbooks. To use this criterion, the eigenvalues (proportion of the variance explained) associated with the components are plotted against the components in the order of their extraction. The maximum number of factors to extract can be decided at the point where the plot begins to level off. Generally, the latent root method suggests at least one, and maybe two or three less components compared to the scree plot method [Cattell (1966) cited in Hair et al. (1998, p. 104)]. Although this method is cited in nearly every textbook about PCA/FA, it has not been utilised much in ratio classification studies [Martikainen et al. (1994) is one of the few studies that mainly relied on the scree plot criterion, see Appendix 3.1].

Parallel Analysis (PA). This method is originated by Horn (1965). It has been found by simulation studies to outperform other stopping rules including the latent root and the scree plot criterion by giving a better estimate of the number of factors to be retained (Sharma, 1996, p. 79)[74]. However, to the best of our knowledge, PA has not been applied in any ratio classification study. This could be due to the technical difficulties in performing this analysis as it has not been offered by the popular statistical software packages. Nevertheless, recent publications such as Hayton et al. (2004); O'Connor (2000); and Ledesma and Valero-Mora (2007) offered some programmes and explanations of this analysis. These can be used to perform the analysis using popular statistical software packages (for example SAS and SPSS). Amongst these publications, O'Connor (2000) is of specific interest to the current study which, in fact, utilises the programmes offered on Professor B. O'Connor's website to perform PA.

In PA, the size of the sample and the number of variables are used to construct some correlation matrices for random datasets with the same number of variables and sample size as the real dataset. Then the real and the random datasets are factor analysed; the average of the eigenvalues is then calculated for each of the components of the random datasets. This results in a set of mean eigenvalues for the random data to which the eigenvalues of the real data are compared. Significant components are those with an eigenvalue higher than the average eigenvalue of the random datasets (Hayton et al., 2004, p. 199). More conservatively, the real eigenvalues are also compared to the 95th percentile of each of the randomly generated components (Hayton et al., 2004, p. 199). As long as the real eigenvalue of a real component is higher than that for the random data (whether it is the mean or the 95th percentile), this component is considered nontrivial and should be retained. The accurate number of components can also be determined graphically by plotting the eigenvalues of the real data and the (average and the 95th percentile) eigenvalues of the random data on the x-axis, and the corresponding number on factors of the y-axis. When the lines of the real and random data intersect, the number of factors to retain is then determined.

In addition to the latent root, scree plot, and PA, many other stopping rules have been mentioned in the relevant textbooks. Amongst these, Hair et al. (1998, pp. 104-105) briefly explains the '*a priori*', 'percentage of variance' and the 'heterogeneity of the

[74] See Ledesma and Valero-Mora (2007, pp. 3-4) for a brief review of the simulation studies in favour of PA.

respondents' criterion. The 'percentage of variance' is also explained in Stevens (2002, p. 390); in addition, the book cites a method that uses a statistical significance test to decide on the number of components.

In regards to the stopping rules used in the ratio classification literature, the interpretability of the components appears to be one of the important stopping rules [e.g. Laurent (1979) and Ketz et al. (1990) in Appendix 3.1]. Also, a number of studies [Pinches et al. (1973), Johnson (1979) and Ezzamel et al. (1987a)] used multiple stopping rules; amongst which was to check for factor discontinuities. Last but not least, it can be noticed that studies tend generally to use more than one criterion, as Appendix 3.1 demonstrates. This practice seems to be recommended in most textbooks which also suggest running different trials of PCA using different numbers of components; this procedure helps in uncovering the true components/dimensions [see for example Hair et al. (1998, pp. 105-106)].

In this study, the number of components to be retained is solely decided by PA; this method is used for the first time in relation to ratio classification. Also this study reports the results of the commonly used eigenvalue/Kaiser criterion and Cattell's scree plot only for comparison purposes. After extracting the specified number of components, an attempt is normally made to interpret the initial solution. However, it is often the case that a rotation is performed for this solution to facilitate the interpretation process. The issues of component interpretability and rotation are discussed in the following subsection.

3.3.3 Interpretation

Interpreting the solution means assigning meaningful labels to the different components. This is carried out by examining the variables that load highly onto each of the components. As mentioned earlier, variables that have a high loading onto a given component have something in common, and so the name of the component is based on this common feature. Finding a suitable name for a component requires a specialist who is capable of assessing what the variables which load highly onto the given component have in common and then of expressing this articulately.

Nevertheless, some steps and guidelines can be followed to facilitate this process. These involve rotating the solution and then deciding how high a variable loading should be in order to consider it influential in the labelling of the component. These points are explained in the following subsections.

However, at this point it is relevant to recall that a factor (or component) loading is the simple correlation between the variable and the component. In this sense, variables that load highly onto the component should influence the label which is given to the component. These loadings are provided in the 'component matrix'[75] (one of PCA's outputs); the columns in this matrix represent the extracted components while the rows represent the variables. Squaring a variable loading and multiplying it by 100 gives the percentage of variance in the variable that is accounted for or explained by the component. The sum of the squared loadings of a variable onto all the extracted components is the proportion of the variance in this variable that is explained by the solution: in other words, the communality. The sum of the squared loadings of all variables onto a component gives the proportion of the variance accounted for by this component (also called the eigenvalue). The proportion of the variance explained by a number of components equals the sum of the eigenvalues of these components divided by the total variance in the data (i.e. the number of variables, recalling that, in PCA, each variable has a variance of one).

Most variables in the initial solution load highly onto the first component which makes it explain the highest percentage of variability in the data. Variables, however, have smaller loadings onto successive components so these account for less and less variance. Finding suitable labels for components in the initial solution is often problematic. The interpretation step is, however, facilitated once the solution is rotated as the following subsection explains.

3.3.3.1 Rotation

Rotation means rotating the components (axes) about the origin until a preferred position is achieved; this makes interpreting the components easier (Hair et al., 1998,

[75] Note that this matrix takes different names based on the rotation method used. Subsection 3.3.3.1 elaborates on this point.

pp. 106-107). Rotation reallocates the loadings of variables so that the first component does not necessarily account for the highest proportion of the variance; the other components will then make a reasonable contribution to the proportion of the variance explained by the solution. There are two rotation methods to choose from: orthogonal and oblique.

The orthogonal rotation method keeps the components orthogonal (i.e. uncorrelated or independent) from each other as they were in the initial solution. The component matrix produced by an orthogonal rotation is called the 'rotated component matrix'. The oblique rotation method, however, allows the components to be correlated with each other. It produces two matrices: the 'factor pattern' and the 'factor structure' matrices (Stevens, 2002, p. 393). The elements in the factor pattern matrix signify the importance of a variable to the factor once the influence of all the other variables is accounted for. The factor structure matrix is equivalent to the rotated component matrix as it provides simple correlations of the variables with the factors. It is important to state that the objective in both rotation methods is to simplify the solution in order to facilitate assigning labels to the components. The oblique rotation, however, has one added feature as it produces correlated components (Hair et al., 1998, p. 110).

A simpler structure can be achieved either by simplifying the columns (components) or rows (variables) of the component matrix. In other words, these columns or rows should contain either very high (close to one) or very low (close to zero) loadings. Focusing on the rows or the columns, different methods exist to perform orthogonal and oblique rotations (Hair et al., 1998, pp. 109-110). Orthogonal methods include: varimax (the most common) which simplifies the columns of the component matrix in a way that loadings onto a component will be either very high or very low; quartimax which focuses on rows (variables) to achieve either very high or very low loadings for a variable onto the components; and equimax (the least used method) which aims to simplify the solutions by focusing on both the columns and rows. Similarly, oblique methods also attempt at simplifying either the rows, or the columns or both, in addition to producing correlated factors. Amongst the oblique methods are: promax, orthoblique, and oblimin (Hair et al., 1998, p. 110).

In regard to the rotation step in the previous studies, the following points summarise the major trends in the literature. First, the majority of studies performed one or two rotational techniques; however, a few studies either interpreted the initial (unrotated) solutions (e.g. Kallunki et al., 1996), or did not report which rotation method they used (e.g. Chen and Shimerda, 1981). Second, a number of studies employed the two rotation methods; some of these obtained similar results [Pinches et al. (1973), Mear and Firth (1986) and Ezzamel et al. (1987a)]. Other studies found that the two methods arrived at slightly different results (Ketz et al., 1990); nevertheless, the various orthogonal rotation methods returned generally similar results, and so did the different oblique rotation methods. Third, a few studies, those conducted using hospital ratios, made a presumption regarding the independence of the performance dimensions prior to choosing between the orthogonal and oblique rotational techniques. As mentioned in Chapter 2 (Subsection 2.4.5), Counte et al. (1988) and Zeller et al. (1996) assumed that hospital dimensions are correlated; thus, they chose an oblique rotation method. Cleverly and Rohleder (1985), on the other hand, assumed the dimensions to be uncorrelated and thus performed an orthogonal rotation method. Other studies, however, did not seem to use the same argument to justify their choice of rotational technique. The last point to mention is that the varimax orthogonal method appears to be the most popular in the ratio classification literature and also in the studies that used PCA/FA as a data reduction technique [see Appendices 2.2 and 2.3].

Based on the points mentioned above, it appears that a rotational method has to be chosen for this study. Thus, supported by its popularity in the literature, this study chooses to perform the varimax orthogonal rotation method. This choice is also supported by the guidelines summarised in some textbooks (for example, Hair et al., 1998). Hair et al. (1998, p. 110) suggested that the aim of the research should be considered when a rotational method is chosen. The orthogonal rotation method is appropriate when the research is driven by data reduction purposes, and when the aim is to identify uncorrelated or independent dimensions in a dataset. However, oblique rotational methods are preferred if the ultimate aim is to identify theoretically meaningful dimensions. This is because only a few components can be ‘realistically’ independent of each other (Hair et al., 1998, p. 111). Given that this study is driven by data reduction purposes, and that it aims to find a small set of uncorrelated components that can be used in further statistical analysis, performing an orthogonal rotational technique appears to be the most appropriate choice. The choice between the various orthogonal methods is mostly driven by the availability of these methods in the statistical software utilised to perform the analysis. This study chooses the varimax method as it is often the default choice in most statistical software packages besides its popularity in the relevant literature.

3.3.3.2 Significant loadings

The step that follows rotating the solution involves studying the rotated component matrix. This can be done by assessing the practical and statistical significance of the loadings and also by considering the number of variables and the sample size. The following paragraphs elaborate on this.

Practical significance. A variable with a loading of greater than ± .30 is considered to meet the lowest acceptable standard[76]. A variable with a factor loading of ± .40 is considered to be important, whereas loadings greater than ± .50 are considered to be practically significant (Hair et al. 1998, p. 111). Thus, variables with larger loadings in absolute size are more important when interpreting the rotated component matrix. This is because, as mentioned earlier, the loading of a variable onto a component is the correlation between the variable and that particular component. The squared loading is the amount of the variable's variance explained by the component. Therefore, around 10% of the variable's variance is explained by a factor when the factor loading is .30. Similarly, a factor would explain around 25% of the variance when the factor loading is .50. Hence, in order for the component to explain around 50% of the variable's variance, the loading needs to be greater than .70. However, all of this applies only when the sample size is in excess of 100 (Hair et al. 1998, p. 111).

Statistical significance. Since factor loadings are the correlation coefficients between variables and factors, the statistical significance of these coefficients can be assessed

[76] A negative sign of a factor loading means that the variable has a negative relationship with the factor onto which it loads. The significance of loadings is only judged by the size of the absolute loadings, regardless of their sign (Hair et al., 1998, p. 113).

using a similar approach to when assessing the statistical significance of correlation coefficients. However, since loadings have considerably larger standard errors than typical correlations, stricter criteria should be used to determine their statistical significance [Hair et al. (1998, p. 111); Stevens (2002, pp. 393-394)]. To do this, Hair et al. (1998, p. 112, Table 3.2) provide guidelines concerning the sample size required for each factor loading to be considered significant (see also Table 11.1 in Stevens, 2002, p. 394).

Factor being analysed and the number of variables. The practical and statistical significance of the loadings does not take into consideration the component that is being analysed or the total number of variables in the dataset. Since the later components contain more unique and error variance than the first components, the acceptable level of loadings to be considered significant should be increased when moving from the first to the last component (Hair et al. 1998, p. 112). Also, the number of variables should be considered when deciding on the significance of the loading where the acceptable level for considering a loading as significant decreases as the number of variables being analysed increases (Hair et al. 1998, p. 112). To put it briefly, for large samples, smaller loadings are considered significant; for samples with a large number of variables, smaller loadings are also considered significant. Finally, for a large number of components, the loadings of the later components have to be larger in order to be considered significant.

In the literature. Previous studies have only considered the practical significance of the loadings without any reference to statistical significance, the number of factors or the number of variables. Only loadings of |.70| [or greater] were considered significant in Pinches et al. (1973, 1975), Johnson (1979), and Ezzamel (1987a), amongst others. Variables with such loadings have nearly 50% of their variance explained by the component; thus they should be considered whereas factor loadings of less than |.70| are considered too weak to be reported. The current study, however, uses the statistical significance guidelines given in Hair et al. (1998, p. 112, Table 3.2); it also considers the number of components, variables and sample size when judging the significance of factor loadings.

In summary, Section 3.3 gives explanations of the steps required to perform PCA. As stated earlier, conducting PCA requires a series of decisions to be made and appropriate cut-offs to be chosen. This section justifies a number of decisions made by the study; other related points are discussed in Chapter 4. The study uses two statistical measures to assess the suitability of the data for PCA: these are BTS and KMO. The number of factors to be retained and interpreted in this study is solely decided by PA; however, the results of the eigenvalue and the scree plot criteria are reported for comparison purposes. This is the first 'ratio classification' study that uses PA as a stopping rule. To facilitate the interpretation step, a varimax orthogonal rotation is used before assigning appropriate labels to the components.

The outputs of this study can be used in different ways: selecting 'surrogate variables', computing 'factor scores', and creating 'summated scales'. Nevertheless, to ensure that these results are generalisable and can thus be used for a wider range of purposes, a certain level of stability should be evident in the results. Checking for component stability requires using a number of factor comparison techniques. Details regarding these techniques are given in the following section.

3.4 Assessing stability/similarity of the patterns: factor comparison methods

Subsequent to identifying the patterns of financial ratios, the stability of these patterns has been assessed in almost every study in the ratio classification literature. The stability of the patterns has been checked over time [Pinches et al. (1973, 1975)], across different industries (Johnson, 1979), and between raw and transformed ratios (Martikainen, 1995a), amongst other issues (see Appendix 3.1). These studies used different techniques to measure the stability of the identified ratio patterns; it is often the case that two to three techniques were used in the same study. The most popular techniques in the literature have been visual comparisons, correlation coefficients, congruency coefficients, and transformation analysis. Besides these, a few studies also used differential R-factor analysis [Pinches et al. (1973); Ezzamel et al. (1987a)], higher order hierarchical FA (Pinches et al., 1975), and canonical analysis (Johnson, 1979) [see Appendix 3.1]. Nevertheless, the latter approaches were less popular and their use has been limited to these studies. Textbooks, on the other hand, appear to give less emphasis to factor comparison methods. Amongst the few books that offer explanations of some techniques are Levine (1977), Rummel (1970) and Harman (1967). Given the above, this study employs four methods to check the stability of the ratio patterns. These methods, chosen based on their popularity in the literature and textbooks, and also for their accessibility, are: visual inspection, correlation and congruency coefficients, and transformation analysis. The following subsections give further details of these techniques.

3.4.1 Visual comparison

Visual inspection of the similarity of the factor patterns between different samples or time periods were carried out in nearly every ratio classification study [see Appendix 3.1]. Visual comparisons in these studies generally covered the following points: the percentage of variance explained by the different solutions, which ratios loaded onto which factors, and the ratios with the highest and lowest loadings in the different solutions. The visual approach is recommended as a starting point of comparison in Rummel (1970, p. 460), which adds that this approach can provide the researcher with a general impression of the similarity of the solutions; also, it may allow the researcher to identify small, yet significant, differences between the solutions which cannot be measured by other 'mathematical' comparison techniques. Thus, according to Rummel (1970), other mathematical factor comparison techniques can be used to enhance the results of the visual inspections and/or in large studies where it is impractical to conduct visual comparisons. In accordance with the previous literature and the comments of Rummel (1970, p. 460), checking the stability of the components identified in this study always commences with visual comparisons which cover different issues to be clarified later in each of the analysis chapters.

3.4.2 Correlation analysis

The correlation analysis has been used by several studies for checking the stability of the ratio patterns in terms of the size of the factor loadings and the loading of a specific ratio onto a specific factor over time and across different samples. Amongst the studies that used correlation analysis are: Pinches et al. (1973, 1975), Cowen and

Hoffer (1982), and Ezzamel et al. (1987a). These studies, for example, calculated the correlation coefficients using the loadings of all ratios onto the factors in the adjacent years, and also for the first and the last year in the periods these studies covered. They then assessed the stability/similarity of the factors by the absolute size of the correlation coefficient where a large coefficient indicates that the factor exhibits high stability/similarity over time or accros the different samples, and *vice versa*. Although the use of correlation analysis has been popular in the ratio classification literature (see Appendix 3.1), the relevant textbooks appear not to cite this method amongst factor comparison techniques. Nevertheless, this study follows the past literature by assessing the correlation coefficients between the components of the different solutions, over time and across the different bank samples.

3.4.3 Congruency coefficients

Congruency coefficients have also been used in the literature on the classification patterns of financial ratios as a technique for factor comparisons over time and across different samples. Amongst the studies that employed this method are: Johnson (1979), Gombola and Ketz (1983b), and Ketz et al. (1990) [see Appendix 3.1]. Unlike the use of correlation analysis as a factor comparison technique; the congruency coefficient is widely cited in the relevant textbooks [Harman (1967, pp. 269-270), Rummel (1970, pp. 461-462) and Levine (1977, pp. 45-46)]. The following formula is used to calculate the congruency coefficient (Harman 1967, p. 270):

$$CC_{pq} = \frac{\sum_{j=1}^{n} {}_1a_{jp} \cdot {}_2a_{jq}}{\sqrt{\left(\sum_{j=1}^{n} {}_1a_{jp}^2\right)\left(\sum_{j=1}^{n} {}_2a_{jq}^2\right)}} \qquad \textbf{(3.1)}$$

where: CC_{pq} is the coefficient of congruence; the prefixes 1 and 2 refer to samples 1 and 2, respectively; n is the number of variables in the two samples; p is the number of factors in sample 1; q is the number of factors in sample 2; a_{jp} is the loading of variable j onto factor p; and a_{jq} is the loading of variable j onto factor q.

Note that CC_{pq} is not the correlation coefficient, given that the *a*'s are not centred on their means and that *n* is the number of the variables, not the number of cases (Harman, 1967, p. 270). Nevertheless, similar to the correlation coefficient, the value of the congruency coefficient ranges between +1 for perfect agreement, -1 for perfect inverse agreement, and takes the value of 0 when there is no agreement between the two factors (Harman, 1967, p. 270). For assessing the significance of the congruency coefficients, this study relies on Table 3.1 which shows the names assigned to ranges of the coefficient to describe the goodness-of-match of the factors. Such goodness-of- match names are taken from Richman and Lamb (1985, Appendix) and have never been used in previous ratio classification studies.

Table 3.1: Congruence coefficient goodness-of-match names

Range of congruence coefficient	Name
0.98-1.00	excellent
0.92-0.97	good
0.82-0.91	borderline
0.68-0.81	poor
Less than 0.68	terrible

Source: Richman and Lamb (1985, Appendix)

3.4.4 Transformation analysis

As mentioned earlier, a substantial part of this study is devoted to comparing the identified components over time and across different samples. Transformation analysis is the most complicated method of all those to be used in the current study. Appendix 3.1 shows that this method was used in the studies of Yli-Olli and Virtanen (1989), Martikainen et al. (1994) and Martikainen et al. (1995a, 1995b). These studies which are good exemplars of the recent ratio classification literature have all been carried out by Finnish researchers. Performing transformation analysis in this study represents the first attempt to spread this analysis from Finland, the place it was originally created. Not only this, but this study develops a significance test that can be used to test the outputs of the transformation analysis.

The mathematical explanations in regard to transformation analysis can be obtained by referring to the Finnish research papers mentioned above. These studies cited the original papers concerning transformation analysis, amongst which are those of

Ahmavaara (1954, 1963) which initiated transformation analysis. Also, transformation analysis is covered as one of the 'matrix comparison' methods in Rummel (1970, pp. 463-471) and under 'target analysis' in Levine (1977, pp. 37-42). The early application of transformation analysis in finance was carried out by Yli-Olli (1983) after it had been utilised in Finnish sociological research (Martikainen et al., 1994, Appendix 1). The following paragraphs give a brief description of transformation analysis based on the explanations given in the different Finnish studies [Yli-Olli and Virtanen (1989), Martikainen et al. (1994) and Martikainen et al. (1995a, 1995b)].

Transformation analysis allows the user not only to check the correlation and the congruence between factors in different data, but also to identify the factors and variables that contribute to the dissimilarities that may occur between two different factor solutions. In the literature, transformation analysis has been used to compare factor solutions for the same sample between two different points in time [e.g. Yli-Olli and Virtanen (1989)]; it has also been used in cross-sectional comparisons [e.g. Martikainen et al. (1994)].

Transformation analysis produces two matrices: the transformation matrix and the residual matrix. The transformation matrix, call it M_{12}, is estimated in a way that makes the following equation hold:

$$L_2 = L_1 M_{12} \qquad \textbf{(3.2)}$$

where L_1 and L_2 are the matrices of the factor loadings for groups of objects 1 and 2 (group 1 and group 2 could be the same sample in two different years or simply two different samples). If the two factor matrices are similar, the transformation matrix M_{12} is then an identity matrix. However, if there exists some discrepancy between the two factor solutions, M_{12} is not an identity matrix (i.e. the off-diagonal items of M_{12} are non-zero). Checking the goodness of fit for Equation (3.2) can be carried out using the residual matrix E_{12}, where:

$$E_{12} = L_1 M_{12} - L_1 \qquad \textbf{(3.3)}$$

The elements of this matrix take the value of zero when the two factor matrices have a perfect match. However, in practice, the meaning of the factors would not be the same due to inconsistencies in the loading of some variables. These variables can be uncovered by spotting the non-zero elements in the residual matrix.

Estimating the transformation matrix is generally carried out by the method of least squares which minimises the sum of squares for the residuals. Also, estimating the transformation matrix depends on the further constraints placed on this matrix. Here, one of three transformation analysis models could be chosen: the naïve, the relativistic and the symmetric models[77]. Amongst these, the symmetric model, which requires the transformation matrix to be orthogonal, has been used in the relevant ratio classification studies; thus, it is applied in this study.

In order to assess the significance of the diagonal elements of the transformation matrices, a robust criterion is needed. The relevant studies which used transformation analysis considered that if the diagonal elements are equal to or above 0.95 then they are significant enough to deem the factors in the two datasets to be unchanged. If the factors witnessed some changes between the two solutions, these changes can be uncovered by the non-zero off-diagonal elements in the transformation matrix which refer to the 'explained' or 'normal' changes in the factors between the two solutions under comparison. However, there is no reference in the literature regarding how large is 'large' in terms of these elements. Thus, they have been often judged based on their relative size compared to other elements in the matrix (i.e. factors that have the largest off-diagonal elements are interpreted to have the highest explained/normal shift between the two solutions).

The empirical meaning of some variables may also have changed between the two factor solutions. These changes are labelled as the 'abnormal' or 'unexplained' changes between the different solutions. Uncovering such changes is carried out using the residual matrix as the size of the abnormal transformations (the sum of the squared residuals for every variable) and the cumulative abnormal transformation (the sum of the abnormal transformations for all variables) can be used to verify whether the empirical meaning of the ratios has changed. In the literature [see, for example,

77 Only brief descriptions of these methods are given in the relevant ratio studies; see, for example, Martikainen et al. (1995b, pp. 1710-1712).

Martikainen et al. (1995a, p. 41)] a value of an abnormal transformation greater than .20 is considered large enough to claim there is a change in the empirical meaning of that variable. No criterion, however, has been used in the literature to assess the absolute size of the cumulative abnormal transformation; nevertheless, the relative size of the cumulative abnormal transformations is often considered in the published work in the area.

Nevertheless, an important issue in regard to transformation analysis is that there is no test of significance that can be applied to the results (Martikainen et al., 1994, p. 63). Thus, the question arises here as to how certain one can be regarding the conclusions drawn using the results of the transformation analysis. This issue is discussed in the following paragraphs.

3.4.4.1 Significance test for transformation analysis

As previously noted, in the absence of changes over time in the nature of the underlying factor structure one would expect the transformation matrix to be 'close to' the identity matrix. Suppose then that M is the given transformation matrix. Now, if M is the identity matrix, it is well known that $\det(M) = 1$, where $\det(\cdot)$ is the determinant of the affected matrix. It is more convenient, however, to base tests of the stability of the factor structure not on M but rather on the matrix $B = MM^T$, where M^T is the transpose of the given transformation matrix. Note here that if M is the identity matrix $\det(B) = \det(M).\det(M^T) = 1$ or that M and B will both have a unit determinant. However, B is positive definite, and the distributional properties of random positive definite matrices are well documented in the literature. In particular, Grübaum (1975) and Cicuta and Mehta (2000) show that if the diagonal elements of B are unity -except for a normally distributed perturbation with a mean of zero - and the off-diagonal elements are comprised completely of normally distributed perturbations with a mean of zero, then $E[\det(B)] = 1$ and all the higher moments of det(B) are convergent. Here E[.] is the expectation operator.

This means that if one has a 'large' number of serially independent transformation matrices M_t, for t = 1, 2, 3,___, n, then one can compute the positive definite matrices

$B_t = M_t M_t^T$. Now compute the simple average of the determinants of these positive definite matrices; namely, $\overline{\det(B)} = \frac{1}{n}\sum_{t=1}^{n} \det(B_t)$. Moreover, one can also compute the variance statistic $\hat{\sigma}^2 = \frac{1}{n}\sum_{t=1}^{n} (\det(B_t) - \overline{\det(B)})^2$. It then follows from the Central Limit Theorem that the statistic $z = \frac{\overline{\det(B)} - 1}{\hat{\sigma}}.\sqrt{n}$ will be asymptotically distributed as a standard normal variate. Assessing the significance of the z statistic implies testing the null hypothesis that all the transformation matrices included in the test are stable/similar. If the calculated z statistic is insignificant, then, the null hypothesis cannot be rejected.

Nevertheless, there is one caveat to this proposed significance test for transformation analysis. That is, given that the test follows the Central Limit Theorem; a large (>30) sample size (i.e. the number of transformation matrices included in the test) should be used. If a sample size of a smaller number of matrices is used, the results of the test should be interpreted with caution. Nevertheless, this is the first significance test which is derived for transformation matrices; therefore, what is proposed here represents a significant addition to what has previously appeared in the literature.

In summary, this section gives descriptions of four commonly used methods of factor comparison; all these methods are used in this study to assess the stability of the identified components over time and across different samples. These methods are: visual comparison; correlation coefficients; congruency coefficients where a guideline of the significance of these coefficients is used for the first time in the ratio classification studies, and finally; transformation analysis where the significance of its outputs is to be assessed using a unique test developed in this study. The outcomes of these methods are used collectively to evaluate the stability of the components. If a satisfactory level of stability is proved using all these methods, the generalisibility of the results of this study would be enhanced significantly.

3.5 Summary

Principal component analysis has been used extensively in the ratio classification literature. The aim in the literature has always been to identify a smaller set of financial ratios that can explain most of the variability in a larger set. Analogous to the ratio classification literature, studies in different areas in finance have been increasingly utilising PCA as a preliminary step for data reduction purposes, prior to carrying out further multivariate statistical analysis. In the literature, the major points that summarise the use of PCA are as follows: the extensive use of the latent root criterion to decide on the number of components; the varimax rotational method as the most preferred technique to facilitate interpreting solutions; loadings that equal or exceed .70, in absolute terms are considered the minimum necessary when assigning names to the extracted components. Furthermore, in the ratio classification studies, the stability of the identified components is most often investigated by carrying out visual comparisons. Also, the correlation and congruency coefficients are popular techniques through which to assess the similarity of the components. Recent literature, mainly from Finland, has also employed transformation analysis to assess the stability of the components.

Drawing on the ratio classification literature, the current study chooses to use PCA to identify the classification patterns of financial ratios. PCA is a data reduction technique in which a small number of new variables (components) are formed by linear combinations of the original variables. The new variables can replace the original ones without much loss in information content. Although some differences exist between the PCA and FA techniques, PCA can be loosely classified as one of the EFA methods; EFA starts with little or no prior knowledge regarding the structure of the data. The alternative to EFA is CFA which tests whether a predetermined grouping scheme of financial ratios can hold empirically. Given that little evidence exists regarding the classifications of bank ratios, EFA appears more appealing to this study than CFA.

Unlike most of the previous literature, this study reports the results of BTS and KMO methods, which assess the adequacy of the data for PCA. Also, it uses parallel analysis (PA), for the first time in the ratio classification literature, to decide on the number of components to retain. Furthermore, the study performs a varimax orthogonal rotation which facilitates interpreting the components, as well as reducing the extent of multicollinearity amongst the resulting components.

To assess the stability of the identified components over time and across the different samples of banks, this study conducts visual comparisons of these components; it also computes the correlation and congruency coefficients and uses them to measure the degree of similarity of the components. In regard to the coefficients of congruency, the study assigns component labels to describe the goodness of match, unlike previous literature that solely judges the relative size of these coefficients. Furthermore, the study performs transformation analysis and this helps to uncover the components or variables that stand behind any dissimilarity in the solutions. In this regard, the study makes a contribution to this analysis by developing a significance test that can be based on the outputs of the transformation analysis. The study uses the results of all the methods mentioned above to arrive at a statement of how stable the components are over time and across the different banking samples.

The outputs of PCA (and FA) are highly dependent on the inputs of the analysis; the expression ‘garbage in, garbage out’ is often used to emphasise the importance of the data to the results of PCA/FA (Hair et al., 1998, p. 97). The following chapter introduces the data on which this study is based. These include: the variable (ratio) selection and sample size, amongst other issues.

Chapter 4 Data

4.1 Introduction

The ratio classification literature lacks research that is specifically designed to identify the patterns of bank ratios and investigate their time and cross-sectional stability. Although a number of banking studies have classified ratios for data reduction purposes, these studies have often combined ratios with non-ratio variables; they also used fairly small samples of banks. In these samples, banks with different characteristics were often pooled together (e.g. failed and non-failed, acquiring and acquired, established and De Novo, etc). Thus, it can be concluded that bank ratios have not received sufficient attention in the classification literature when compared to other industries that have been extensively examined (e.g. manufacturing, retail, hospitals, amongst others). This study aims to address the identified gaps by investigating the patterns of financial ratios for different banking samples and by assessing their stability over time and across different bank types. The objective of the present chapter is to introduce the various banking samples used in the study.

This chapter is structured as follows: Section 4.2 introduces the U.S. Uniform Bank Performance Report (UBPR) which is the main source of data for this study. Section 4.3 describes the types of bank covered by the UBPR that are investigated in this study; these include: commercial, savings, and De Novo or newly charted commercial banks. Section 4.4 presents the list of ratios on which the analysis is based while Section 4.5 discusses the issue of data transformation and introduces the arcsinh transformation method that is applied to all ratios used in this study. Section 4.6 gives the statistical software packages utilised to run the different analyses and, finally, Section 4.7 concludes the chapter and introduces Chapter 5 which deals with ratio patterns for U.S. commercial banks.

4.2 Data source: the UBPR

This study uses data reported in the U.S. Uniform Bank Performance Report (UBPR). The UBPR is a financial database published by the U.S. Federal Financial Institutions Examination Council (FFIEC) and gathered with the collaboration of various U.S. federal regulatory agencies. The report is prepared in a concise format which facilitates a detailed analysis of a bank's performance across the various dimensions of its operations. Also, it allows bankers, examiners and researchers to assess the impact of managerial decisions, how economic conditions impact banks' performance and balance-sheet composition (FFIEC, 2006, p. IV). The data in the UBPR are delivered in the form of ratios, percentages and dollar values; these are reported quarterly. The UBPR draws its data from the Reports of Condition and Income submitted by the banks. The UBPR is accessible through the FFIEC website[78] and is considered as one of the most comprehensive bank financial information services available (Rose and Hudgines, 2005, p. 148)[79].

The UBPR is formatted in a way that compares a bank's data for five periods. Therefore, obtaining one report for each bank is sufficient to provide five periods' worth of data for the given bank. If the report's date, which has to be selected prior to accessing the report, is set to be the last quarter of a given year, the generated report will then provide data for the bank for the last quarter in every year over a period of five years. However, if another quarter (first, second or third quarter) is chosen as the report's date, the retrieved report will contain data for that specific quarter in the two most recent years, and also for the fourth quarter in the earlier of the three years[80]. Thus, retrieving the report for a bank in the fourth quarter of a given year also results in data for the bank in the four preceding years. These data enable the short-term stability of the patterns of bank ratios over a five-year period to be studied, which is one of the aims of this study.

[78] URL: http://www2.fdic.gov/ubpr/ReportTypes.asp [accessed 12 February 2010].

[79] The UBPR has been increasingly cited in banking textbooks. Amongst these are: Hempel and Simonson (1999), Gup and Kolari (2005), and Koch and MacDonald (2010).

[80] This concerns the standard format of the report; the report can also be obtained using two other formats. The first offers data for five *successive* periods (i.e. quarters), and the second is a *customised* format that allows choosing any 5 periods (or quarters) which can be any quarter for any year. See URL: http://www2.fdic.gov/ubpr/SelectRepDate.asp?pCert=2300 as an example of the three formats of UBPR for a bank selected randomly [accessed 12 February 2010].

In regard to the choice of years 2001-2005 as the study period, at the end of year 2006, when data for this study were being downloaded, the UBPR was publicly available from the first quarter of 2001 until the third quarter of 2006[81]. This means that the quarterly reports were accessible for the banks for a minimum of five years starting in 2001 and ending in 2005. Hence, by selecting the date 31/12/2005 as a base for the report period, the generated reports would then deliver data for the fourth quarter for each of the years 2001-2005; these data are used in Chapters 5-8 of this study. The only drawback to this is that banks that failed, merged or were acquired by other banks in any year prior to 2005 will not be on the list of banks obtained on 31/12/2005; in other words, they are not covered in this study. This is because identifying these banks and obtaining their reports in the years prior to failure, merger or acquisition would consume an enormous amount of time and is likely to be unsuccessful due to the inherent technical difficulties in downloading 'dead' data. To put it simply, for the four years prior to 2005, the number of banks available and thus included in this study, is slightly different from the number of U.S. banks that were actually in operation during these years[82]. The following section reports the types of bank covered by the UBPR and the initial sample sizes used in this study.

4.3 Banks covered

The UBPR covers all insured commercial banks and Federal Deposit Insurance Corporation (FDIC)-supervised savings banks. The banks covered by the UBPR can be classified based on their charter types and their primary regulatory agencies as follows (FFIEC, 2006, p. II-1):

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[81] The UBPR for years earlier than 2001 became available online only after the data were collected for this study. In other words, this study made use of all the UBPRs that were accessible at the time when the data were being collected (December 2006-January 2007). Furthermore, given the massive effort required in downloading and retrieving the UBPR, increasing the datasets by obtaining reports for years before 2001 and after 2005 was believed to be impractical.

[82] The downloaded UBPRs were checked thoroughly to make sure that they were identical in format and outline. Then an Excel macro programme was performed over all the downloaded reports. This programme opens each file (i.e. UBPR), copies the required information (i.e ratio figures) and pastes them into one general file. The new file contained selected data for all the banks for five years. This, in turn, was used to form five separate files that contain the data for each of the years 2001-2005. PCA's are then performed on each of these files in the empirical chapters 5-7 and parts of Chapter 8.

- National banks which are regulated by the Office of the Comptroller of the Currency (OCC).
- State-chartered banks which are members of the Federal Reserve System and regulated by the Federal Reserve Board.
- State-chartered banks which are not members of the Federal Reserve System and are regulated by the Federal Deposit Insurance Corporation (FDIC).
- FDIC-supervised savings banks which are regulated by the FDIC.

These banks are divided, given their unique operating characteristics, into the following four main groups (FFIEC, 2006, pp. II-1-II-2): commercial (which include De Novo or newly chartered), savings, credit card speciality, and bankers' banks. Banks under each of these categories are classified into peer groups based on certain criteria explained in the following subsections. Setting banks into peer groups enables one to calculate a number of average ratios for each of these peer groups; these average ratios can then be used as benchmarks to which the performance of a particular bank in a given peer group can be compared (FFIEC, 2006, p. II-1).

In regard to the number of banks for which the UBPR is available, there is a fairly small number of credit card and bankers' banks: 39 and 20 banks, respectively (FFIEC, 2006, p. II-2). These numbers fall far below the minimum sample size required to obtain reliable PCA's results[83]; thus, these banks are not included in our study. Nevertheless, the UBPR is available for thousands of commercial banks, hundreds savings banks and a reasonable number of De Novo commercial banks. This provides comprehensive datasets on which to base our study. The following subsections give further details regarding the initial number of banks available under each of these categories.

[83] Further details about the importance of large sample sizes in PCA are given at the end of Section 4.4.

4.3.1 Commercial banks (Chapters 5 and 6)

The UBPR offers quarterly data for nearly 7,800 U.S. insured commercial banks[84]. The report classifies these banks into 15 peer groups according to the following three criteria[85]. Firstly, for each quarter, banks were grouped according to their 90-day average assets[86] into the following six classes (FFIEC, 2006, p. II-2):

1. In excess of $3 billion.
2. Between $1 billion and $3 billion.
3. Between $300 million and $1 billion.
4. Between $100 million and $300 million.
5. Between $50 million and $100 million.
6. Less than $50 million.

Secondly, banks with an asset size of less than $300 million (i.e. groups numbered 4, 5 and 6) were grouped according to the number of full service banking offices. Banks in each of the two asset size groups $100-$300 million and $50-$100 million were classified into two groups: banks with three or more banking offices and those with two or fewer. Banks in the asset size group of less than $50 million were sub-divided into banks with two or more banking offices, and those with only one office. Thirdly, each of the sub-groups based on the first two criteria (asset size and number of banking offices) were further divided according to where the bank operates: in a metropolitan or non-metropolitan area. Thus, after considering the above three criteria of asset size, number of banking offices and location, the U.S. insured commercial banks were classified into 15 groups. Table 4.1 summarises the

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[84] This figure is reported in the UBPR's manual (FFIEC, 2006, p. II-1). Nevertheless, the number of insured commercial banks that were actually listed on the report's website [between December 2006 and January 2007] for the reporting date of 31/12/2005 was 6,898 banks.

[85] Note that prior to 31/3/2004, there were 24 commercial peer groups. As the number of U.S. banks has been declining over the years, the number of banks in some groups fell below 100. The peer group statistics in such groups could be less reliable given that the average ratios can be influenced by the small number of banks. Thus, these small groups were combined and new groups were formed which resulted in 15 peer groups (see: FFIEC, 2004)

[86] The 90-day average assets are reported by banks in the Call Report schedule RC-K submitted every quarter. To calculate this average, either daily or weekly asset figures are averaged over the quarter (i.e. over 90 days).

classification of the commercial banks, as well the number of banks within each group for the last quarter of 2005[87].

Table 4.1: Peer groups' description and number of U.S. insured commercial banks (Q4, 2005)

Peer Group Number	Average Assets for latest Quarter	Number of Banking Offices	Location	Number of Banks (Q4 2005)
1	More than $3 billion	-	-	183
2	$1- $3 billion	-	-	272
3	$300 million - $1 billion	-	-	1,075
4	$100 - $300 million	3 or more	Metropolitan	861
5	$100 - $300 million	3 or more	Non-metropolitan	818
6	$100 - $300 million	2 or fewer	Metropolitan	334
7	$100 - $300 million	2 or fewer	Non-metropolitan	261
8	$50 - $100 million	3 or more	Metropolitan	219
9	$50 - $100 million	3 or more	Non-metropolitan	354
10	$50 - $100 million	2 or fewer	Metropolitan	396
11	$50 - $100 million	2 or fewer	Non-metropolitan	629
12	Less than $50 million	2 or more	Metropolitan	153
13	Less than $50 million	2 or more	Non-metropolitan	348
14	Less than $50 million	1	Metropolitan	293
15	Less than $50 million	1	Non-metropolitan	702
Total				**6,898**

Source: FFIEC (2006, p. II-2) and Researcher

The 15 peer groups of the U.S. insured commercial banks comprise the samples used in Chapters 5 and 6 of this study. In Chapter 5, the classification patters of the U.S. commercial banks are investigated; thus, all these groups are combined together into one large sample of 6,898 banks in year 2005 (refer to the end of Section 4.2 for a clarification of the number of banks in previous years). In addition, as explained later (at the end of section 4.3), banks which do not have the complete observations (i.e. ratios) available have to be dropped from the analysis. Thus the 6,898 commercial banks for year 2005 make up the initial and not the final sample size of Chapter 5. Chapter 5 (Section 5.2) reports further details about this point. Chapter 6 investigates the patterns of financial ratios for groups of banks arranged in different asset-size classes. For the purpose of Chapter 6, the 15 peer groups in Table 4.1 are reduced to

[87] Half way through the data collection process for this study (precisely on 5th January 2007), some changes took place in regard to the allocation of banks to peer groups 4-15. Nearly 510 banks were reassigned to rural and urban areas (450 banks were shifted from rural to urban groups and over 50 banks were moved from urban to rural peer groups) [see: FFIEC (2007)]. Nevertheless, the study managed to incorporate these changes into Table 4.1 which is correct as of January 2007.

4 groups. Groups 1-3 are combined together to form a new group, G1; groups 4-7 make a new group, G2, groups 8-11 make G3; and finally, groups 12-15 form G4. Note that the asset-size classes in the new groups G2-G4 were already decided by the FDIC; these classes are believed to reflect the differences in performance between the banks. However, in order to obtain samples of more or less similar size, and given that each of peer groups 1-3 contain a relatively small number of banks, it was decided to combine all these groups into one (G1). Chapter 6 (Section 6.2) gives further details regarding the initial and final number of banks included in each of the four newly formed asset-size groups in years 2001-2005.

4.3.2 Savings banks (Chapter 7)

The UBPR offers quarterly data for nearly 500 U.S. insured savings banks[88]. Unlike the commercial banks, the UBPR groups the FDIC-insured savings banks only by their asset size, using the average assets for the latest quarter (see footnote 86). As Table 4.2 shows, there are four peer groups for the savings banks which take the peer group numbers 101-104; the ranges of asset size for these groups are slightly different from those for the commercial banks. Nevertheless, given the generally modest number of banks in each of these groups, and given the importance of having a large sample for the sound application of PCA, it seems more appropriate that Chapter 7 studies the classification patterns of savings banks without any reference to the size of these banks. Thus, by compiling all four groups, a total of 444 savings banks for the last quarter in year 2005 make up the sample that is used in Chapter 7. In this context, refer to the end of Section 4.2 for a clarification of the number of banks in previous years. Nevertheless, further details about the number of savings banks initially available for years 2001-2004 and also in terms of final samples are given in Chapter 7 (Section 7.2).

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[88] Similar to footnote 84, this figure is reported in the UBPR's manual (FFIEC, 2006, p. II-1). However, the number of insured savings banks listed on the report's website were 444 banks for the report's date of 31/12/2005 at the time when the data for this study were being collected (December 2006-January 2007).

Table 4.2: Description and number of U.S. savings banks' groups (Q4, 2005)

Peer Group Number	Average Assets for latest Quarter	Number of Banks (Q4 2005)
101	More than $1 billion	48
102	$300 million - $1 billion	143
103	$100 - $300 million	143
104	Less than $100 million	110
Total		**444**

Source: FFIEC (2006, p. II-2) and Researcher

4.3.3 De Novo commercial banks (Chapter 8)

The UBPR separates the commercial De Novo (or newly-chartered) banks from their incumbent commercial banks on the grounds that the two types of bank operate differently. The UBPR combines commercial banks that received their charter in a particular year into one group; it keeps these banks together for a period of five years and names their group by the year of their charter (for example, banks chartered in 2005 are called 2005 De Novo banks). After five years, however, the UBPR assigns these commercial banks to a suitable peer group of the 15 introduced previously in Subsection 4.3.1 (FFIEC, 2006, pp. II-1-II-2). For example, banks chartered in year 2001 are put into a group called 2001 for 5 years; in 2006, each of these banks joined one of the 15 peer groups based on asset size, location and number of branches. Table 4.3 gives the number of chartered banks in each of the years 2001-2005[89].

Table 4.3: U.S. commercial De Novo banks in 2001-2005

Group	De Novo Banks
2001	109
2002	85
2003	105
2004	118
2005	162

Banks in Table 4.3 form the samples used in Chapter 8 which explores the classification patterns of ratios for De Novo banks. Each of these banks has to be downloaded separately in the different years, unlike the case of commercial and savings banks. Given that banks in each of the groups in Table 4.3 are kept in their group for five years, and given that the UBPR reports data for five years, by setting

[89] Note that these numbers are correct at the time when these data were being collected (December 2006-January 2007). Also note that the report's date used when downloading these banks was 31/12/2005.

the report's date as 31/12/2005, the reports for banks chartered in 2005 will then contain data for these banks in that year only (i.e. it contains one year's worth of data). The reports for banks established in 2004 and retrieved in 2005 will contain 2 years' worth of data (2004 and 2005) and so on for groups 2001-2003. Given this, the only group for which data for the whole 5 years are available is the 2001 De Novo banks. This makes this group the subject of substantial analysis, as carried out in Chapter 8. Chapter 8 also discusses the issue of the small size of the De Novo samples.

Finally, it is likely that some files (i.e. downloaded UBPRs) might be electronically/automatically corrupted and some values within these files might not be available; thus, the figures introduced in Tables 4.1-4.3 do not necessarily represent the effective sample sizes. Furthermore, it should be noted that all banks with complete observations available in *any* of the years 2001-2005 are included in this study. In this regard, this study follows the methodology of Ezzamel et al. (1987a) in which the ultimate size of samples is determined by including banks with a complete set of ratios available in *any* year over the study period[90]. Nevertheless, the final samples used in the different analyses are all reported in the related empirical chapters (Chapters 5-8). In the following section, however, the list of ratios obtained for each of the banks is introduced.

4.4 Ratio selected

The UBPR offers an enormous amount of banking data in the form of ratios, percentages and dollar values. Since this study is only interested in financial ratios, the question is how to choose from amongst the hundreds of ratios published in the UBPR. A good starting point would be to check the ratio selection procedures followed in the relevant classification studies and in banking research which have performed PCA/FA using bank ratios. To facilitate this step, the study uses Appendix

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[90] Note that the methodology of Ezzamel et al. (1987a) differs from that employed by Pinches et al. (1975). The latter restricted their sample to firms with complete observations in *all* the years of the study which, although resulting in a more homogeneous sample, imparted a survival bias as Ezzamel et al. (1987a, p. 523) noted. Nevertheless, Ezzamel et al. (1987a) replicated their study using the sampling procedure of Pinches et al (1975); this caused some enhancements in both the proportion of variance explained by the factors and the stability of these factors over time.

3.1 which outlines the ratio selection procedures followed in a number of previous studies[91]. Also, it refers to Section 2.6 and Appendix 2.3 in Chapter 2 which summarise the application of PCA/FA in banking research.

In the classification literature, various criteria have been used in selecting the ratios to be analysed. Amongst these criteria, Appendix 3.1 shows that ratios were chosen in a number of studies after a thorough review of research and textbooks that involved financial ratios [for example: Pinches et al. (1975), Johnson (1979), Laurent (1979), and Ezzamel et al. (1987a)]. Also, a few studies chose to use only ratios which were analysed in the past classification literature [for example: Devine and Seaton (1995) selected 44 ratios from the list of 48 ratios used in Pinches et al. (1975)]. The selection of ratios in some other studies was based on some *a priori* dimensions in which these studies were interested [Ylli-Oli and Virtanen (1989), Martikainen et al. (1995a)].

In regard to the relevant banking studies, in general, the variables and ratios used were selected to closely serve the purposes of the study. For example, Whalen and Thomson's (1988) study, which predicted banks' examination ratings, used a number of ratios which were preferred by regulators. Likewise, Yeh's (1996) study used ratios that were popular amongst Taiwanese regulators for evaluating the efficiency of banks. Other banking studies relied heavily on the variables that were reported in the previous literature or that were provided by the unique data source they had accessed [Jackson (1974), Ali et al. (1995), and Canbas et al. (2005), amongst others]. The last point to mention in this regard is that some studies did not report any selection criteria at all [Cheng and Ariff (2007), Shih et al. (2007) and Johnson and Meinster (1975)].

With regard to the banks' preliminary dimensions of performance from which the ratios that were factor analysed were selected, only two studies, Poon et al. (1999) and Zopounidis et al. (1995), provided such key dimensions. Variables in Poon et al. (1999) were chosen to reflect the following pre-determined dimensions: profitability, efficiency, asset composition, interest composition, interest coverage, leverage and risk. In Zopounidis et al. (1995), the following characteristics were initially covered:

[91] Note that the first part of Appendix 3.1 is introduced in Chapter 3.

development, liquidity, investment policy, management efficiency (capital structure), and earning quality (profitability).

However, in choosing ratios for their study, Salmi et al. (1990, p. 14) adopted a more systematic approach which required the selected ratios: 1- to fulfil some theoretical considerations; 2- to have some stable statistical properties in prior research; 3- to be relevant to the area of study; and 4- to be accessible and non-problematic to calculate. While Salmi et al. (1990) gave no explanations concerning the stable statistical properties the selected ratios should exhibit, the current study incorporates all the rest of the criteria when choosing the list of variables.

In regard to the ratios selected for the present study, it must first be recalled that ratios published in the UBPR are reported under some *a priori* categories which include: earnings and profitability, margin analysis, loan and lease analysis, liquidity, capitalisation, and growth rates. By selecting a few ratios from each category, the chosen set of variables would represent the whole report and hence, meet these theoretical considerations. Although the data provided in the UBPR can be used to calculate more ratios, the current study uses only the ratios given in the report; it does not attempt to construct other ratios. This is because, given the immense number of ratios given in the UBPR, it is unlikely that the report excludes any important or any of the frequently used ratios. In addition, calculating more ratios would add unnecessary complexity to the study.

Taking all the above into account, a list of over 100 ratios was initially obtained from the downloaded UBPRs. This list was chosen in light of the only two textbooks available regarding banking ratios: Golin (2001) and Palat (1989) [reviewed in Chapter 2, Section 2.3]. Nevertheless, this number was far higher than the average number of ratios often analysed in the classification literature, as well as in banking studies [see Appendices 3.1 and 2.3 for the number of ratios analysed in these studies]. Therefore, in order to define a smaller set of variables, some practical issues had to be considered. For instance, ratios which are the inverse of others were excluded from the larger set. Also, the study discarded ratios which are computed by adding up or subtracting other ratios in the set. In addition, the use of ratios describing the percentage composition of assets and liabilities were kept to a minimum. Last but not least, the study ran various trials of PCA over the different samples; ratios that did not seem to contribute significantly to the final solutions were excluded[92]. The aim of filtering ratios in this manner was to obtain the most parsimonious set of ratios for the available banks; utilising such a parsimonious set is widely emphasised as a basis for conducting a sound PCA [see, for example, Hair et al. (1998, p. 99)].

The study finally defined a set of fifty-six ratios representing each of the broad categories in the UBPR; these were mentioned earlier. These ratios, and the identifying numbers given to each, are listed in Table 4.4 while the definitions of the components of ratios are given in Appendix 4.1. These definitions were carefully gathered using the UBPR manual referred to in this study as FFIEC (2006). This set was used in all the analyses carried out in Chapters 5-7. Nevertheless, in order to account for some practical issues, smaller sets, chosen from the list of 56 ratios, were used in Chapter 8; further explanations are given in Chapter 8.

Table 4.4: Variables' numbers and ratios*

Variable Number	Ratio	Variable Number	Ratio
X1	INT INC \ AVR AST	X29	G R TIER ONE CAP
X2	INT EXP \ AVR AST	X30	G R NET LN&LS
X3	NET INT INC \ AVR AST	X31	G R S T INV
X4	NONINT INC \ AVR AST	X32	G R S T NON CORE FUNDING
X5	NONINT EXP \ AVR AST	X33	EFFICIENCY RATIO
X6	PROVISION LN&LS LOSSES \ AVR AST	X34	AVR PERSONNEL EXP PER EMPL($000)
X7	PRETAX OPER INC \ AVR AST	X35	AST PER EMPLOYEE ($MILLION)
X8	PRETAX NET OPER INC \ AVR AST	X36	YIELD ON TOT LN&LS (TE)
X9	NET OPER INC \ AVR AST	X37	YIELD ON TOT INV SEC (TE)
X10	NET INC \ AVR AST	X38	COST OF ALL INT-BEARING FUNDS
X11	AVR EARN AST \ AVR AST	X39	S T INV \ TOT AST
X12	AVR INT-BEARING FUNDS \ AVR AST	X40	MARKETABLE EQ SEC \ TOT AST
X13	INT INC \ AVR EARN AST	X41	CORE DEP \ TOT AST
X14	INT EXP \ AVR EARN AST	X42	S T NCORE FUNDING \ TOT AST
X15	NET INT INC \ AVR EARN AST	X43	NET S T NCORE FUND DEPENDENCE
X16	NET LOSS \ AVR TOT LN&LS	X44	BROK DEP \ DEP

[92] See Hair et al. (1998, pp. 113-114) for a brief description of how to evaluate the contribution of a variable to the solution.

Variable Number	Ratio	Variable Number	Ratio
X17	EARN COV OF NET LOSS	X45	S T INV \ S T NCORE FUND
X18	LN&LS ALLOW \ NET LOSSES	X46	S T AST \ S T LIABS
X19	LN&LS ALLOW \ LN&LS NOT HFS	X47	NET S T LIAB \ TOT AST
X20	LN&LS ALLOW \ TOT LN&LS	X48	NET LN&LS \ DEP
X21	NON-CUR LN&LS \ GRS LN&LS	X49	NET LN&LS \ CORE DEP
X22	NET NCORE FUND DEPENDENCE	X50	TOT HTM SEC \ TOT SEC
X23	NET LN&LS \ TOT AST	X51	TOT AFS SEC \ TOT SEC
X24	TIER ONE LEVERAGE CAP	X52	PLEDGED SEC \ TOT SEC
X25	CASH DIV \ NET INC	X53	NET INC \ AVR TOT EQ
X26	RETAIN EARNS \ AVR TOT EQ	X54	G R TOT EQCAP
X27	RESTR+NONAC+RE ACQ \ EQCAP+ALLL	X55	TIER ONE RBC \ RISK-WGT AST
X28	G R AST	X56	TOT RBC \ RISK-WGT AST

* The order of ratios in this table is based on their appearance in the UBPR. Ratios X1-X32 are extracted from Page 1 of the UBPR entitled 'Summary Ratios'; ratios X33-X38 are from Page 3 of the report entitled 'Noninterest Income and Expenses and Yields'; ratios X39-X52 are from Page 10 of the report entitled 'Liquidity and Investment Portfolio'; and finally, ratios X53-X56 are from Pages 11 and 11A of the report entitled 'Capital Analysis and Risk Base Capital'.

Having introduced the banks and ratios used in this study; there is one important point that needs to be emphasised here. A sound application of PCA/FA requires using a high cases-to-variable ratio (i.e. banks-to-ratio). Relevant PCA/FA textbooks often cite many cut-offs regarding the minimum ratio of cases-to-variable required. For example, Hair et al. (1998, pp. 98-99) and Stevens (2002, p. 395) recommend a minimum of a 5-to-1 ratio. Also, some textbooks advise that factor analysis should not be undertaken if the absolute size of a sample is below 50 cases [for example, Hair et al. (1998, p. 98)]. However, this issue should not be a concern here, given that the datasets in this study are amongst the largest to be used in the ratio classification literature. Interestingly, previous literature has not addressed the issue of the suitability of sample size with regard to PCA/FA. As can be seen from Appendix 3.1, samples of less than 50 firms were used in a number of classification studies [amongst these are: Martikainen et al. (1995a), Yli-Olli and Virtanen (1989) and Ketz et al. (1990)]. Also, small samples were often used in banking research that performed PCA/FA as a preliminary step prior to more advanced statistical analysis, as Appendix 2.3 shows.

4.5 Data transformation

A common log transformation was applied to the financial ratios in some studies to improve normality, reduce outliers, and mitigate problems with the homoscedasticity of the distributions. Amongst the studies that performed a common log transformation are: Pinches et al. (1973, 1975), Johnson (1979), Cowen and Hoffer (1982) and Mear and Firth (1986) in the ratio classification literature (see Appendix 3.1); and Ali et al. (1995) and Charbaji (2001) in the banking literature (see Section 2.6 and Appendix 2.3 in Chapter 2). Studies that did not apply any transformation to the data did not often comment on the normality of the distributions of their data. However, Ezzamel et al. (1987a, p. 532), who chose to use ratios in their raw form, justified their decision on two counts: firstly, financial ratios are used by different parties in their raw form (i.e. without transformation); and secondly, many transformation methods exist and there is no general consensus on which method is the best. The question that arises at this point is whether the use of transformed data has a significant effect on the financial patterns of ratios: i.e. can this affect the results of the PCA/FA?

This question was briefly addressed in Devine and Seaton (1995) as their main results were obtained using untransformed data. However, as mentioned in Chapter 2 (Subsection 2.4.2), Devine and Seaton (1995) replicated their analysis using transformed ratios; the results from transformed and raw ratios were different. Interestingly, they noted that using a log transformation leads to the elimination of firms with ratios which take negative values; so, they discarded such cases from their sample and re-performed the analysis using raw ratios. The results this time were similar to those from the transformed ratios. The conclusion drawn by Devine and Seaton (1995) was that PCA is insensitive to the normality of the data; in other words, using transformed and raw ratios would lead to the same results.

The last point was investigated in detail by Martikainen et al. (1995a) who investigated whether the distributional properties of ratios influence their classification patterns. The study found that improving the approximation to normality by means of a square root transformation, and by deleting outliers, had a significant effect on the classification patterns of ratios. The stability of these patterns over time was also improved by transforming the data and eliminating outliers. Accordingly, the current study uses transformed data.

However, the transformation used here is different from those previously applied in the literature. The current study uses one of the inverse hyperbolic functions to transform the ratios. This is called the arcsinh transformation and is carried out by applying the following transformation to all 56 ratios used in this study (Courant and John, 1965, p. 233):

$$t.r = \log(r + \sqrt{r^2 + 1}) \quad \textbf{(4.1)}$$

where (r) is the ratio in its raw form and ($t.r$) is the transformed ratio. Unlike most transformation procedures applied in the literature, the above formula can be used for ratios with negative values; hence, it helps in transforming such ratios where other techniques (e.g. square root and logarithm) cannot be used. Moreover, the arcsinh transformation is broadly logarithmic. When r is large and positive, $t.r \approx \log(2r)$; when r is large and negative, $t.r$ is large and negative. These are properties which broadly characterise the standard logarithmic transformation.

4.6 Programmes and software used

To perform the analyses, the study uses two statistical software packages, SPSS and SURVO[93]. SPSS (the Statistical Package for Social Science) versions 14.0-17.0 are used to perform PCA throughout the study. Parallel Analysis, the technique used to decide on the number of components, is run using SPSS and the syntax offered on Professor O'Connor's website[94]. The software SURVO (versions 2.44 and 2.51) is used to perform Transformation Analysis. All other procedures are carried out using Excel spreadsheets; these include extracting the data from the downloaded UBPRs, computing the coefficients of congruency and the z-scores for the significance test for transformation matrices.

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[93] SURVO is available via the URL: http://www.survo.fi/english/ [accessed on 19 November 2009]
[94] This can be accessed via the URL: https://people.ok.ubc.ca/brioconn/nfactors/nfactors.html [accessed 18 November 2009].

4.7 Summary

The UBPR is the main source for the data on which this study is based. It provides a large number of banking ratios, all computed in the same manner to enable performance comparisons to be made between banks. Given the format of the UBPR, downloading the report for the date 31/12/2005 enabled data to be obtained for the last quarter in every year between 2001 and 2005. The only disadvantage to the five-period feature of the report, was that banks that were in operation only in years prior to the report's date (i.e. years 2001-2004), were not on the report's lists as of 31/12/2005; thus, these banks could not be included in this study's analysis.

Nevertheless, the UBPR was obtained for the commercial, savings and De Novo banks that were on the report's website as of 31/12/2005. This resulted in five-years' worth of data for nearly 7,000 insured commercial banks, 444 savings banks, and a few hundred De Novo or newly chartered commercial banks; ratio data for these banks are used in Chapters 5, 7 and 8 of this study, respectively. Furthermore, the insured commercial banks were classified into four groups based on their asset size; these make up the samples used in Chapter 6.

For each of these banks, a list of over 100 ratios was initially obtained. However, seeking a more parsimonious set of ratios, and after considering some practical issues, this list was reduced to a total of 56 ratios. These ratios were selected to represent the main dimensions of performance covered by the UBPR and included: earnings and profitability, margin analysis, loan and lease analysis, liquidity, capitalisation, and growth rates. All these ratios were subjected to an arcsinh transformation in order to improve the distributional properties of the data.

The final samples used in this study consisted of banks that had all 56 ratios available in any of the years 2001-2005. The sample sizes are reported in the relevant empirical chapters: i.e. Chapters 5-8. In these chapters, PCAs were performed using SPSS; also, the SURVO software package was used to perform transformation analysis. Simpler analyses were carried out using Excel Spreadsheets.

Last but not least, this thesis has so far covered all the theoretical, methodological and data aspects of the study. After the introductory chapter in which the research questions were posed, Chapter 2 thoroughly reviews the relevant ratio classification literature and identifies the gaps which will be filled by this study. Chapter 3, the methodology chapter, explains the study's approach in order to fill this literature gap while Chapter 4 introduces the bank samples and the list of ratios analysed in the study. The following chapters (5-8) represent the empirical analysis and results of the study. Each of these chapters addresses one of the primary research questions and the relevant secondary questions that were posed in Chapter 1. In the following chapter, Chapter 5, the ratio patterns for the U.S. insured commercial banks are identified and their stability over the period between 2001 and 2005 is assessed.

Chapter 5 The Classification Patterns of Financial Ratios for Commercial Banks

5.1 Introduction

This chapter reports on some empirical evidence on the types of financial patterns for commercial banks. The aim is to enhance the usefulness of bank financial ratios and facilitate the selection of appropriate ratios for various decision-making and research purposes. The chapter employs Principal Component Analysis (PCA) to classify a set of 56 bank ratios for a large sample of U.S. commercial banks. Various methods are used to check the time stability of the patterns over the period 2001-2005.

The rest of the chapter is organised as follows: Section 5.2 briefly introduces the methodology and the datasets used. Section 5.3 reports some descriptive statistics for the year 2005. In Section 5.4, PCA is carried out and the financial patterns for the banks are identified, first for year 2005, then for the four preceding years. Section 5.5 presents the results of the different factor comparison techniques used to assess the short-term stability of bank patterns. The chapter is concluded with Section 5.6 which summarises the chapter and introduces the chapters that follow.

5.2 Methodology and sample

Methodology. As explained earlier in Chapter 3, all the empirical work in this study was carried out using much the same methodology. The chief technique was PCA which was used to identify the patterns of ratios (also referred to in this study as components, factors, dimensions, and groups of ratios). The number of components was decided solely by using Parallel Analysis (PA) although the results of the eigenvalue criterion and Cattell's scree plot are also reported. To assess the time stability of the identified patterns, the study used visual comparisons, correlation and congruency coefficients, and transformation analysis. The statistical software package SPSS 14.0 was used to carry out the descriptive statistics and PCA while the software SURVO 2.44 was used to perform transformation analysis. All the other analyses were carried out using Excel spreadsheets.

Sample. As mentioned in Chapter 4, the Uniform Bank Performance Report (UBPR) was the main source of data for this study. This report was retrieved for all the U.S. insured commercial banks for the fourth quarter of the year 2005 (i.e. the report's date was 31/12/2005). The UBPR arranges these banks into 15 peer groups based on the bank's asset size, location and number of banking offices. For the purpose of this chapter, banks in these 15 peer groups were grouped into one sample. Table 5.1 gives the total number of U.S. insured commercial banks for the years 2001-2005. As the table shows, the number ranges between 6,898 and 7,654 banks in 2005 and 2001 respectively[95]. Nevertheless, as mentioned in Chapter 4, obtaining the reports for these banks in each year was problematic. However, given that the UBPR for a given bank retrieved for the last quarter of 2005 delivers data for this bank for the last quarter in every year over a five-year period, the reports were downloaded only for the 6,898 banks listed on the UBPR's website for the date 31/12/2005. So, while there were over 7,000 banks in operation in years 2001-2004, only banks which were still in operation in year 2005 (6,898 banks) were actually available for use in this study's samples.

Table 5.1: Number of U.S. insured commercial banks (2001-2005)

Year	Total number of banks in 15 peer groups	Banks with complete observations
2001	7,654	5,568
2002	7,534	5,732
2003	7,389	5,729
2004	7,155	5,531
2005	6,898	5,399

For each of the 6,898 banks in years 2001-2005, a set of 56 ratios was obtained. This set of ratios is introduced in Chapter 4 (Table 4.4) and the descriptions of these ratios

[95] These figures were obtained by compiling all banks in peer groups 1-15 as reported on the UBPR's websites in the last quarter of years 2001-2005.

are given in Appendix 4.1. Also, it was stated in Chapter 4 (Section 4.4) that the study only considered banks for which all the 56 ratios were available in any year in the period between 2001 and 2005. The number of banks with full valid observations for years 2001-2005 is reported in the last column of Table 5.1. This number ranges between 5,399 and 5,732 banks in years 2005 and 2002 respectively. This is considered to be, by far, amongst the largest samples used in any ratio classification study.

Data transformation. The main results in this chapter were derived using transformed data. A hyperbolic inverse sinh (arcsinh) transformation was applied to all the 56 ratios in all the years covered in the study [see Chapter 4 (Section 4.5) for the formula of the archsinh transformation]. Nevertheless, some results, obtained using ratios in their raw form, are reported later in this chapter (Subsection 5.4.2)[96]. The following section, however, reports on some descriptive statistics and demonstrates how the arcsinh transformation improved normality in the distributions of ratios.

5.3 Descriptive statistics for U.S. commercial banks (2005)

This section summarises some descriptive statistics for all 56 ratios listed in Table 4.4 for U.S. commercial banks in the year 2005. Table 5.2 shows the number of missing observations, as well as the range, mean, standard deviation, and standardised values for the skewness and kurtosis measures.

In 2005 there were 6,898 U.S. insured commercial banks; these were assigned to the 15 peer groups as reported in Chapter 4 (Subsection 4.3.1). However, after disregarding banks with any missing observations, the number dropped to 5,399 banks. In other words, the 56 ratios were all available for a proportion of 78.27% of the banks comprising the whole population of U.S. insured commercial banks.

[96] Note that uncovering the impact of transformed data onto the patterns of bank ratios is not amongst the objectives of this study. Thus, the results of raw data are only reported for comparison purposes and they are unique to this chapter; in other words, other chapters (Chapters 6-8) only report the outputs of transformed data.

As shown in Table 5.2, 36 ratios were not available for some banks; nevertheless, these 36 ratios vary in the number of missing observations. Seventeen ratios (X22, X25, X28, X29, X33, X35, X38, X39, X40, X41, X42, X44, X48, X53, X54, X55 and X56) had a small number of missing values, ranging between 1 and 10 banks for each of these ratios. However, another 17 ratios (X16, X19, X20, X21, X30, X31, X32, X34, X6, X7, X43, X45, X46, X49, X50, X51 and X52) were missing for a slightly larger number, ranging between 11 and 83 banks. Nevertheless, the two ratios that were not available for a substantial number of banks were X17 and X18 (Earning Coverage to Net Loss and Loans and Leases Allowance to Net Loss, respectively). These two ratios were missing for 1,372 banks in 2005, approximating to 20% of the whole population. The two ratios have the 'Net Loss' item as their denominator. The 'Net Loss' is obtained by deducting the 'Gross Recoveries' from the 'Gross Losses'. Nevertheless, according to the UBPR Users' Guide (FFIEC, 2006, p. III-5), when the Gross Recoveries exceed the Gross Losses, an 'N/A' sign is shown. Thus, ratios X17 and X18 could not be calculated for these 1,327 banks simply because these banks did not report a 'Net Loss'. Nevertheless, in the case of ratio X16 (Net loss to Average Total Loans and Leases) both negative and positive net losses were used in the calculation, and only 24 observations were missing.

Table 5.2: Descriptive statistics for raw ratios for U.S. commercial banks (2005)*

Variables	**Missing observations**	**Range** (Statistic)	**Mean** (Statistic)	**Std. Deviation** (Statistic)	**Skewness** (Standardised)	**Kurtosis** (Standardised)
X1	0	260.50	5.81	3.22	2439.97	96355.50
X2	0	141.56	1.76	1.76	2469.96	98139.29
X3	0	119.43	4.05	1.67	1643.40	55749.89
X4	0	353.43	1.18	6.94	1135.25	23258.07
X5	0	234.98	3.34	5.15	1057.68	20324.33
X6	0	83.50	0.19	1.05	2336.02	90574.91
X7	0	507.90	1.70	4.96	1587.35	63015.21
X8	0	506.88	1.69	4.96	1594.37	63155.39
X9	0	407.20	1.22	3.70	312.67	46135.87
X10	0	407.20	1.22	3.70	312.33	46071.15
X11	0	110.04	93.23	4.33	-268.39	2049.45
X12	0	129.93	74.99	9.16	-83.88	196.44
X13	0	303.33	6.27	4.97	1873.31	53957.03
X14	0	152.30	1.88	1.91	2407.73	94357.47
X15	0	277.62	4.38	3.74	2085.00	72286.69
X16	24	643.88	0.30	7.70	2784.54	115082.75
X17	1,372	56297.78	102.40	869.71	1499.21	45586.85
X18	1,372	3687.00	41.64	150.35	353.67	2829.36

Variables	Missing observations	Range (Statistic)	Mean (Statistic)	Std. Deviation (Statistic)	Skewness (Standardised)	Kurtosis (Standardised)
X19	32	51.44	1.43	1.08	673.15	12587.49
X20	29	51.44	1.41	1.03	721.47	14884.71
X21	29	88.82	0.86	1.58	896.37	23493.49
X22	10	64298.24	-1.86	791.10	-2635.81	106422.67
X23	0	97.05	63.28	16.33	-31.24	-32.06
X24	0	190.08	10.59	6.12	381.98	3520.61
X25	3	10204.69	51.66	150.25	479.23	14411.32
X26	0	1628.55	5.02	20.89	-2095.96	77397.30
X27	0	122.87	5.09	7.33	128.39	387.79
X28	8	6560.55	10.54	84.03	2283.73	86163.34
X29	8	6551.16	12.24	89.87	1955.59	67169.35
X30	35	4700.71	13.52	88.28	1392.17	33137.41
X31	78	419400.00	509.42	8456.42	1260.55	26938.91
X32	49	16002.34	39.87	251.92	1523.27	43129.01
X33	2	4355.50	64.14	51.70	2349.20	91352.98
X34	11	7610.25	53.62	93.23	2626.42	106244.56
X35	10	9761.43	7.69	173.24	1724.89	45653.17
X36	26	385.12	7.26	4.75	2492.23	98710.28
X37	64	299.37	4.16	3.75	2203.54	80097.27
X38	6	171.42	2.32	2.11	2531.01	101368.16
X39	2	99.08	8.61	9.75	107.29	231.67
X40	1	94.27	0.18	1.64	1193.73	29278.61
X41	1	92.55	68.23	12.34	-64.30	64.43
X42	1	91.84	14.20	9.14	59.86	61.17
X43	12	64243.72	-9.71	791.07	-2635.51	106402.96
X44	1	6623.20	4.04	80.18	2767.68	114212.58
X45	39	1267518.57	332.55	15331.68	2785.27	115076.23
X46	24	3151115.15	658.25	38319.89	2743.82	112566.82
X47	0	202.28	-0.23	17.32	-17.13	-10.96
X48	1	1206472.20	456.61	18748.97	1924.34	56919.54
X49	21	338857.52	163.33	4149.19	2689.74	109387.11
X50	82	100.00	16.36	30.54	64.50	-12.59
X51	83	100.00	83.63	30.55	-64.44	-12.72
X52	83	100.00	46.51	29.78	3.51	-69.22
X53	1	1826.61	11.77	20.93	-2066.53	77937.04
X54	10	6571.41	10.96	90.94	1893.98	64727.54
X55	2	7057.33	17.89	90.18	2395.48	91954.53
X56	2	7056.45	19.01	90.15	2396.56	92013.80
Missing N (listwise)	1,499					

* Refer to Table 4.4 for the list of ratios and Appendix 4.1 for ratio calculations.

The range, mean values and the standard deviations are given in Table 5.2 for all the ratios in year 2005. However, for the current chapter, attention needs to be paid mainly to two statistics: the skewness and kurtosis measures, which are used as simple tests of normality in the distribution. If the standardised value of the measure is significantly different from zero, it is unlikely that the cross-sectional distribution of the ratio is normal.

As for skewness, the values of that measure are significantly different from zero, which is compatible with a departure from normality for all the 56 ratios in 2005. The skewness value for the ratios ranges between -2635.81 and +2785.27 for the ratios X22 and X27 respectively. Thus, the univariate distributions of the ratios examined in this study are severely skewed. Ten of the 56 ratios (X11, X12, X22, X23, X26, X41, X43, X47, X51 and X53) are negatively or left skewed, i.e. most of the observations for these ratios are placed to the left of the mean of their probability distributions. Nevertheless, the univariate distribution of the majority of the ratios is positively or right skewed. The ratio with the least asymmetric distribution is X52, with 3.51 as the value of its standardised skewness measure.

So, it appears that the skewness statistics for the 56 ratios are strongly compatible with the hypothesis that the data are not normally distributed; but what of the peakedness or the flatness of their distributions? This is shown by the kurtosis measure. When the kurtosis value is significantly different from zero, the distribution is either peaked or flat. A positive kurtosis value means that the distribution is peaked and has thin tails, whereas it is flat with fat tails for a negative kurtosis value. The last column in Table 5.2 shows that the distributions of the ratios are not only asymmetric, but also given the high values of kurtosis statistics, these distributions are flat for some ratios and peaked for the rest. The kurtosis values range between 69.22 and 115082.75 for the ratios X52 and X16 respectively. The kurtosis measure is negative for only five ratios (X12, X23, X47, X50 and X51), whereas the distributions of the rest of the ratios are peaked with thin tails. For all 56 ratios, the kurtosis statistic is incompatible with the normal distribution.

Accordingly, the high values of the two normality measures reported in Table 5.2 imply that the distribution of the ratios departs significantly from normality. To mitigate the observed non-normality, all 56 ratios were transformed using the inverse hyperbolic sinh (arcsinh) transformation introduced in Chapter 4 (Section 4.5). Table 5.3 reports the descriptive statistics of the transformed ratios. As can be seen from the table, the inverse hyperbolic sinh transformation seems to significantly reduce the skewness and kurtosis values. For the transformed ratios, the skewness values range between -980.5 and +205.41 for ratios X11 and X40 respectively. Now the distributions of 37 ratios become left-skewed (i.e. with negative skewness values). The ratio with the least skewed distribution is X38 with a skewness statistic of -2.14, which, however, is still significantly different from zero. The kurtosis statistics have also fallen after transforming the data and now range between -78.98 for ratio X47 and 21119.33 for ratio X11. The ratio with the least peaked distribution is X17 (with a kurtosis statistic of +2.46).

Table 5.3: Descriptive statistics for transformed ratios for U.S. commercial banks (2005)*

Variables	**Range** (Statistic)	**Mean** (Statistic)	**Std. Deviation** (Statistic)	**Skewness** (Standardised Statistic)	**Kurtosis** (Standardised Statistic)
X1	6.26	2.44	0.18	-35.95	1088.06
X2	5.65	1.29	0.28	-9.25	124.55
X3	5.94	2.08	0.22	-30.55	400.22
X4	7.08	0.72	0.49	124.40	380.33
X5	6.15	1.82	0.36	67.21	285.66
X6	6.48	0.17	0.26	130.04	582.58
X7	12.30	1.19	0.54	-62.28	220.44
X8	12.30	1.18	0.54	-61.99	214.97
X9	12.01	0.95	0.49	-51.06	246.69
X10	12.01	0.95	0.49	-50.56	244.87
X11	4.56	5.23	0.08	-980.50	21119.33
X12	5.56	5.00	0.24	-422.54	3533.27
X13	6.41	2.51	0.17	69.56	1695.66
X14	5.72	1.35	0.28	-5.78	145.91
X15	7.16	2.15	0.22	6.43	698.95
X16	9.80	0.18	0.34	117.18	611.21
X17	19.06	3.71	1.65	-8.17	2.46
X18	8.91	3.13	1.38	22.28	-36.55
X19	4.63	1.09	0.33	51.20	77.39
X20	4.63	1.09	0.33	46.41	62.68
X21	5.18	0.62	0.59	42.13	-22.07
X22	17.45	2.19	2.72	-49.79	-35.39
X23	5.27	4.78	0.48	-206.87	859.44
X24	4.75	2.99	0.31	72.93	129.88
X25	18.41	3.65	2.06	-48.07	-19.10
X26	12.99	1.90	1.61	-65.63	11.98
X27	5.50	1.67	1.20	5.01	-67.33
X28	14.70	1.71	2.17	-28.84	-54.51
X29	14.38	2.20	1.74	-48.59	-5.70
X30	14.43	2.00	2.22	-38.58	-43.92
X31	18.94	1.40	4.68	-6.88	-76.82
X32	15.67	1.89	3.58	-23.74	-69.02

Variables	Range (Statistic)	Mean (Statistic)	Std. Deviation (Statistic)	Skewness (Standardised Statistic)	Kurtosis (Standardised Statistic)
X33	15.25	4.81	0.31	-280.65	4383.66
X34	9.63	4.61	0.31	-88.52	1085.47
X35	9.80	1.90	0.46	143.77	834.17
X36	6.65	2.66	0.18	-128.11	2180.82
X37	9.67	2.10	0.23	-62.76	1210.68
X38	5.84	1.55	0.24	-2.14	238.41
X39	5.29	2.33	1.10	-10.05	-59.58
X40	5.24	0.09	0.35	205.41	736.31
X41	5.22	4.88	0.41	-292.37	1497.72
X42	5.21	3.14	0.71	-33.87	-10.18
X43	17.00	1.33	2.81	-31.73	-58.89
X44	9.49	0.74	1.27	51.68	-31.03
X45	14.75	4.36	1.64	-12.04	-39.17
X46	15.66	5.25	0.73	20.06	205.92
X47	10.62	0.12	3.02	-4.01	-78.98
X48	15.83	4.98	0.54	-53.26	1282.49
X49	15.91	5.19	0.53	-74.30	805.00
X50	5.30	1.56	2.00	26.38	-68.44
X51	5.30	4.76	1.40	-97.01	63.22
X52	5.30	4.06	1.36	-62.27	-3.44
X53	14.33	2.93	1.08	-129.61	277.92
X54	14.39	1.50	2.18	-21.74	-55.33
X55	9.56	3.36	0.43	86.67	246.33
X56	7.41	3.45	0.41	99.31	295.90

* Refer to Table 4.4 for the list of ratios and Appendix 4.1 for ratio calculations.

In summary, given the decrease in the absolute values of the skewness and kurtosis measures for the 56 ratios, the inverse hyperbolic sinh (arcsinh) transformation seems to succeed in enhancing the distribution's approximation to normality. Nevertheless, although the inverse sinh transformation affected different ratios in different degrees, it is evident that the univariate distributions of all the 56 ratios are still not compatible with the normal distribution.

5.4 Financial patterns of U.S. commercial banks (2001-2005)

The first part of this section reports the results of different steps carried out to perform PCA for the data in year 2005. The second part gives the results of PCA for years 2001-2004; it also reports some results that were obtained using raw (or untransformed) ratios.

5.4.1 Financial patterns of U.S. commercial banks in 2005

Although normality in the data is one of the statistical assumptions required by factor analysis, it is only crucial if a statistical test is applied to check the significance of the factors; however, such tests are rarely used (Hair et al., 1996, p. 99). Nevertheless, given that the arcsinh transformation was applied and helped to significantly reduce the skewness and kurtosis in the data, all the analyses carried out in this study used transformed data, unless otherwise stated.

So, after choosing to use ratios in their transformed form, a number of sequential steps were carried out to perform PCA over the 56 ratios for the 5,399 U.S. commercial banks available in year 2005. The following paragraphs report on the outputs of these steps.

Factorability of correlation matrix. The first step in PCA involves calculating the correlation matrix in order to assess its factorability. This is carried out by checking the size of the correlation coefficients and also by applying the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (MSA) and Bartlett's Test of Sphericity (BTS) to our ratio data. The outcome of this step gives some hint about the existence of underlying patterns in the data. If the results of these preliminary tests indicate that such underlying dimensions do not exist in the data, then performing PCA over these data would be pointless. Details regarding the factorability step are given in Chapter 3 (Subsection 3.3.1). However, the results concerning the data for year 2005 are reported below.

A visual inspection of the correlation matrix[97] calculated for the year 2005 demonstrated that there was a substantial number of correlation coefficients greater than .30 in absolute terms. However, since the sample used in this chapter was large and large samples tend to produce smaller correlation coefficients, 'not very high' correlation coefficients should not cause any concern here (Tabachnick and Fidell, 2007, p. 614). There should only be concern when there is no correlation greater than 0.30 in absolute terms.

[97] The correlation matrices are not reported in this study because of space limitations.

The results of these two statistical tests for the year 2005 are shown in Table 5.4. The BTS is significant at the .0001 level, which indicates that the overall correlation coefficients are significant. Moreover, the KMO MSA of .781 falls in the 'middling' range, using the guidelines given in Sharma (1996, p. 116). Hence, the overall results indicate that some underlying dimensions do exist in the data and that the use of PCA is therefore appropriate to uncover these dimensions.

Table 5.4: KMO and BTS for U.S. commercial banks in 2005 (transformed)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.781
Bartlett's Test of Sphericity	Approx. χ^2	582,608.598
	df	1540
	Sig.	.000

Initial solution. Table 5.5 shows the eigenvalue for each component, the percentage of the variance explained by each component, and the cumulative variance accounted for by successive components. Note that PCA initially derived 56 components which is equal to the number of variables/ratios. This is because each ratio is standardised so that it has a mean of zero and a standard deviation of one, so the total variance in dataset equals 56; also, PCA assumes that a variable shares all its variance with other variables. Nevertheless, the different components account for different proportions of the variance. As can be seen from Table 5.5, the eigenvalue of the first component is 10.124 which means that this component alone explains around 18% of the total variance existing in the dataset. The second component, however, accounts for less variance (13.2 %). The first two components thus explain over 31% of the total variance. Each of the following components accounts for less and less of the total variance.

Table 5.5: Total variance explained for U.S. commercial banks in 2005 (transformed)

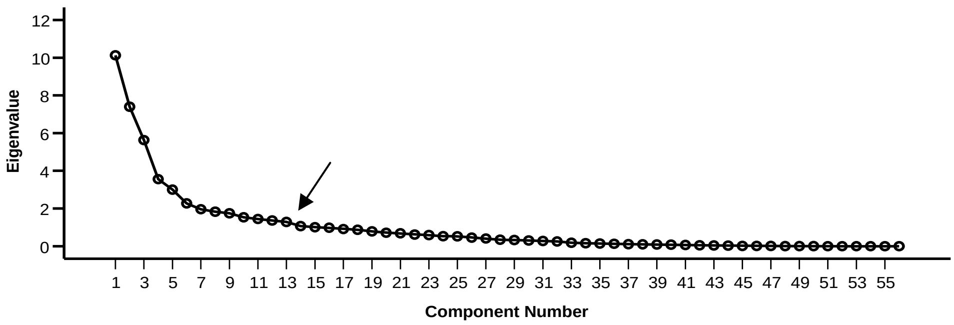
Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	10.124	18.079	18.079
2	7.397	13.209	31.288
3	5.630	10.054	41.342
4	3.554	6.347	47.689
5	3.003	5.363	53.051
6	2.273	4.059	57.111
7	1.959	3.498	60.609

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
8	1.831	3.270	63.879
9	1.746	3.117	66.996
10	1.533	2.738	69.734
11	1.442	2.575	72.309
12	1.366	2.439	74.748
13	1.286	2.296	77.044
14	1.060	1.892	78.936
15	1.010	1.803	80.739
16	0.980	1.750	82.490
17	0.909	1.623	84.113
18	0.873	1.559	85.672
19	0.790	1.411	87.083
20	0.713	1.274	88.357
21	0.680	1.215	89.571
22	0.617	1.101	90.672
23	0.593	1.059	91.731
24	0.526	0.939	92.670
25	0.521	0.931	93.601
26	0.452	0.807	94.408
27	0.408	0.729	95.138
28	0.343	0.612	95.750
29	0.327	0.585	96.334
30	0.303	0.541	96.876
31	0.273	0.488	97.363
32	0.246	0.439	97.803
33	0.181	0.322	98.125
34	0.160	0.286	98.411
35	0.145	0.258	98.669
36	0.129	0.230	98.899
37	0.105	0.187	99.087
38	0.101	0.180	99.267
39	0.091	0.163	99.430
40	0.081	0.145	99.574
41	0.062	0.111	99.685
42	0.050	0.090	99.775
43	0.038	0.068	99.843
44	0.032	0.057	99.900
45	0.017	0.030	99.930
46	0.013	0.024	99.954
47	0.010	0.018	99.972
48	0.005	0.009	99.981
49	0.003	0.005	99.986
50	0.003	0.005	99.991
51	0.002	0.004	99.995
52	0.001	0.003	99.997
53	0.001	0.002	100.000
54	0.000	0.000	100.000
55	0.000	0.000	100.000
56	0.000	0.000	100.000

Deciding on the number of components. There are many criteria that can be applied to the initial solution reported in Table 5.5 to determine how many factors to retain in the final solution [see Chapter 3 (Subsection 3.3.2) for further details regarding this step]. The most common criterion is the latent root (or eigenvalue greater than one) which keeps all the components with eigenvalues which exceed unity. Any component with an eigenvalue of less than unity contributes less to the cumulative variance; it is thus considered insignificant and should not be retained. As can be seen from Table 5.5, 15 components have eigenvalues that exceed unity. These 15 components collectively explain over 80.74% of the variance which exists in the set of 56 ratios.

Another widely used method for determining the number of factors is called Cattell's scree plot. Figure 5.1 shows the eigenvalues associated with the components plotted against the components in the order of their extraction for the transformed data in year 2005. As can be seen from the figure, at around component 14, the plot starts to straighten. The scree plot method hence implies that 13 factors should be retained.

Figure 5.1: Cattell's scree plot for commercial banks in 2005 (transformed)



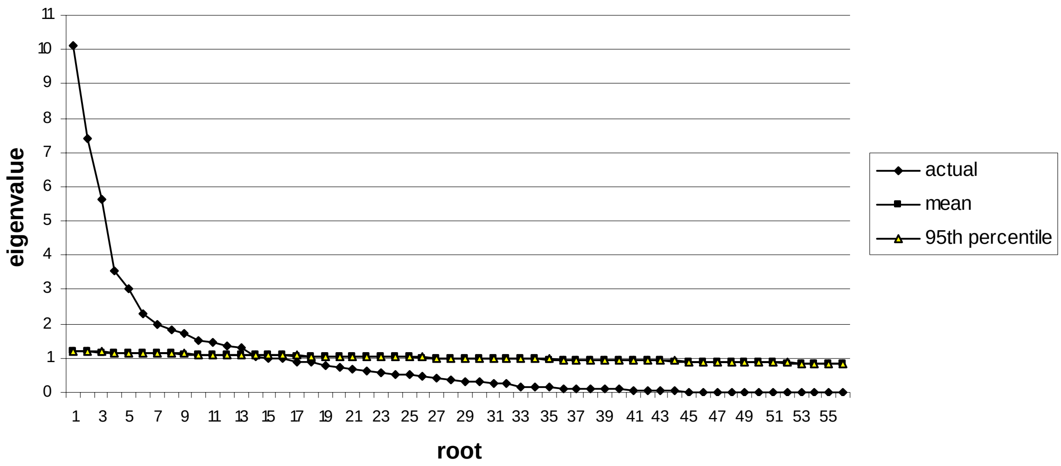
However, a method called Parallel Analysis (PA) has been proved to outperform both the latent root and the scree plot criterion by giving a better estimate of the number of factors that should be retained [see, for example, Hayton et al. (2004), amongst others]. Thus, this method was adopted in this study as the main criterion to decide on the number of components to retain. For this, the study used the SPSS syntax offered on the website of Professor B. O'Conner. However, before running the programme for the 5,399 banks in the year 2005, it was important to decide on the number of random datasets required for the analysis. As a general rule, the higher the number of random datasets generated, the more accurate the results of the analysis (Hayton et al., 2004, p. 199). For this reason, this study took the most conservative approach and ran parallel analyses using 1,000 random datasets; each of the generated datasets consisted of 56 variables and 5,399 cases. The numerical results of PA are shown in Table 5.6 and these are also plotted in a graph in Figure 5.2.

Table 5.6: Parallel analysis output for U.S. commercial banks in 2005 (transformed)

Root	Actual eigenvalue	Average eigenvalue	95^{th} percentile eigenvalue
1	10.124320	1.199344	1.216934
2	7.396896	1.183478	1.196110
3	5.630149	1.171048	1.181430
4	3.554379	1.160600	1.169968
5	3.003028	1.151048	1.160032
6	2.273226	1.142035	1.150556
7	1.959053	1.133754	1.141448
8	1.831056	1.125726	1.133312
9	1.745794	1.118123	1.125795
10	1.533355	1.110672	1.117903
11	1.441981	1.103506	1.110645
12	1.365689	1.096647	1.103387
13	1.285569	1.090148	1.097076
14	1.059792	1.083602	1.090437
15	1.009624	1.076903	1.083464
16	.980273	1.070498	1.076602
17	.908912	1.064178	1.070338
18	.873163	1.057916	1.064238
19	.790098	1.051956	1.058123
20	.713428	1.045735	1.051667
21	.680200	1.040048	1.046047
22	.616502	1.034114	1.039878
23	.592818	1.028351	1.034078
24	.526059	1.022404	1.028131
25	.521199	1.016891	1.022731
26	.452018	1.011111	1.016725
27	.408468	1.005443	1.011237
28	.342786	.999596	1.005062
29	.327381	.994027	.999600
30	.303151	.988343	.993883
31	.273120	.982693	.988289
32	.246026	.977088	.982507
33	.180533	.971505	.977094
34	.160072	.965976	.971895
35	.144713	.960328	.965821
36	.128772	.954614	.959989
37	.104917	.949158	.954791
38	.100857	.943374	.949204
39	.091325	.937756	.943523

Root	Actual eigenvalue	Average eigenvalue	95th percentile eigenvalue
40	.080996	.932052	.937952
41	.062044	.926317	.932147
42	.050163	.920504	.926666
43	.038049	.914731	.920865
44	.032039	.908916	.914833
45	.016686	.902745	.908700
46	.013360	.896716	.903197
47	.010093	.890277	.896815
48	.005033	.883952	.891022
49	.003035	.877402	.884458
50	.002958	.870736	.878212
51	.001983	.863800	.871023
52	.001445	.856400	.863704
53	.001243	.848361	.856597
54	.000125	.839930	.848810
55	.000030	.830185	.839550
56	.000012	.817239	.828304

Figure 5.2: Plot of actual vs. randomly generated eigenvalues for commercial banks in 2005 (transformed)



As Table 5.6 shows, the eigenvalues of the first 13 components are all higher than both the mean and the 95th percentile eigenvalue of the randomly generated datasets. Thus, the results of PA indicate that, similar to the scree plot results, there are only 13 underlying dimensions in the actual data of 2005, not 15 factors as the latent root method suggested. Similar to Table 5.6, Figure 5.2 shows that the curve of the actual data intercepts with the two curves of the random data at component 14; this means that the first 13 components are the only significant components and thus should be retained. By referring to Table 5.5, these 13 components explain over 77% of the variance in the sample.

Rotating solution. Following the decision to retain 13 factors, the next step involved interpreting these factors: i.e. finding suitable labels for each of them. However, the solution needed to be rotated so that the interpretation process became easier [see Chapter 3 (Subsection 3.3.3.1) for further details about factor rotation methods]. The varimax rotation is one of the most widely used orthogonal rotational methods. This method simplifies the columns of the component matrix by making the loadings of the variables onto the components either very high or very close to zero. The rotated component matrix obtained in this step can then be used to interpret the factors.

Interpreting components. The rotated component matrix for U.S. commercial banks in 2005 is shown in Table 5.7. The columns represent the 13 components and the rows represent the 56 ratios. The loadings appearing in the matrix are crucial when defining and labelling the components [further details regarding this step are given in Chapter 3 (Subsection 3.3.3.2)]. Given the guidelines reported in Table 3.2 in Hair et al. (1998, p. 112), factor loadings equal to or greater than |.30| are considered to be significant for a sample size of 350 and above. Thus, for the commercial bank sample in 2005 (5,399 banks), a minimum value of |.30| was required for loadings to be considered significant. Thus, in Table 5.7 all loadings less than |.30| were suppressed [see ratios X40 and X52 at the bottom of the table; these two ratios did not have significant loadings (i.e. >|.30|) onto any of the components].

Labelling components. Note that the components given in Table 5.7 are arranged according to the decreasing proportion of the variance that each component explains. The ratios are then rearranged according to their decreasing loadings onto each factor. The label to be given to a component is influenced by the ratios that have the highest loadings onto that component. In this sense, the following labels were assigned to the 13 components which were found to represent the financial patterns of the U.S. commercial banks in the year 2005: (C1) Profitability, (C2) Short-term liquidity, (C3) Margin (Yields) I, (C4) Margin (Costs) II, (C5) Loans and leases, (C6) Risk-Based Capital, (C7) Asset Quality I, (C8) Capital Growth, (C9) Asset Quality II, (C10) Efficiency I, (C11) Efficiency II, (C12) Growth, and (C13) Investment Securities. In this chapter and in the following chapters, abbreviations of these labels are used. These are introduced in Table 5.8.

Table 5.7: Rotated component matrix for U.S. commercial banks in 2005 (transformed)[*]

Variable Number	Ratio	Component												
		1	2	3	4	5	6	7	8	9	10	11	12	13
X9	NET OPER INC \ AVR AST	0.949												
X10	NET INC \ AVR AST	0.949												
X8	PRETAX NET OPER INC \ AVR AST	0.948												
X7	PRETAX OPER INC \ AVR AST	0.946												
X53	NET INC \ AVR TOT EQ	0.889												
X33	EFFICIENCY RATIO	-0.754									0.433			
X45	S T INV \ S T NCORE FUND		-0.838											
X43	NET S T NCORE FUND DEPENDENCE		0.797											
X39	S T INV \ TOT AST		-0.793											
X46	S T AST \ S T LIABS		-0.779											
X47	NET S T LIAB \ TOT AST		0.763											
X22	NET NCORE FUND DEPENDENCE		0.717		0.310									
X42	S T NCORE FUNDING \ TOT AST		0.515		0.316								0.510	
X37	YIELD ON TOT INV SEC (TE)		0.358											
X3	NET INT INC \ AVR AST			0.910										
X15	NET INT INC \ AVR EARN AST			0.897										
X13	INT INC \ AVR EARN AST			0.895										
X1	INT INC \ AVR AST			0.883	0.318									
X36	YIELD ON TOT LN&LS (TE)			0.813										
X2	INT EXP \ AVR AST				0.888									
X14	INT EXP \ AVR EARN AST				0.885									
X38	COST OF ALL INT-BEARING FUNDS				0.862									
X12	AVR INT-BEARING FUNDS \ AVR AST				0.536		0.418							
X41	CORE DEP \ TOT AST		-0.327		-0.458	-0.310						-0.341	-0.313	
X44	BROK DEP \ DEP				0.382	0.351						0.364		
X48	NET LN&LS \ DEP					0.828								
X49	NET LN&LS \ CORE DEP				0.337	0.797								
X23	NET LN&LS \ TOT AST					0.789	0.340							
X24	TIER ONE LEVERAGE CAP						-0.887							

Variable Number	Ratio	Component												
		1	2	3	4	5	6	7	8	9	10	11	12	13
X55	TIER ONE RBC \ RISK-WGT AST					-0.363	-0.844							
X56	TOT RBC \ RISK-WGT AST					-0.356	-0.842							
X18	LN&LS ALLOW \ NET LOSSES							0.912						
X16	NET LOSS \ AVR TOT LN&LS							-0.766						
X17	EARN COV OF NET LOSS	0.441						0.760						
X6	PROVISION LN&LS LOSSES \ AVR AST	-0.308		0.405				-0.543						
X21	NON-CUR LN&LS \ GRS LN&LS							-0.473		0.433				
X27	RESTR+NONAC+RE ACQ \ EQCAP+ALLL							-0.456		0.341				
X29	G R TIER ONE CAP								0.879					
X54	G R TOT EQCAP								0.839					
X26	RETAIN EARNS \ AVR TOT EQ	0.399							0.784					
X25	CASH DIV \ NET INC	0.496							-0.505					
X19	LN&LS ALLOW \ LN&LS NOT HFS									0.916				
X20	LN&LS ALLOW \ TOT LN&LS									0.915				
X4	NONINT INC \ AVR AST										0.804			
X5	NONINT EXP \ AVR AST	-0.367		0.440							0.720			
X11	AVR EARN AST \ AVR AST										-0.619			
X34	AVR PERSONNEL EXP PER EMPL($000)											0.747		
X35	AST PER EMPLOYEE ($MILLION)										-0.453	0.672		
X32	G R S T NON CORE FUNDING												0.585	
X28	G R AST								0.410				0.573	
X31	G R S T INV		-0.366										0.470	
X30	G R NET LN&LS								0.322				0.352	
X50	TOT HTM SEC \ TOT SEC													-0.898
X51	TOT AFS SEC \ TOT SEC													0.893
X40	MARKETABLE EQ SEC \ TOT AST													
X52	PLEDGED SEC \ TOT SEC													

* Loadings smaller than .30 are suppressed (Table 3.2 in Hair et al., 1998, p. 112).

Table 5.8: Abbreviations of components

Abbreviation	Component
AQ	Asset Quality
AQ-I	Asset Quality-I
AQ-II	Asset Quality-II
AQ-III	Asset Quality-III
CG	Capital Growth
Eff	Efficiency
Eff-I	Efficiency-I
Eff-II	Efficiency-II
Fnd	Funding
Fnd-II	Funding-II
Grth	Growth
IS	Investment Securities
Ln&Ls	Loans and Leases
M(Y)-I	Margin (Yield)
M(C)-II	Margin (Cost)
Prof	Profitability
RBC	Risk-Based Capital
Sh-t inv	Short-term Investment
Sh-t liq	Short-term Liquidity

Thus, it can be argued that these 13 components represent nine broad areas of commercial banks' performance. These areas are:

1. Profitability (C1): expressed mainly as earnings related to average assets.
2. Liquidity position mainly in the short-term (C2): measured by relating the short-term investment, non-core funding and short-term assets to the total assets.
3. Margin-Yields and Costs (C3 and C4): expressed as the interest income and interest expenses as related to average assets.
4. Loans and leases (C5): as a percentage to total assets, deposits and core deposits.
5. Capital: this comprises two distinctive factors (C6 and C8). The first (Risk Based Capital or RBC) represents tier one capital and total risk-based capital to the adjusted assets and the risk-weighted assets. The second factor (Capital Growth or CG) represents the growth rate of tier one capital and equity capital, in addition to the ratio of the retained earnings to equities.
6. Asset Quality (I and II) (C7 and C9): is reflected by the percentage of loans (allowance, losses, non-current and restructured) to the average assets or to each other.

7. Efficiency (I and II) (C10 and C11): is represented by non-interest income and expenses to average assets, and also by the personnel expenses and assets per employee.
8. Growth rates (C12) of some asset and liability items including the short-term non-core funding, assets, short-term investments, and loans and leases.
9. Investment securities to total securities (C13): whether held to maturity or available for immediate sale.

5.4.2 Financial patterns of U.S. commercial banks in 2001-2004

Similar analyses were carried out to classify the 56 ratios listed in Table 4.4 for commercial banks in each of the years 2001 to 2004. But first, this subsection commences by reporting some initial results obtained using raw and transformed data. In the second part of this subsection, however, the financial patterns of U.S. commercial banks are identified using transformed data for the samples in years 2001-2004.

5.4.2.1 Initial results for raw and transformed data

Starting with the raw or untransformed ratios, PCAs were carried out using the raw ratios on a yearly basis for the period between 2001 and 2005. A summary of the initial results is presented in Table 5.9; these include the number of factors suggested using two factor retention criteria: the 'latent root greater than 1' and PA; and the percentage of the variance explained by the factor solutions for each of the years 2001-2005.

Table 5.9: Summary of initial results using raw ratios (2001-2005)

Year	Number of factors Eigenvalue >1	% of variance explained	Number of factors PA	% of variance explained
2001	18	81.842%	15	76.301%
2002	15	83.990%	15	83.990%
2003	18	82.582%	15	77.035%
2004	18	82.613%	17	80.783%
2005	15	86.414%	13	82.765%

As Table 5.9 shows, the number of derived factors using the latent root criterion varies across the years of the study. In year 2001, there were 18 factors with eigenvalues in excess of unity. These factors account for 81.84% of the variance in the data. Using the same criterion, there were 15 factors in year 2002 accounting for a higher percentage of the variance (83.99%). In 2003 and 2004, 18 factors had eigenvalues which exceeded unity; these factors account for around 82.6% of the total variance. In year 2005, although the number of factors fell to 15, these factors explain the highest percentage of the variance (86.41%) compared to the preceding years.

Similarly, the number of factors obtained using PA varied considerably over the five-year period, as shown in Table 5.9. In 2001, PA suggested 15 factors which explained in total 76.30% of the variance. In the following two years also, 2002 and 2003, 15 factors were suggested; these explained slightly different percentages of variance (83.99% and 77.04%, respectively). In year 2004, a solution of 17 factors was suggested; this explained 80.78% of the variance. Finally, the analysis for year 2005 suggested 13 factors accounting for 82.77% of the variance.

So, as can be seen from Table 5.9, the use of raw data resulted in some inconsistency in the outputs of the latent root criterion and PA. This appeared in terms of the number of factors derived and the percentage of the variance explained by the factors over the period.

The results of the transformed data are summarised in Table 5.10 (see Appendix 5.1 for full PA outputs). The consistency in the results can be immediately noticed when checking the table. For each year in the period covered there were 15 factors, each with an eigenvalue exceeding unity. However, when PA was conducted, 13 factors were identified in all years except 2001 where 14 factors appeared significant. Furthermore, factor solutions for transformed data accounted for fairly stable percentages of variance over the years. Solutions identified using the latent root criterion accounted for 80.74%-81.21% of the total variance over the period. Using PA, the range of explained variance was between 77.04% and 77.50% for the 13-factor solutions in years 2002-2005, whereas the 14-factor solution in year 2001 explained 79.34% of the variance. Nevertheless, it is important to emphasise that the main results in this study were only obtained after an arcsinh data transformation was applied to all the ratios; also, PA was the sole retention technique used in order to decide on the number of factors to retain.

Table 5.10: Summary of initial results using transformed ratios (2001-2005)

Year	Number of factors Eigenvalue >1	% of variance explained	Number of factors parallel analysis	% of variance explained
2001	15	81.192%	14	79.344%
2002	15	81.082%	13	77.307%
2003	15	81.209%	13	77.497%
2004	15	80.942%	13	77.245%
2005	15	80.739%	13	77.044%

5.4.2.2 Financial patterns 2001-2004

Table 5.11 presents the rotated component matrices for the transformed data in years 2001-2004. Results for the year 2005 are also summarised here for comparison purposes. As mentioned earlier, factors appear in the rotated component matrix according to the decreasing variance explained by each factor. Also, for each factor, ratios are re-ordered according to the decreasing loadings (in absolute terms) they have onto each factor. Thus, when preparing Table 5.11, the order of factors and ratios in year 2001 was considered as the base on which results of the following successive years were presented. Also, it should be recalled here that the number of components retained in the interpretation step was decided by PA; this identified 14 components in year 2001 and 13 factors in the following 4 years.

Table 5.11: Factor loadings for U.S. commercial banks in 2001-2005 (transformed)

Ratio Number	Ratio	Factor Loadings				
		2001	2002	2003	2004	2005
Component 1: Profitability (Prof)						
X8	PRETAX NET OPER INC \ AVR AST	0.939	0.919	0.933	0.939	0.948
X7	PRETAX OPER INC \ AVR AST	0.938	0.914	0.928	0.936	0.946
X9	NET OPER INC \ AVR AST	0.933	0.918	0.933	0.939	0.949
X10	NET INC \ AVR AST	0.933	0.917	0.933	0.939	0.949
X53	NET INC \ AVR TOT EQ	0.886	0.864	0.884	0.882	0.889
X33	EFFICIENCY RATIO	-0.792	-0.690	-0.750	-0.743	-0.754

Ratio Number	Ratio	Factor Loadings				
		2001	2002	2003	2004	2005
X25*	CASH DIV \ NET INC	0.645	0.625	0.546	0.539	-
Component 2: Short-term Liquidity (Sh-t liq)						
X45	S T INV \ S T NCORE FUND	-0.851	-0.845	-0.841	-0.825	-0.838
X39	S T INV \ TOT AST	-0.814	-0.739	-0.785	-0.741	-0.793
X43	NET S T NCORE FUND DEPENDENCE	0.805	0.826	0.817	0.808	0.797
X22	NET NCORE FUND DEPENDENCE	0.748	0.736	0.733	0.715	0.717
X46	S T AST \ S T LIABS	-0.726	-0.775	-0.774	-0.776	-0.779
X47	NET S T LIAB \ TOT AST	0.696	0.753	0.753	0.758	0.763
X31*	G R S T INV	-0.542	-	-	-	-
X42	S T NCORE FUNDING \ TOT AST	0.482	0.587	0.523	0.593	0.515
X41*	CORE DEP \ TOT AST	-	-0.389	-	-	-
X37*	YIELD ON TOT INV SEC (TE)	-	-	-	0.319	0.358
Component 3: Margin (yield) (M(Y)-I						
X13	INT INC \ AVR EARN AST	0.891	0.891	0.898	0.895	0.895
X1	INT INC \ AVR AST	0.861	0.871	0.881	0.877	0.883
X3	NET INT INC \ AVR AST	0.834	0.905	0.899	0.902	0.910
X15	NET INT INC \ AVR EARN AST	0.825	0.893	0.889	0.893	0.897
X36	YIELD ON TOT LN&LS (TE)	0.812	0.800	0.744	0.772	0.813
X37*	YIELD ON TOT INV SEC (TE)	-	0.320	-	-	-
Component 4: Margin (cost) M(C)-II						
X14	INT EXP \ AVR EARN AST	0.900	0.938	0.932	0.913	0.885
X2	INT EXP \ AVR AST	0.894	0.931	0.927	0.912	0.888
X38	COST OF ALL INT-BEARING FUNDS	0.857	0.905	0.906	0.895	0.862
X12	AVR INT-BEARING FUNDS \ AVR AST	0.535	0.530	0.542	0.526	0.536
X41*	CORE DEP \ TOT AST	-	-	-	-	-0.458
X44*	BROK DEP \ DEP	-	-	-	-	0.382
Component 5: Risk-Based Capital (RBC)						
X24	TIER ONE LEVERAGE CAP	-0.912	0.908	0.907	-0.894	-0.887
X55	TIER ONE RBC \ RISK-WGT AST	-0.899	0.876	0.890	-0.860	-0.844
X56	TOT RBC \ RISK-WGT AST	-0.895	0.874	0.886	-0.856	-0.842
Component 6: Loans and Leases (Ln&Ls)						
X49	NET LN&LS \ CORE DEP	0.872	0.892	0.874	0.855	0.797
X48	NET LN&LS \ DEP	0.827	0.882	0.816	0.840	0.828
X23	NET LN&LS \ TOT AST	0.724	0.821	0.716	0.777	0.789

Ratio Number	Ratio	Factor Loadings				
		2001	2002	2003	2004	2005
X41*	CORE DEP \ TOT AST	-0.491	-	-0.508	-	-
X30*	G R NET LN&LS	-	0.348	-	-	-
X44*	BROK DEP \ DEP	-	-	0.462	0.395	-
Component 7: Capital Growth (CG)						
X29	G R TIER ONE CAP	0.883	0.901	0.900	0.906	0.879
X54	G R TOT EQCAP	0.865	0.881	0.890	0.897	0.839
X26	RETAIN EARNS \ AVR TOT EQ	0.805	0.799	0.807	0.796	0.784
X25*	CASH DIV \ NET INC	-	-	-	-	-0.505
Component 8: Asset Quality 1 (AQ-I)						
X18	LN&LS ALLOW \ NET LOSSES	0.894	0.921	0.931	0.921	0.912
X16	NET LOSS \ AVR TOT LN&LS	-0.791	-0.806	-0.790	-0.797	-0.766
X17	EARN COV OF NET LOSS	0.613	0.744	0.762	0.756	0.760
X6	PROVISION LN&LS LOSSES \ AVR AST	-0.565	-0.613	-0.569	-0.565	-0.543
X21*	NON-CUR LN&LS \ GRS LN&LS	-	-0.484	-	-	-0.473
X27*	RESTR+NONAC+RE ACQ \ EQCAP+ALLL	-	-0.476	-0.420	-0.439	-0.456
Component 9: Asset Quality 2 (AQ-II)						
X19	LN&LS ALLOW \ LN&LS NOT HFS	0.902	0.910	0.916	0.908	0.916
X20	LN&LS ALLOW \ TOT LN&LS	0.900	0.908	0.912	0.905	0.915
X21*	NON-CUR LN&LS \ GRS LN&LS	-	-	0.492	0.488	-
X30*	G R NET LN&LS	-	-	-0.355	-0.368	-
Component 10: Efficiency 1 (Eff-I)						
X4	NONINT INC \ AVR AST	0.699	0.740	-0.744	0.771	0.804
X11	AVR EARN AST \ AVR AST	-0.660	-0.604	0.579	-0.564	0.720
X5	NONINT EXP \ AVR AST	0.645	0.712	-0.759	0.760	-0.619
X35*	AST PER EMPLOYEE ($MILLION)	-	-	0.622	-0.608	-
Component 11: Growth (Grth)						
X28	G R AST	0.805	0.590	0.596	0.469	0.573
X32	G R S T NON CORE FUNDING	0.786	0.643	0.601	0.503	0.585
X30*	G R NET LN&LS	0.588	-	-	-	0.352
X31*	G R S T INV	-	0.529	0.485	0.512	0.470
X41*	CORE DEP \ TOT AST	-	-	-	-0.453	-
Component 12: Efficiency 2 (Eff-II)						

Ratio Number	Ratio	Factor Loadings				
		2001	2002	2003	2004	2005
X34	AVR PERSONNEL EXP PER EMPL($000)	0.782	0.840	0.630	0.673	0.747
X35*	AST PER EMPLOYEE ($MILLION)	0.594	0.604	-	-	0.672
X44*	BROK DEP \ DEP	0.451	0.373	-	-	-
X52*	PLEDGED SEC \ TOT SEC	-0.320	-	-0.415	-0.431	-
X40*	MARKETABLE EQ SEC \ TOT AST	-	-	0.359	0.399	-
Component 13: Investment Securities (IS)						
X51	TOT AFS SEC \ TOT SEC	0.888	0.890	0.893	0.895	-0.898
X50	TOT HTM SEC \ TOT SEC	-0.879	-0.876	-0.891	-0.896	0.893
Component 14: Asset Quality 3 (AQ-III)						
X27*	RESTR+NONAC+RE ACQ \ EQCAP+ALLL	0.786	-	-	-	-
X21*	NON-CUR LN&LS \ GRS LN&LS	0.784	-	-	-	-
Ratios with no significant loadings		X37, X40	X52, X40	X37	-	X52, X40

1. Only significant loadings (i.e. equal to or greater than |.30|) are reported (Table 3.2 in Hair et al., 1998, p. 112), otherwise a (-) sign is shown instead.
2. Ratios loaded on different factors in different years are marked with an asterisk (*).

As can be seen from Table 5.11, 14 factors were retained for the sample in year 2001 given the results of PA. These 14 factors accounted for 79.34% of the variability of the 56 ratios. For this year, two ratios failed to load significantly onto any factor: X37 and X40. The first 13 components in year 2001 were assigned the same labels given to the components of year 2005 (see Section 5.4.1). Besides these components, Component 14 (C14) was labelled as Asset Quality III (AQ-III) as it had ratios X27 and X21 loading significantly as shown in Table 5.11.

For year 2002, 13 factors were retained as PA suggested. This factor solution accounted for 77.31% of the variance in the data. The 13 factors were also assigned the same labels as the factors in year 2005. In years 2003 and 2004, however, although 13 components were retained according to PA, only 12 components were found to be meaningful and thus were successfully labelled. Component 13 in the solutions of 2003 and 2004 (C12 in Table 5.11) had three ratios loading significantly. These ratios are the average personnel expenses per employee (X34), pledged securities to total securities (X52), and marketable equity securities to total assets

(X40). Each of these ratios measures a different dimension of a bank's performance; therefore, there was no apparent name which could be given to this factor. Thus, in years 2003 and 2004, Efficiency of bank performance was represented by only one component (C10) whereas two Efficiency components (Eff-I and Eff-II) were found in years 2001, 2002 and 2005.

Furthermore, as can be seen from Table 5.11, there were 11 ratios, out of 56 studied, loading significantly onto different components over the five-year period. These ratios were the non-current loans to gross loans ratio (X21), the cash dividends to net income ratios (X25), the ratio of restructured loans to equity capital and allowance (X27), the growth rate of net loans and leases (X30), the growth rate of short-term investments (X31), assets per employee ratio (X35), yield on total investment securities (X37), marketable equity securities to total assets ratio (X40), core deposits to total assets ratio (X41), broker deposits to deposits ratio (X44), and ratio of the pledged securities to total securities (X52). The most inconsistent ratio amongst these was X41 which joined four different groups/components over the years. Also, ratios X30 and X40 loaded significantly onto three different components over the period. In addition, the ratios which failed to load onto any component in any of the years were X37, X40, and X52 with the exception of year 2004 in which all 56 ratios loaded significantly onto the components.

Overall, the analyses carried out in this section identified distinctive groups of ratios for U.S. commercial banks for each year between 2001 and 2004; thus these groups of ratios were not unique to year 2005. Over the years 2001 to 2005, the number of meaningful patterns ranged between 12 and 14. However, the question to ask is to what extent the identified patterns are stable over the short-term. This is investigated in the following section.

5.5 Short-term stability of financial patterns for U.S. commercial banks (2001-2005)

In order to assess the short-term stability of the patterns of ratios over the period 2001-2005, a visual comparison of these patterns was first carried out. The financial patterns were then compared over the period using correlation and congruency coefficients which, as previously noted in Chapter 3 (Section 3.4), have been widely used for factor comparisons in the related literature [for example, Pinches et al. (1973, 1975), Cowen and Hoffer (1982) and Ezzamel et al. (1987a) used correlation coefficients whereas Johnson (1979), Gombola and Ketz (1983b) and Ketz et al. (1990) used congruency coefficients]. Finally, following the more recent studies in the field [Yli-Olli and Virtanen (1989), Martikainen et al. (1994), Martikainen et al. (1995a, 1995b)], transformation analysis was employed to assess further the short-term stability of the derived patterns.

5.5.1 Visual comparison

An overall impression of the similarity of the components can be obtained by visually comparing the components over the years. To enable such a comparison to be made, Table 5.12 was prepared; it shows the identified components in each year in the order of their extraction and the associated cumulative percentage of the variance explained by the successive components[98]. As mentioned in Chapter 3 (Subsection 3.3.3.1), rotating the factor solution reallocates the eigenvalues (or the proportion of explained variance) so that the first component does not necessarily account for the highest proportion of the variance. However, it should be noted here that after the rotation is performed, SPSS allows the option of extracting the factors based on the decreasing proportion of the variance they explain. This option was utilised in all the analyses carried out in this study; in other words, the rotated components were reported in the outputs of SPSS based on the decreasing proportion of explained variance. Therefore,

[98] This table was prepared by referring to the original rotated component matrices which are not shown here. This is to avoid redundancy as the content of these matrices is presented in a different form in Table 5.11. Also, the cumulative proportion of explained variance in Table 5.12 is taken from Table 5.5 for the year 2005 and from the outputs of PCAs for years 2001-2004. These are not shown here because of space limitations.

Table 5.12: Financial patterns for U.S. commercial banks in 2001-2005 (transformed)*

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
2001	Prof	Sh-t liq	M(Y)-I	M(C)-II	RBC	Ln&Ls	CG	AQ-I	AQ-II	Eff-I	Grth	Eff-II	IS	AQ-III
Cumulative	15.404	30.123	39.677	46.269	51.940	56.467	60.694	64.403	67.485	70.194	72.748	75.176	77.326	79.344
2002	Prof	Sh-t liq	M(Y)-I	M(C)-II	Ln&Ls	AQ-I	RBC	CG	AQ-II	Eff-I	Grth	Eff-II	IS	-
Cumulative	15.451	29.700	38.990	46.288	52.225	56.543	60.721	64.328	67.457	70.122	72.647	75.088	77.307	
2003	Prof	Sh-t liq	M(Y)-I	Ln&Ls	M(C)-II	RBC	AQ-I	CG	AQ-II	Eff-I	Grth	IS	No Name	-
Cumulative	16.516	29.802	39.221	46.453	52.279	56.948	61.071	64.406	67.436	70.297	72.903	75.331	77.494	
2004	Prof	Sh-t liq	M(Y)-I	Ln&Ls	M(C)-II	RBC	AQ-I	CG	AQ-II	Eff-I	Grth	IS	No Name	-
Cumulative	17.352	30.287	40.290	47.581	52.975	57.326	61.127	64.502	67.529	70.206	72.708	75.155	77.245	
2005	Prof	Sh-t liq	M(Y)-I	M(C)-II	Ln&Ls	RBC	AQ-I	CG	AQ-II	Eff-I	Eff-II	Grth	IS	-
Cumulative	18.079	31.288	41.342	47.689	53.051	57.111	60.609	63.879	66.996	69.734	72.309	74.748	77.044	

* Refer to Table 5.8 for the full names of the components.

Table 5.13: Correlation coefficients between components of commercial banks (2001-2005)*

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
	Prof	**Sh-t liq**	**M(Y)-I**	**M(C)-II**	**RBC**	**Ln&Ls**	**CG**	**AQ-I**	**AQ-II**	**Eff-I**	**Grth**	**Eff-II**	**IS**	**No Name**
2001-2002	0.995	0.987	0.987	0.977	-0.987	0.975	0.991	0.962	0.957	0.974	0.824	0.940	0.989	-
2002-2003	0.994	0.994	0.985	0.994	0.994	0.971	0.984	0.995	0.993	-0.984	0.988	-	0.975	-
2003-2004	0.996	0.991	0.994	0.992	-0.992	0.986	0.994	0.997	0.988	-0.986	0.963	-	0.989	0.939
2004-2005	0.995	0.993	0.986	0.950	0.993	0.976	0.993	0.996	0.986	0.962	0.946	-	0.984	-
2001-2005	0.981	0.987	0.982	0.957	0.986	0.954	0.951	0.959	0.960	0.967	0.802	0.918	0.966	-

1. Refer to Table 5.8 for the full names of the components.
2. All correlations are significant at 0.05 level (2-tailed).
3. When no component appeared in either year, a (-) sign is shown instead.

it can be said that the order in which the components appear in the rotated component matrix reflects the relative importance of the components in the solution. So, the case where the components maintain the same order over years or across different samples can be considered as a sign of time or cross sectional stability.

As shown in Table 5.12, 14 components were successfully labelled in 2001, 13 were successfully labelled in 2002, 12 in years 2003 and 2004, and 13 in 2005. The proportion of variance explained by the meaningful (that is, successfully labelled) components over the years were 79.34%, 77.31%, 75.33%, 75.16% and 77.04%, respectively. So, the solution in year 2001, which consisted of the highest number of components (14), accounted for the highest proportion of variance over the years whereas the solutions with a smaller number of components explained a slightly less proportion of variance. In other words, the higher the number of derived components, the higher the proportion of variance explained by the solution.

Also, it can be seen from Table 5.12 that the first three components, Prof, Sh-t liq, and M(Y)-I, were extracted in the same order over the five years; combined, these three components explained between 39% and 41% of the total variance that existed in the datasets. The rest of the components, however, were extracted in rather different orders over time; however, the exception to this was the solutions for the years 2003 and 2004. Components in these two years seemed to have the highest degree of consistency over the period, especially in regard to the number of meaningful components in these two years (12), the order in which these components were extracted, and the cumulative proportion of variance accounted for by the successive components over the two years.

All the same, it is often difficult to report on the similarity/dissimilarity of the content of the components using only visual comparisons. By carrying out further statistical analyses more insights regarding the extent of similarity in the components' content can be obtained. In the previous literature, correlation, congruency and transformation analyses were the most widely used methods for this purpose. All these three methods were performed to compare the factor solutions for years 2001-2005. The results are reported in the following subsections.

5.5.2 Correlation coefficients

As mentioned in Chapter 3 (Subsection 3.4.1), a number of ratio classification studies used correlation analysis to assess the stability of the identified patterns. In such studies, the correlation coefficients were calculated using the loadings of all ratios onto the factors in the adjacent years, and also for the first and the last year in the period. The size of the correlation coefficient was then used to assess the extent of stability of the factors over time (or across different samples) where the larger the coefficient (in absolute terms), the more stable the factors. Following the same methodology, the current study calculated the correlation coefficients between the extracted components of the adjacent pairs of years for the period 2001-2005 and also, between the components of years 2001 and 2005; the results are reported in Table 5.13 [refer to Table 5.8 for the full names of the components].

An overall assessment of the time stability of the components can be gained by looking at the last row in Table 5.13 which shows the correlation coefficients for the components between the start (2001) and end (2005) of the period. As can be seen, the highest correlation coefficient was reported for the Sh-t liq component; given this, the Sh-t liq group of ratios appeared to be the most stable group over the period. The correlation coefficients were also high for Prof, M(Y)-I and RBC which are all considered amongst the most stable ratio groups. On the other hand, it appeared that the Grth component had the smallest correlation coefficients; hence, it appeared to be the least stable ratio group over the period. Also, the Eff-II component had a relatively low correlation between 2001 and 2005 which indicates a low level of time stability. Nevertheless, the correlations for the rest of the components were of a good magnitude; hence, it can be said that these components were reasonably stable over the period of our analysis.

In order to obtain further insight into the patterns of change in the ratio groups within the five-year period, it is important to examine the size of the correlation coefficients of the components for the successive pairs of years (2001-2002, 2002-2003, 2003-2004, and 2004-2005) shown in Table 5.13. Over the period 2001-2002, the Grth factor had the smallest correlation coefficient (.824) amongst all the components which indicates that the largest pattern of change in components in this period occurred in this component. Over the following pairs of years (except for the period 2002-2003), the correlation coefficients for Grth were amongst the smallest. This implies that the Grth group of ratios was the most unstable over the period covered by the study. Also, relatively small correlation coefficients were found for the Eff-II component for the period 2001-2002. Here it is important to recall that Eff-II was only identified as a significant group of ratios in 2001, 2002 and 2005; thus, it was only possible to compare this factor for the periods 2001-2002 and 2001-2005. In 2003 and 2004, the last component (C13) could not be assigned any label and so assessing the size of the correlation coefficient for this component serves no useful purpose. Nevertheless, sizeable correlations were found between the undefined components in 2003 and 2004, and the Eff-II factor in 2002 and 2005[99].

Furthermore, Table 5.13 shows that the AQ-I component had the highest correlation coefficients over all pairs of years except for 2001-2002 for which a relatively smaller coefficient was reported. Here, it should be noted that in year 2001 the study classified the asset quality ratios into three groups (AQ-I, AQ-II and AQ-III), whereas only two asset quality groups were identified in the following years (AQ-I and AQ-II). Interestingly, AQ-III in 2001 showed some sizeable and significant correlations with each of AQ-I and AQ-II in 2002[100].

In summary, given the correlation coefficients of the components identified over the five-year period, the Grth and Eff-II groups of ratios were the most unstable, whereas the AQ-I (C8) and Prof (C1) were the amongst the most stable groups of ratios over

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[99] These correlations were .905 and .907 for 2002-2003 and 2004-2005 respectively. Note that these figures are not shown in Table 5.13.
[100] These correlations were .432 and .369, also not shown in Table 5.13.

time. Nevertheless, it can be asked here whether these results hold when the congruency coefficients calculated between the components are examined. This is investigated in the following sub-section.

5.5.3 Congruence coefficients

As mentioned in Chapter 3 (Subsection 3.4.3), congruency coefficients were used in the ratio classification literature as a method to compare ratio groups over time and across industries. For this study, the congruency coefficients were calculated using formula 3.1 in Chapter 3. The goodness of match of these coefficients was assessed using the guidelines in the appendix of Richman and Lamb (1985) given in Table 3.1 in Chapter 3.

Table 5.14 reports the congruency coefficients computed between the components identified over the period. In this table, the coefficients of congruence were calculated using the loadings of all the 56 ratios onto the 13 components for all the pairs of years between 2001 and 2005 (10 pairs) [a similar procedure was followed in Ketz et al. (1990)]. Also, the last row in the table reports the mean values for the components calculated using the coefficients (in absolute terms) over the 10 pairs of years [Ketz et al. (1990, p. 71)].

The means of the congruency coefficients of components were first examined using the guidelines reported in Chapter 3 (Table 3.1). Accordingly, the components with average coefficients in excess of .98 can be described as having an ‘excellent’ match over the years; these were: Prof, Sh-t liq, M(Y)-I, RBC, CG and AQ-I. The components which exhibited an average ‘good’ match over the years were M(C)-II, Ln&Ls, AQ-II, Eff-I, IS and Eff-II. Furthermore, although Eff-II had an average ‘good’ match over the years, it was nonetheless an inconsistent component as it could not be identified in all the years. As for the Grth component, its average congruency coefficient was the smallest of all the components; overall, it had a ‘borderline’ match over the period.

Table 5.14: Serial congruency coefficients between components of. commercial banks (2001-2005)

		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
		Prof	**Sh-t liq**	**M(Y)-I**	**M(C)-II**	**RBC**	**Ln&Ls**	**CG**	**AQ-I**	**AQ-II**	**Eff-I**	**Grth**	**Eff-II**	**IS**	**No Name**
2001	**2002**	0.995	0.986	0.988	0.978	-0.986	0.977	0.992	0.963	0.959	0.973	0.834	0.939	0.989	-
	2003	0.989	0.991	0.992	0.975	-0.985	0.968	0.973	0.974	0.958	-0.945	0.821	-	0.971	-
	2004	0.985	0.984	0.991	0.964	0.973	0.966	0.963	0.969	0.941	0.920	0.698	-	0.973	-
	2005	0.982	0.986	0.983	0.957	0.986	0.957	0.955	0.959	0.962	0.967	0.813	0.920	0.966	-
2002	**2003**	0.995	0.994	0.987	0.994	0.994	0.972	0.985	0.995	0.994	-0.984	0.988	-	0.975	-
	2004	0.990	0.995	0.983	0.987	-0.986	0.986	0.977	0.995	0.989	0.971	0.959	-	0.975	-
	2005	0.985	0.984	0.975	0.943	-0.985	0.973	0.969	0.992	0.987	0.984	0.964	0.938	0.976	-
2003	**2004**	0.997	0.991	0.995	0.992	-0.991	0.986	0.994	0.997	0.989	-0.985	0.965	-	0.989	0.935
	2005	0.991	0.986	0.979	0.939	-0.988	0.952	0.994	0.993	0.981	-0.974	0.975	-	0.990	-
2004	**2005**	0.996	0.993	0.988	0.953	0.993	0.977	0.994	0.996	0.986	0.962	0.950	-	0.984	-
Mean		0.991	0.989	0.986	0.968	0.987	0.971	0.980	0.983	0.975	0.967	0.897	0.932	0.979	

1. Refer to Table 5.8 for the full names of the components.
2. Mean values are calculated using the coefficients in absolute terms (Ketz et al., 1990, p. 71).
3. When no component appeared in either year, a (-) sign is shown instead.

When assessing the congruency coefficients for the pairs of adjacent years (2001-2002, 2002-2003, 2003-2004 and 2004-2005), the following components were found to have an ‘excellent’ match in all four pairs of years: Prof, Sh-t liq, M(Y)-I, RBC and CG. Furthermore, the goodness of match for M(C)-II, Ln&Ls, AQ-I, AQ-II, Eff-I and IS can be described as either ‘excellent’ or ‘good’ over all years. Nevertheless, the smallest congruency coefficient of all components was found for the Grth group between 2001 and 2002; this fell into the ‘borderline’ range for goodness of match. However, the Grth factor had an ‘excellent’ match between 2002 and 2003, and a ‘good’ match in the years that followed. Last but not least, the unlabelled component had a ‘good’ match between years 2003 and 2004, as was the match for Eff-II in 2001 and 2002[101].

5.5.4 Transformation analysis

Transformation analysis is the fourth and last procedure used in this study to assess the time stability of the components. As mentioned in Chapter 3 (Subsection 3.4.4), transformation analysis identifies the components and variables which contribute to any divergence between the solutions over time or across different samples. This analysis results in two matrices: the transformation and residual matrices. The transformation matrix helps to uncover the components which are involved in the explained changes between the solutions whereas the residual matrix shows the variables which are behind any unexplained changes (also called abnormal transformations) between the solutions.

Transformation matrices. As mentioned in Chapter 3 (Subsection 3.3.4), when the transformation matrix has close-to-one diagonal elements and close-to-zero off diagonal elements, the two factor solutions under comparison are considered similar. Using the SURVO 2.44 statistical package, the transformation matrices were

[101] The similarity between the Eff-II and the undefined components was assessed using congruency coefficients. The matches between these factors could be described as ‘borderline’ in 2002-2003 and 2004-2005. Also, congruency coefficients were computed between AQ-III in 2001 and both AQ-I and AQ-II in 2002; the matches could be described as ‘terrible’ in both cases. Note that these results are not shown in Table 5.14.

Table 5.15: Time-series transformation matrices of components of U.S. commercial banks (2001-2005)

			C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
		2002	Prof	Sh-t liq	M(Y)-I	M(C)-II	Ln&Ls	AQ-I	RBC	CG	AQ-II	Eff-I	Grth	Eff-II	IS
2001	**C1**	Prof	**0.991**	0.030	0.023	-0.025	-0.026	0.057	0.007	-0.003	-0.004	-0.047	0.098	-0.021	-0.010
	C2	Sh-t liq	-0.019	**0.986**	0.030	-0.029	0.010	0.014	-0.014	0.014	-0.029	-0.039	-0.136	0.042	-0.025
	C3	M(Y)-I	-0.009	-0.038	**0.992**	0.054	0.067	-0.016	0.004	0.005	0.000	0.019	-0.078	-0.015	0.021
	C4	M(C)-II	0.003	0.058	-0.035	**0.978**	-0.029	-0.012	0.022	-0.016	0.008	-0.029	0.188	-0.002	0.003
	C5	RBC	0.011	-0.010	-0.002	0.022	0.059	-0.003	**-0.993**	0.005	-0.001	0.001	-0.003	0.018	0.001
	C6	Ln&Ls	0.016	0.021	-0.059	-0.002	**0.971**	-0.021	0.073	-0.019	0.032	0.024	0.101	-0.077	-0.000
	C7	CG	0.017	-0.020	-0.017	0.033	0.012	0.003	0.017	**0.988**	0.001	0.045	-0.094	0.034	-0.004
	C8	AQ-I	-0.032	-0.041	-0.009	0.057	0.077	0.943	-0.021	0.003	0.063	0.048	-0.159	-0.058	0.031
	C9	AQ-II	-0.026	0.058	0.028	-0.060	-0.082	0.043	0.012	0.004	0.947	-0.059	0.196	0.036	-0.016
	C10	Eff-I	0.024	0.064	0.004	-0.014	-0.043	-0.007	-0.003	-0.025	0.012	**0.976**	0.196	0.040	-0.024
	C11	Grth	-0.108	0.080	0.083	-0.153	-0.010	0.070	-0.045	0.138	-0.131	-0.172	0.861	-0.068	0.007
	C12	Eff-II	0.023	-0.056	0.006	0.017	0.116	-0.010	0.004	-0.014	0.025	-0.033	-0.004	**0.963**	-0.064
	C13	IS	0.011	0.027	-0.018	-0.009	-0.005	-0.015	0.005	-0.001	0.003	0.016	0.016	0.077	**0.995**
	C14	AQ-III	0.052	-0.050	-0.042	0.084	0.140	-0.317	-0.069	0.052	0.282	0.063	-0.261	-0.214	0.045
		2003	Prof	Sh-t liq	M(Y)-I	Ln&Ls	M(C)-II	RBC	AQ-I	CG	AQ-II	Eff-I	Grth	IS	No Name
2002	**C1**	Prof	**0.997**	-0.026	-0.016	0.026	-0.011	-0.001	-0.005	-0.041	-0.004	0.027	-0.005	0.009	-0.030
	C2	Sh-t liq	0.026	**0.997**	-0.016	0.025	0.020	0.000	-0.020	-0.012	0.017	-0.022	0.059	0.002	0.001
	C3	M(Y)-I	0.022	0.015	**0.994**	-0.049	0.001	0.004	-0.002	-0.002	0.011	-0.056	0.010	-0.014	0.078
	C4	M(C)-II	0.011	-0.022	-0.002	0.024	**0.999**	0.025	0.001	-0.008	0.004	0.005	0.005	-0.005	0.027
	C6	Ln&Ls	-0.031	-0.015	0.069	**0.968**	-0.016	-0.059	0.039	0.048	-0.068	0.065	-0.057	0.032	-0.188
	C8	AQ-I	0.008	0.019	-0.005	-0.028	-0.002	0.004	**0.997**	-0.006	-0.033	-0.019	0.022	-0.008	0.056
	C5	RBC	-0.002	-0.001	0.001	0.057	-0.026	**0.998**	-0.002	-0.005	-0.012	0.025	0.012	0.009	-0.007
	C7	CG	0.043	0.012	-0.004	-0.042	0.008	0.009	0.003	**0.998**	0.000	-0.019	0.000	-0.008	0.016
	C9	AQ-II	-0.001	-0.016	-0.001	0.051	-0.003	0.008	0.039	0.004	**0.994**	0.013	-0.004	0.012	-0.083
	C10	Eff-I	0.023	-0.027	-0.055	0.081	0.001	0.020	-0.018	-0.017	0.012	**-0.993**	0.021	0.009	0.029
	C11	Grth	0.000	-0.059	-0.001	0.045	-0.006	-0.016	-0.016	0.004	-0.004	0.025	**0.995**	0.002	-0.055
	C12	Eff-II	0.021	-0.010	-0.065	0.200	-0.032	-0.006	-0.047	-0.007	0.072	0.052	0.042	-0.006	**0.971**
	C13	IS	-0.008	-0.001	0.012	-0.033	0.006	-0.007	0.006	0.007	-0.009	0.006	0.000	**0.999**	0.015

			C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
		2004	Prof	Sh-t liq	M(Y)-I	Ln&Ls	M(C)-II	RBC	AQ-I	CG	AQ-II	Eff-I	Grth	IS	Eff-II
2003	**C1**	Prof	**0.999**	0.024	-0.003	-0.038	0.014	0.010	0.007	-0.005	0.006	0.006	0.016	-0.006	0.013
	C2	Sh-t liq	-0.022	**0.997**	0.002	0.013	-0.027	0.018	0.012	0.010	-0.018	-0.019	-0.064	0.005	0.010
	C3	M(Y)-I	0.005	-0.006	**0.997**	0.027	0.016	-0.010	0.009	0.004	-0.014	0.014	-0.066	0.003	-0.015
	C6	Ln&Ls	0.034	-0.002	-0.018	**0.985**	0.038	-0.034	-0.027	-0.015	0.032	0.032	0.123	-0.001	0.086
	C4	M(C)-II	-0.017	0.031	-0.012	-0.042	**0.997**	-0.011	0.000	-0.004	0.007	-0.008	0.040	-0.010	-0.017
	C5	RBC	0.008	0.021	-0.005	-0.036	-0.015	**-0.997**	-0.001	0.008	0.013	-0.023	0.045	0.007	-0.036
	C8	AQ-I	-0.005	-0.015	-0.012	0.032	0.003	-0.003	**0.998**	0.001	0.019	-0.004	-0.037	-0.001	-0.013
	C7	CG	0.007	-0.012	-0.009	0.021	0.007	0.005	-0.003	**0.998**	-0.001	0.016	-0.047	-0.005	-0.019
	C9	AQ-II	-0.009	0.021	0.021	-0.042	-0.012	0.017	-0.014	0.007	**0.995**	-0.025	0.066	0.003	0.044
	C10	Eff-I	0.008	-0.024	0.009	0.039	-0.002	0.017	-0.007	0.012	-0.021	**-0.996**	-0.065	0.010	0.026
	C11	Grth	-0.019	0.058	0.068	-0.106	-0.045	0.052	0.042	0.050	-0.073	-0.068	**0.979**	0.012	-0.055
	C13	IS	0.007	-0.005	-0.005	0.005	0.010	0.007	0.000	0.003	0.000	0.011	-0.013	**0.999**	-0.038
	C12	No Name	-0.016	-0.007	0.018	-0.091	0.012	-0.032	0.018	0.023	-0.049	0.020	0.042	0.039	**0.991**
		2005	Prof	Sh-t liq	M(Y)-I	M(C)-II	Ln&Ls	RBC	AQ-I	CG	AQ-II	Eff-I	Eff-II	Grth	IS
2004	**C1**	Prof	**0.998**	-0.007	0.010	0.026	-0.016	0.005	-0.004	-0.020	-0.003	0.026	0.018	-0.033	0.001
	C2	Sh-t liq	0.008	**0.996**	-0.013	0.025	-0.025	-0.022	-0.007	-0.005	0.028	0.025	0.008	0.066	-0.008
	C3	M(Y)-I	-0.005	0.011	**0.996**	-0.043	-0.005	-0.004	0.006	0.002	0.005	-0.038	-0.051	0.051	0.010
	C6	Ln&Ls	0.009	0.020	0.018	0.077	**0.983**	-0.005	0.005	0.004	0.010	0.042	0.160	0.002	-0.010
	C4	M(C)-II	-0.028	-0.009	0.040	**0.973**	-0.053	0.035	0.011	0.013	-0.066	-0.075	-0.115	-0.151	0.018
	C5	RBC	-0.002	0.020	0.000	-0.028	0.008	**0.998**	0.000	0.007	0.010	-0.004	-0.008	0.049	0.008
	C8	AQ-I	0.008	0.007	-0.012	-0.018	0.008	-0.002	**0.997**	0.011	0.016	-0.026	-0.067	0.010	0.006
	C7	CG	0.022	0.000	-0.005	-0.004	-0.003	-0.010	-0.012	**0.998**	0.014	-0.007	-0.001	0.052	0.008
	C9	AQ-II	-0.004	-0.024	0.006	0.055	-0.021	-0.002	-0.010	-0.008	**0.991**	0.028	0.036	-0.110	-0.009
	C10	Eff-I	-0.027	-0.014	0.035	0.031	-0.015	0.010	0.017	0.013	-0.035	**0.976**	-0.174	-0.110	0.017
	C11	Grth	0.019	-0.078	-0.027	0.181	-0.046	-0.038	0.007	-0.050	0.083	0.132	0.148	**0.952**	-0.038
	C13	IS	0.000	0.005	-0.012	-0.008	0.008	-0.010	-0.006	-0.010	0.013	-0.008	0.022	0.037	**0.999**
	C12	No Name	-0.032	-0.001	0.065	0.075	-0.167	0.021	0.074	0.014	-0.066	0.137	0.948	-0.180	-0.008

1. Elements above .950 are in bold (Martikainen et al., 1994, p. 63).
2. Refer to Table 5.8 for the full names of the components.

estimated for the extracted components between the adjacent years over the period 2001-2005. The resulting matrices are reported in Table 5.15[102]. Because the components were generally extracted in different orders over the years, the highest (close-to-one) elements in Table 5.15 were not necessarily the diagonal ones. Nevertheless, the size of these elements is what matters here. As mentioned in Chapter 3 (Subsection 3.4.4), elements that fall below .95 indicate a change in the corresponding components over time. When a component is found to have a low element between two periods, its row and column in the transformation matrix should be scanned visually; any sizeable elements found would then show which components were behind the change. Accordingly, it can be seen from Table 5.15 that the elements of the transformation matrices in the periods 2002-2003 and 2003-2004 were all above .95; this indicates a high degree of similarity between the components over these years. Also, the solutions for the years 2004 and 2005 were all above .95 except for the undefined and Eff-II components which fell slightly below this criterion. Nevertheless, apparent changes occurred for some components between 2001 and 2002. These changes involved AQ-I, AQ-II and Grth. The AQ-III row in the matrix shows that this component was behind these changes given the sizeable elements it had with AQ-I (-.317), AQ-II (.282) and Grth (-.261)[103]. Other components, however, showed a satisfactory level of similarity between the two years.

Residual matrices. The residual matrix resulting from the transformation analysis allows one to check whether the empirical meaning of some ratios has changed over successive years. The residual matrices for the four pairs of successive years between 2001 and 2005 are summarised in Appendix 5.2. For convenience, the last columns of these matrices have been extracted and are presented in Table 5.16. In examining the residual matrix, the size of the abnormal transformation[104] of single ratios and the cumulative abnormal transformations can be used to verify whether the empirical meaning of the ratios has changed over time. As mentioned in Chapter 3 (Subsection

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[102] To facilitate the analysis, Eff-II and the undefined components were considered as counterparts; thus they were compared to each other over all available years. Recall here that in previous subsections these two components were found to have reasonably high correlation and congruency coefficients.

[103] Note that only the absolute size of elements in the transformation matrix should be considered (Martikainen et al., 1995a, p. 40).

[104] Abnormal transformation is the sum of the squared residuals of a single variable.

3.4.4), previous studies considered a value of an abnormal transformation greater than .20 to be large enough to conclude that there has been a change in the empirical meaning of a given variable [for example, Martikainen et al. (1995a, p. 41)].

Table 5.16: Cumulative abnormal transformations between components of commercial banks (2001-2005)*

Variable	2001-2002	2002-2003	2003-2004	2004-2005
X1	0.013	0.010	0.003	0.010
X2	0.022	0.005	0.004	0.019
X3	0.026	0.009	0.002	0.008
X4	0.018	0.010	0.006	0.019
X5	0.007	0.004	0.003	0.007
X6	0.011	0.028	0.020	0.009
X7	0.004	0.011	0.002	0.005
X8	0.003	0.005	0.002	0.005
X9	0.003	0.005	0.003	0.008
X10	0.003	0.005	0.003	0.008
X11	0.030	0.005	0.018	0.025
X12	0.014	0.002	0.002	0.005
X13	0.011	0.012	0.003	0.016
X14	0.023	0.004	0.005	0.024
X15	0.021	0.009	0.002	0.006
X16	0.006	0.011	0.008	0.011
X17	0.025	0.003	0.003	0.008
X18	0.007	0.002	0.002	0.005
X19	0.010	0.008	0.010	0.012
X20	0.009	0.007	0.010	0.011
X21	0.147	0.032	0.037	0.017
X22	0.005	0.004	0.007	0.006
X23	0.009	0.014	0.001	0.017
X24	0.017	0.005	0.010	0.007
X25	0.016	0.009	0.005	0.011
X26	0.003	0.006	0.014	0.006
X27	0.154	0.029	0.025	0.013
X28	0.055	0.018	0.065	0.036
X29	0.003	0.005	0.003	0.003
X30	0.043	0.012	0.031	0.035
X31	0.110	0.027	0.034	0.040
X32	0.039	0.026	0.033	0.034
X33	0.024	0.025	0.003	0.003
X34	0.024	0.056	0.008	0.060
X35	0.007	0.014	0.004	0.022
X36	0.027	0.018	0.018	0.043
X37	0.103	0.063	0.112	0.027
X38	0.022	0.009	0.007	0.029
X39	0.015	0.004	0.006	0.009
X40	0.052	0.026	0.023	0.080
X41	0.019	0.004	0.007	0.010
X42	0.023	0.008	0.008	0.040
X43	0.007	0.002	0.004	0.007

Variable	2001-2002	2002-2003	2003-2004	2004-2005
X44	0.022	0.008	0.008	0.017
X45	0.008	0.003	0.004	0.006
X46	0.029	0.010	0.006	0.017
X47	0.033	0.008	0.007	0.017
X48	0.004	0.014	0.002	0.019
X49	0.005	0.014	0.002	0.008
X50	0.002	0.005	0.002	0.005
X51	0.002	0.002	0.002	0.002
X52	0.030	0.028	0.012	0.087
X53	0.003	0.006	0.005	0.001
X54	0.006	0.096	0.004	0.027
X55	0.007	0.002	0.007	0.004
X56	0.007	0.002	0.008	0.004
Cumulative abnormal transformation	**1.348**	**0.769**	**0.645**	**0.990**

* Refer to Table 4.4 for the full names of ratios.

As can be seen from Table 5.16, none of the ratios in any period had an abnormal transformation that exceeded .20. Nevertheless, the table shows that the highest abnormal changes that occurred over the period 2001-2002 were in the context of ratios X21, X27, X31 and X37. By referring to the residual matrix for 2001-2002 in Appendix 5.2, it can be seen that most of these transformations can be tied to components AQ-I, AQ-II, Grth and Eff-II. As for the rest of the successive pairs in Table 5.16, given the small values of the abnormal transformation of almost all of the 56 individual ratios in these periods, it can be concluded that no apparent changes occurred in the meaning of the ratios.

Overall assessment. The cumulative abnormal transformations can be used to obtain an overall assessment of the level of unexplained shifts in the meaning of ratios that occurred over the years. As can be seen from the last row of Table 5.16, the cumulative abnormal transformations were the highest between years 2001 and 2002 and the lowest between years 2003 and 2004.

Given the overall results of the transformation analyses, it could be said that the financial patterns showed a high degree of stability in the short-term. The stability level was higher in the years 2003 and 2004 where the same number of meaningful (that is, successfully labelled) factors was derived. On the other hand, the lowest degree of similarity was found between the solutions of years 2001 and 2002. This could be attributed to the existence of 14 significant components in the year 2001; whereas, in all other years there were only 13 significant components.

Transformation matrices' significance test. In order to assess how certain one can be regarding the conclusions drawn from the transformation analysis summarised in previous paragraphs, the current study developed a significance test for the time series stability of the transformation matrices [see Chapter 3 (Subsection 3.4.4.1) for a description of the test]. However, before applying this significance test, it should be recalled that the components in this chapter were generally produced in a slightly different order across the five years (see Table 5.12). So, before performing the significance test, the components in years 2002-2005 were rearranged to follow the same order of extraction as in the year 2001. Also, given that AQ-III (C14) was only identified in year 2001, this component was omitted from the rotated component matrix for the year 2001; the transformation matrix between 2001 and 2002 was then re-estimated using only 13 components. The resulting transformation matrix was then used to perform the significance test. The statistics required to calculate the z-score are all reported in Table 5.17.

Table 5.17: Results of transformation matrices' significance test for commercial banks (2001-2005)

Period	$Det(B) = Det(M.M^T)$
2001-2002	0.998771
2002-2003	1.001835
2003-2004	1.000267
2004-2005	1.001773
$\overline{Det(B)}$	1.000661
$\hat{\sigma}$	0.001454
n	4
$z = \frac{\overline{Det(B)} - 1}{\hat{\sigma}} \sqrt{n}$	0.909998

As can be seen from Table 5.17, the resulting z-score is insignificant at any reasonable level. Hence, the null hypothesis that there is no difference between the transformation matrices over time could not be rejected. However, it is important to highlight one caveat in regard to this test: with only four transformation matrices, the sample size on which this test was based was, strictly speaking, too small to apply the Central Limit Theorem. Given this, the above results should be interpreted with a degree of caution. However, this significance test is the first to be derived for transformation matrices and therefore the analysis here represents a significant addition to what has previously appeared in the literature.

5.6 Summary

The purpose of this chapter was to identify the financial patterns in a set of 56 financial ratios for samples of thousands of U.S. commercial banks and to assess the short-term stability of the identified patterns over the period from 2001 to 2005. To improve normality in the distribution of the data, a hyperbolic arcsinh transformation was applied to all the ratios in all the years; this helped significantly in mitigating the substantial non-normality in the data. To identify the patterns, PCA with a varimax rotation was performed on the data on a yearly basis. Parallel analyses were made to decide the correct number of factors to retain and interpret for each of the five years. The stability of the derived factors was assessed using visual comparisons, correlation and congruency coefficients, and transformation analysis. Most of the analysis in this study was carried out using two software packages: SPSS for PCA and PA, and SURVO for transformation analysis.

The study identified 13 meaningful financial patterns for the year 2005; these accounted for 77% of the variance in the 56 ratios. The factors were given the following labels: Prof, Sh-t Liq, M(Y)-I, M(C)-II, Ln&Ls, RBC, AQ-I, CG, AQ-II, Eff-I, Eff-II, Grth, and IS (refer to Table 5.8 for the full names of the patterns). To check whether the derived financial patterns for the year 2005 were not unique or a random occurrence in that year, the financial patterns for the same set of 56 ratios were derived for every year between 2001 and 2004; then, the short-term stability of these patterns was assessed over the whole period (2001-2005). All these patterns, except for the Eff-II, were identified in all the years covered by our study. Using various factor comparison techniques, all the identified patterns except the Grth and Eff-II showed a high degree of stability over the short-term. Thus, to sum up, it was possible to classify empirically banks' financial ratios into distinctive groups; these groups were stable over the short-term.

The objective of the following chapters (Chapters 6-8) is to test empirically whether the financial patterns of bank ratios differ in different dimensions. The dimensions considered in this study are the bank's size, type and age. To achieve this objective, the large sample of commercial banks used in the current chapter is divided into smaller samples; these are used in Chapter 6. In addition, two more datasets are studied, the first consisting of U.S. savings banks; this is used in Chapter 7, and the second comprised of De Novo or newly-chartered banks which is used in Chapter 8 of this thesis. Using the same methodology followed in this chapter, the patterns of ratios in the different datasets are identified and compared. In addition, however, the following chapter (six) checks whether the patterns of ratios differ for banks arranged in different asset-size classes.

Chapter 6 The Classification Patterns of Financial Ratios for Commercial Banks in Different Asset-Size Groups

6.1 Introduction

The previous chapter identified the classification patterns of financial ratios for commercial banks and tested the time stability of these patterns. Using 56 financial ratios for thousands of U.S. commercial banks, 12 meaningful factors were identified in every year between 2001 and 2005; most of these patterns showed a high degree of similarity over the period.

The results recalled above were found using a sample consisting of all insured U.S. commercial banks regardless of their asset size. Therefore, the primary question is to what extent are the classification patterns of financial ratios for commercial banks belonging to different asset-size classes similar? This would lead to the following supplementary question: do these patterns exhibit the same level of stability over a short period? These questions are addressed in this chapter.

The rest of the chapter is arranged as follows. In Section 6.2, the methodology and data are summarised while in Section 6.3, financial patterns of ratios for groups of different asset-size banks are identified, first for year 2005, then for each of the years 2001-2004. In Section 6.4, various techniques are used to check for any cross-sectional differences among the financial patterns for the different bank groups in year 2005 and the previous years. Section 6.5 checks the time stability of the financial patterns for the asset-size groups between 2001 and 2005. The chapter concludes with Section 6.6 which summarises the results and highlights the questions to be addressed in the following chapters of the thesis.

6.2 Methodology and data

Methodology. As stated earlier, the aim of this chapter is to check the cross-sectional and short-term stability of financial patterns for banks in different asset-size groups. Similar to Chapter 5, Principal Component Analysis (PCA) with varimax rotation was used to derive the financial patterns. To decide on the number of factors to be retained and interpreted, Parallel Analysis (PA) was utilised. Nevertheless, also as stated in earlier chapters, the number of factors suggested by the two widely used methods of 'eigenvalue greater than one' and Cattell's scree plot are also reported for comparison purposes.

For each of the years 2001-2005, banks were classified into four groups according to their asset size. Separate PCA was then performed for each of these groups in each of the years covered. With the financial patterns for different asset-size groups in different years identified, the similarity of the patterns was then compared across the different groups. For that, this chapter used the same four methods as in Chapter 5: visual comparison, correlation, congruence coefficients, and transformation analysis. The same techniques were then used to check for the short-term stability of the financial patterns of each group over the period 2001-2005.

The SPSS 14.0 statistical software package was used to carry out all different aspects of the analysis except for the transformation analysis for which the software SURVO 2.51 was used.

Data. This chapter uses the same 56 banking ratios as studied in Chapter 5. The ratios are listed in Table 4.4 and the definitions of their components are given in Appendix 4.1. All of these 56 ratios were available for a total number of 5,399 U.S. commercial banks in the year 2005. To satisfy the purpose of this chapter, the banks were classified into four groups according to their average asset size[105] in the fourth quarter of 2005. As explained in Chapter 4 (Subsection 4.3.1), the Uniform Bank Performance Report (UBPR) groups U.S. commercial banks according to their asset size into six classes. Hence, adopting the same grouping approach seemed appealing.

[105] See footnote 86 in Chapter 4 (Subsection 4.3.1) for the calculation of average asset size used to assign banks to asset size groups.

However, since PCA places a few restrictions over the minimum sample size, where the larger the sample the more sound is the analysis[106], it was decided to combine the first three asset groups into one. This resulted into four size classes; in each, there was a relatively reasonable number of banks. The asset size for each of the four groups was as follows:

- Group 1: in excess of $300 million.
- Group 2: between $100 and $300 million.
- Group 3: between $50 and $100 million.
- Group 4: less than $50 million.

Subsequently, these groups are referred to as G1, G2,… and so on.

Table 6.1 shows the number of banks in each of the four groups in the years 2001-2005. It also shows the final number of banks in each group: that is, the number of banks for which all 56 ratios were available. Also, the cases-to-variable ratios are shown in brackets in the table.

Table 6.1: Number of U.S. commercial banks in four asset-size groups (2001-2005)*

	2001		**2002**		**2003**		**2004**		**2005**	
	original	**final**	**original**	**final**	**original**	**final**	**original**	**final**	**original**	**final**
G1	938	880 (15.71)	1,070	996 (17.79)	1,206	1,095 (19.55)	1365	1,191 (21.27)	1,530	1,305 (23.30)
G2	1,980	1,784 (31.86)	2,102	1,886 (33.68)	2,195	1,941 (34.66)	2264	1,937 (34.59)	2,274	1,856 (33.14)
G3	1,824	1,532 (27.36)	1,825	1,541 (27.52)	1,777	1,485 (26.52)	1677	1,350 (24.11)	1,598	1,270 (22.68)
G4	1,887	1,372 (24.50)	1,777	1,309 (23.38)	1,672	1,208 (21.57)	1578	1,053 (18.80)	1,496	968 (17.29)
Total	**6,629**	**5,568**	**6,774**	**5,732**	**6,850**	**5,729**	**6,884**	**5,531**	**6,898**	**5,399**

* Numbers in brackets represent the banks-to-variable ratios.

As can be seen from the rows in Table 6.1, the number of banks with a complete set of ratios available ranged between 880 and 1,305 banks for G1; 1,784 and 1,941 banks for G2; 1,270 and 1,541 for G3; and, 968 and 1,372 for G4. How satisfactory the size of these groups is for PCA can be judged by the cases-to-variable ratios; these were all much higher than the acceptable ten-to-one ratio for the four groups over the

[106] According to Hair et al. (1998, p. 98), the sample size should be at least five times as large as the number of variables on which the PCA is based. More acceptable sample sizes would have a ten-to-one cases-to-variable ratio. In our case, this equals 56 * 10= 560 banks.

five years. Nevertheless, it is noticeable that G2 had the highest ratios over the years compared to other groups whereas G1 had the smallest ratios in the first three years and G4 in the last two years of the period covered by the study.

Data transformation. All the analyses conducted in this chapter used data in the transformed form where the archsinh transformation was applied to improve the approximation of data to normality [see Chapter 4 (Section 4.5) for the arcsinh transformation formula].

6.3 Financial patterns of U.S. commercial banks in different asset-size groups

In this section, the financial patterns for the first asset-size group in year 2005 are first identified, where a detailed analysis is given. Following the same steps, the patterns for banks in the other asset-size groups (G2, G3 and G4) in year 2005 are identified. Finally, patterns for the different asset size groups in years 2001-2004 are extracted.

6.3.1 Analysis for Group 1 (2005)

The analysis starts with the group of banks with asset sizes in excess of $300 million in the year 2005. The sample analysed here consists of 1,305 banks for which the complete set of 56 ratios was available (Table 6.1).

Factorability of correlation matrix. PCA commenced with a spectral demonstration of the correlation matrix[107]; this should contain a substantial number of sizeable correlations (over |.30|) to deem the dataset appropriate for conducting a sound PCA. A visual check of the correlation matrix showed a considerable number of correlations above .30 in the absolute sense. This gave the go-ahead for the next step which involved checking the factorability of the data using two statistical tests.

The two tests were Bartlett's Test of Sphericity (BTS) and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (MSA); the statistics for these two tests for G1 (2005) are reported in Table 6.2. The KMO statistic which signifies the degree of

[107] The correlation matrices are not shown in this study due to space limitations.

common variance amongst the 56 ratios is .736; this can be described as 'middling' using the guidelines of Sharma (1996, p. 116). Also, the BTS is significant at the .000 level which implies that the overall correlation coefficients are significant. Thus, the two widely used statistical tests for the factorability of the data both showed that PCA can be used to identify the different patterns in the data in this study.

Table 6.2: KMO and BTS for Group 1 (2005)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.736
Bartlett's Test of Sphericity	Approx. χ^2	130,053.861
	df	1540
	Sig.	.000

Initial solution. Having assured the suitability of the data in G1 (2005) for PCA, the following step involved introducing the initial solution; this is reported in Table 6.3. In this solution, PCA extracts as many components as variables in the dataset: i.e. 56 components[108]. For these components, the table gives numerical values of the eigenvalues and the percentage of variance explained and, in the last column, it gives the cumulative percentage of variance accounted for by successive components.

Table 6.3: Initial solution for Group 1 (2005)[*]

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	8.063	14.398	14.398
2	7.753	13.845	28.243
3	5.363	9.576	37.819
4	4.045	7.224	45.043
5	3.356	5.993	51.036
6	2.447	4.370	55.406
7	2.224	3.972	59.378
8	1.813	3.238	62.616
9	1.754	3.133	65.749
10	1.649	2.944	68.693
11	1.586	2.833	71.525
12	1.418	2.532	74.057
13	1.235	2.205	76.263
14	1.048	1.871	78.134
15	1.035	1.848	79.982
16	0.971	1.733	81.715
17	0.940	1.678	83.393
18	0.863	1.540	84.933

[108] In Table 6.3, the eigenvalues for components 21 to 49, inclusive, are not shown due to space limitations.

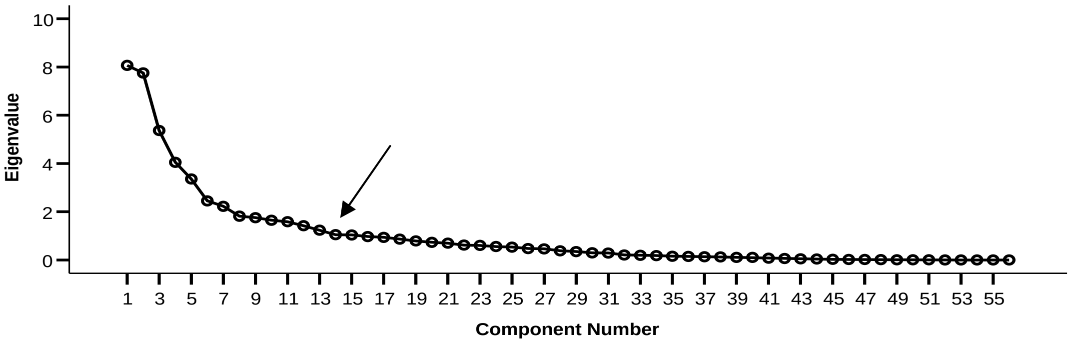
Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
19	0.787	1.405	86.338
20	0.731	1.305	87.642
.	.	.	.
.	.	.	.
.	.	.	.
50	0.006	0.010	99.990
51	0.002	0.004	99.994
52	0.002	0.004	99.998
53	0.001	0.001	100.000
54	0.000	0.000	100.000
55	0.000	0.000	100.000
56	0.000	0.000	100.000

* The eigenvalues of components 21 to 49 inclusive are not shown due to space limitations.

As Table 6.3 shows, the first component had an eigenvalue of 8.06, so it alone accounted for 14.4% of the variance in the dataset. The second component had an eigenvalue of 7.75 and thus explained a slightly lower proportion of the variance (13.85%). Hence, as explained in Chapter 3, the amount and percentage of variance accounted for by each of the components decreases gradually from the first to the last component. What does increase, however, is the cumulative percentage of variance explained collectively by successive components. The first five components, for example, account together for over 51% of the variance, as Table 6.3 shows.

Deciding on how many components to retain. Since PCA is used as a data reduction technique, only a few components from the 56 extracted in the initial solutions should be retained and interpreted. Thus, the retained components should explain a high percentage of the variance in the data. To decide on the number of components to keep, different methods are available. One of these is the latent root technique which keeps all components with an eigenvalue exceeding unity. By applying this method to Table 6.3, 15 components should be retained and these would collectively account for 79.98% of the variance. Deciding on the number of factors to retain can also be done graphically using Cattell's scree plot method. Figure 6.1 depicts the scree plot of G1 in year 2005, where the eigenvalues (vertical axis) are plotted against the component numbers (horizontal axis). At component 14, the plot starts to level off, which suggests retaining 13 components. Hence, according to the latent root criterion, 15 components should be retained, whereas Cattell's scree plot suggested keeping 13 components, so the question is: what is the best number of components to keep?

Figure 6.1: Cattell's scree plot for Group 1 of commercial banks (2005)



As reported in Chapter 3 (Subsection 3.3.2), recent studies have shown that Parallel Analysis (PA) provides a useful criterion for deciding how many components to retain; therefore, in this study, the final word in this regard is to be given to the PA technique.

The output of PA[109] is summarised in Table 6.4. For each of the 56 components[110], PA reported the actual eigenvalue, the mean and the 95th percentile of eigenvalues of the random datasets generated. The key to obtaining the accurate number of components in PA is to keep all the components with an eigenvalue exceeding the mean (or more strictly exceeding the mean of the 95th percentile) eigenvalue of the random datasets. Given this, it can be seen from Table 6.4 that both the mean and the 95th percentile eigenvalue of component 14 exceeded the actual eigenvalue for that component; this suggests that keeping 13 components for G1 in year 2005 would be sufficient.

Table 6.4: Parallel analysis output for Group 1 (2005)*

Root	Actual eigenvalue	Average eigenvalue	95th percentile eigenvalue
1	8.06309	1.42351	1.45883
2	7.75302	1.38752	1.41459
3	5.36268	1.35972	1.38474
4	4.04547	1.33577	1.35841

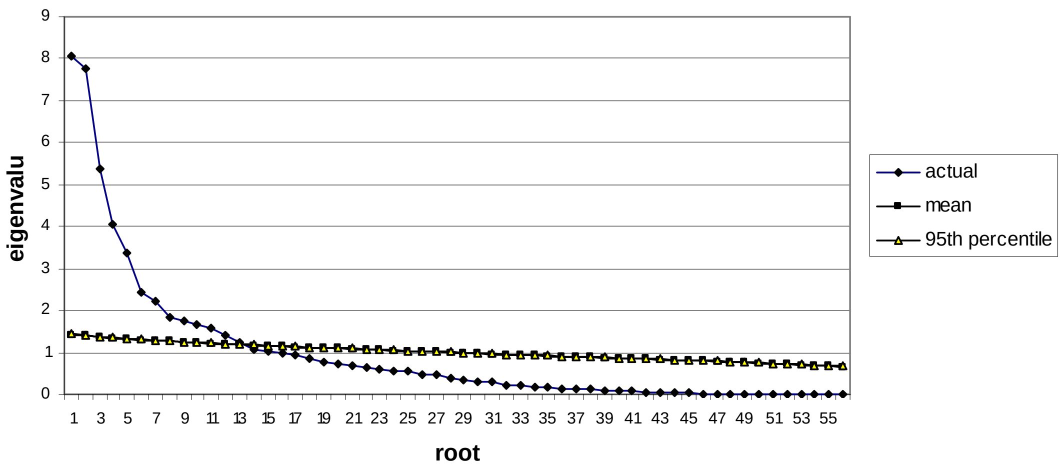
[109] 1,000 random datasets were generated; each dataset has 56 variables and 1,305 cases.
[110] Results for components 21-53 are not shown due to space limitations.

Root	Actual eigenvalue	Average eigenvalue	95th percentile eigenvalue
5	3.35612	1.31457	1.33439
6	2.44705	1.29415	1.31337
7	2.22449	1.27584	1.29375
8	1.81313	1.25916	1.27667
9	1.75424	1.24155	1.25757
10	1.64854	1.22571	1.24225
11	1.58633	1.21070	1.22598
12	1.41800	1.19599	1.21073
13	1.23507	1.18140	1.19542
14	1.04769	1.16700	1.18109
15	1.03477	1.15273	1.16562
16	.97057	1.13927	1.15198
17	.93972	1.12612	1.13913
18	.86250	1.11330	1.12590
19	.78660	1.10037	1.11237
20	.73069	1.08812	1.10060
.	.	.	.
.	.	.	.
.	.	.	.
54	.00012	.68564	.70114
55	.00004	.66881	.68515
56	.00001	.64611	.66616

* The results for components 21-53 inclusive are not shown due to space limitations.

By plotting the values of Table 6.4 in a graphical form (Figure 6.2), the lines of the mean and the 95th percentile eigenvalues are both intercepting with the actual eigenvalue line at component 14, which indicates that there are 13 significant factors for G1 in 2005.

Figure 6.2: Plot of actual vs. randomly generated eigenvalues for Group 1 (2005)



So, concerning the number of components to retain, the results of the PA for G1 (2005) supported the findings of Cattell's scree plot since both methods suggested keeping 13 factors. Nevertheless, it might be recalled that the number of components retained in this study were decided solely by PA and the results of the other techniques were reported for comparison purposes only.

Labelling components. Based on the results of PA, it was decided to retain 13 components for G1 of commercial banks in year 2005; the retained components explained 76.26% of the variance in the dataset (Table 6.3). In order facilitate finding the right label for each component, a varimax rotation was performed on the solution. For every component, this orthogonal rotation method makes small loadings very close to zero, and high loadings very close to one. Then, only significant loadings are taken into consideration when assigning suitable labels to the components. By referring to Table 3.2 in Hair et al. (1998, p. 112), and since the dataset in this research consisted of over 350 banks, loadings equal to or above .30 in the absolute sense were considered significant. However, it should be noted that the label given to a component is mainly driven by the variables which have the highest loadings (in the absolute sense) onto the component. Hence, variables with smaller loadings do not influence the label of the component.

The rotated component matrix for G1 of commercial banks in year 2005 is given in Table 6.5. As can be seen from the table, the rows of the matrix represent the 56 variables and the columns represent the 13 components. Also, factor loadings smaller than |0.30| are not shown, the highest loadings of variables on the components are shaded and ratios with cross-loadings (i.e. those with significant loadings onto three or more components) are in bold.

As can be seen from Table 6.5, all 56 ratios loaded significantly onto the 13 components. Also, some ratios loaded significantly onto more than one component. For instance, ratio X42 loaded significantly onto four components (C3, C4, C10 and C12). Similarly, ratios X6, X25, X48, X49 and X41 loaded significantly onto three components. Variables that have significant loadings onto more than one component (i.e. with cross-loadings) are generally a source of concern as they make the labelling step more difficult, therefore some authors suggest discarding such variables with many sizeable cross-loadings from the analysis (Hair et al., 1998, p. 113).

Table 6.5: Rotated component matrix for Group 1 (2005)

Variable Number	Ratio	Component												
		1	2	3	4	5	6	7	8	9	10	11	12	13
X13	INT INC (TE) \ AVR EARN AST	0.913												
X1	INT INC (TE) \ AVR AST	0.905												
X3	NET INT INC (TE) \ AVR AST	0.875												
X15	NET INT INC-TE \ AVR EARN AST	0.858			-0.339									
X36	YIELD ON TOT LN&LS (TE)	0.790												
X6	**PROVISION: LN&LS LOSSES \ AVR AST**	0.512				0.459				0.350				
X9	NET OPER INC \ AVR AST		0.938											
X10	NET INC \ AVR AST		0.936											
X8	PRETAX NET OPER INC (TE) \ AVR AST		0.936											
X7	PRETAX OPER INC (TE) \ AVR AST		0.929											
X53	NET INC \ AVR TOT EQ		0.880											
X33	EFFICIENCY RATIO		-0.674						0.554					
X45	S T INV \ S T NCORE FUND			-0.884										
X43	NET S T NCORE FUND DEPENDENCE			0.810										
X39	S T INV \ TOT AST			-0.807										
X22	NET NCORE FUND DEPENDENCE			0.734										
X46	S T AST \ S T LIABS			-0.702										
X47	NET S T LIAB \ TOT AST			0.651										
X42	**S T NCORE FUNDING \ TOT AST**			0.544	0.354						0.305		0.310	
X2	INT EXP \ AVR AST				0.934									
X14	INT EXP \ AVR EARN AST				0.917									
X38	COST OF ALL INT-BEARING FUNDS				0.887									
X44	BROK DEP \ DEP				0.524							-0.336		
X12	AVR INT-BEARING FUNDS \ AVR AST				0.408			-0.373						
X18	LN&LS ALLOW \ NET LOSSES					-0.912								
X17	EARN COV OF NET LOSS		0.334			-0.806								
X16	NET LOSS \ AVR TOT LN&LS					0.732								
X21	NON-CUR LN&LS \ GRS LN&LS					0.556								

Variable Number	Ratio	Component												
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
X27	RESTR+NONAC+RE ACQ \ EQCAP+ALLL					0.500						0.357		
X29	G R TIER ONE CAP						0.885							
X54	G R TOT EQCAP						0.864							
X26	RETAIN EARNS \ AVR TOT EQ						0.784							
X25	**CASH DIV \ NET INC**		0.372				-0.454					0.364		
X55	TIER ONE RBC \ RISK-WGT AST							0.895						
X56	TOT RBC \ RISK-WGT AST							0.876						
X24	TIER ONE LEVERAGE CAP	0.305						0.796						
X5	NONINT EXP \ AVR AST								0.888					
X4	NONINT INC \ AVR AST								0.850					
X11	AVR EARN AST \ AVR AST				0.374				-0.476					
X19	LN&LS ALLOW \ LN&LS NOT HFS									0.928				
X20	LN&LS ALLOW \ TOT LN&LS									0.926				
X48	**NET LS&LS \ DEP**	0.401		0.387							0.626			
X49	**NET LN&LS \ CORE DEP**			0.409	0.387						0.594			
X23	NET LN&LS \ AST	0.554									0.555			
X37	YIELD ON TOT INV SEC (TE)										-0.433			
X52	PLEDGED SEC \ TOT SEC										0.375			
X40	MARKETABLE EQ SEC \ TOT AST										-0.365			
X34	AVR PERSONNEL EXP PER EMPL($000)											-0.745		
X35	AST PER EMPLOYEE ($MILLION)								-0.553			-0.652		
X41	**CORE DEP \ TOT AST**			-0.328	-0.427							0.442		
X32	G R S T NON CORE FUNDING												0.636	
X28	G R AST						0.501						0.598	
X30	G R NET LN&LS						0.432						0.467	
X31	G R S T INV			-0.366									0.395	
X50	TOT HTM SEC \ TOT SEC													-0.845
X51	TOT AFS SEC \ TOT SEC													0.844

1. Loadings smaller than |.30| are suppressed (Table 3.2 in Hair et al., 1998, p. 112).
2. Ratios loading significantly onto three or more components are in bold.

However, since the current study involved conducting a number of comparisons between the components of different datasets, it was important to use the same set of ratios in every analysis. Thus, all the analyses in this chapter were carried out using the same list of 56 ratios without omitting the ratios that had no significant loadings or those which loaded significantly onto several components. Nevertheless, as can be seen from Table 6.5, the cross loadings of the ratios listed above are generally of a small absolute size; thus, such variables are expected to have a trivial influence on the labels to be given to the components.

By considering the ratios with the highest significant loadings onto the 13 components of G1, these components were assigned the following labels: C1: M(Y)-I, C2: Prof, C3: Sh-t liq, C4: M(C)-II, C5: AQ-I, C6: CG, C7: RBC, C8: Eff-I, C9: AQ-II, C10: Ln&Ls, C11: Eff-II, C12: Grth, and C13: IS [see Table 5.8 for the full names of the components].

6.3.2 Analyses for Groups 2, 3 and 4 (2005)

Subsequent to identifying and successfully labelling 13 components for G1 of commercial banks in year 2005, the same steps were carried out for the other asset-size groups in the same year. Nevertheless, no further elaboration is reported in this subsection in regard to these steps as focus is given instead to the results. Some of these results are reported in Table 6.6 and Appendix 6.1 which are referred to in the following paragraphs.

Table 6.6: Initial results for Groups 2, 3 and 4 (2005)

	Group 2	Group 3	Group 4
KMO	0.775	0.771	0.777
BTS: Approx. χ^2	233,983.2	159,961.8	121,286.4
df	1540	1540	1540
Sig.	.000	.000	.000
Number of factors			
Eigenvalue >1	16	14	16
Cattell's scree plot	12	13	11
PA	12	13	12
% of variance explained	76.234%	77.583%	75.922%

Financial patterns of Group 2 (G2) (2005). This group consisted of 1,856 banks with asset sizes ranging between $100 and $300 million; each of these banks had the complete set of 56 ratios available (Table 6.1). The factorability of the data reported for banks in this group (Table 6.6) was checked using the KMO test and returned a statistic of .775 which can be considered as 'middling'. Also, the correlations among the 56 variables were overall significant given the BTS statistics reported in the table. In regard to the number of components to retain for this group, PA suggested keeping 12 components whereas, according to the latent root method, 16 components had an eigenvalue in excess of unity. Cattell's scree plot, however, showed that keeping 12 components would be satisfactory. Nevertheless, given the outputs of PA, 12 components were kept and these accounted for 76.23% of the variance in the dataset. Appendix 6.2 shows the matrix of factor loadings for the group after a varimax rotation was applied to the solution. Only one ratio (X40) failed to load significantly onto any component (see Table 4.4 for the names of ratios). Also, a few ratios had significant loadings onto more than one component, amongst which were X6, X5, X16, and X41. With reference to Table 5.8, the 12 components were labelled as follows: C1: Prof, C2: M(Y)-I, C3: Sh-t liq, C4: Ln&Ls, C5: M(C)-II, C6: CG, C7: Eff, C8: RBC, C9: AQ-I, C10: AQ-II, C11: Grth, and C12: IS.

Financial patterns of Group 3 (G3) (2005). The asset size for the 1,270 banks making up this group ranged between $50 and $100 million. As Table 6.6 shows, the degree of common variance among the variables was expressed by the KMO statistic of .771; this could be considered as 'middling'. Furthermore, the BTS statistic was significant which indicated that the correlation matrix contained enough significant correlations. Therefore, it was appropriate to conduct a PCA on the data in G2. Fourteen components were found to have an eigenvalue in excess of one whereas the plot of the eigenvalues against the number of components started to level-off after component 14, which suggested keeping 13 components. PA, nevertheless, suggested keeping 13 components; these explained collectively 77.58% of the variability in the dataset. A varimax rotation was then applied to the solution; the resulted rotated component matrix is given in Appendix 6.2. As it shows, X1, X3, X13, X12 and X21 were amongst the ratios with multiple significant loadings whereas X40 failed to have any significant loading at all. All components, apart from component 13, were successfully labelled as follows: C1: Prof, C2: Sh-t Liq, C3: M(Y)-I, C4: M(C)-II, C5: Ln&Ls, C6: AQ-I, C7: RBC, C8: CG, C9: AQ-II, C10: Grth, C11: Eff-II., C12: IS, and C13: no name was assigned to this component and thus it could be called the 'undefined' or 'unlabelled' component.

Financial patterns of Group 4 (G4) (2005). With 968 banks of average asset sizes of less than $50 million, this was the smallest group of commercial banks in year 2005. As shown in Table 6.6, given a statistic of .777 for the KMO test, the degree of factorability for this group could be considered 'middling'. Also, given the significance of the KMO measure, the overall correlations amongst the variables were significant. The latent root method suggested retaining 16 components whereas Cattell's scree plot suggested keeping only 11. Nevertheless, according to the PA, keeping 12 components would be sufficient. These 12 components accounted for 75.92% of the variance. Appendix 6.2 shows the rotated component matrix for this group. As can be seen at the bottom of the matrix, ratios X40 and X52 did not load significantly onto any of the components. Also, ratios X1, X5, X35, X41 and X42 had significant loadings onto three or more components (see Table 4.4 for a brief description of the ratios). Nevertheless, by considering the ratios with the highest loadings onto each of the components, these 12 components were labelled as follows: C1: Prof, C2: Sh-t liq, C3: M(Y)-I, C4: M(C)-II, C5: Ln&Ls, C6: AQ-I, C7: RBC, C8: CG, C9: AQ-II, C10: Grth, C11: Eff, C12: IS (see Table 5.8 for a further description of the components).

PCA was carried out up to this point for each of the four asset size groups in year 2005. Table 6.7 summarises the labels given to the derived components. In the following sub-section, the results for the four asset-size groups in the years 2001-2004 are discussed.

Table 6.7: Labels assigned to components of four asset-size groups (2005)*

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
G1	M(Y)-I	Prof	Sh-t liq	M(C)-II	AQ-I	CG	RBC	Eff-I	AQ-II	Ln&Ls	Eff-II	Grth	IS
G2	Prof	M(Y)-I	Sh-t liq	Ln&Ls	M(C)-II	CG	Eff	RBC	AQ-I	AQ-II	Grth	IS	-
G3	Prof	Sh-t Liq	M(Y)-I	M(C)-II	Ln&Ls	AQ-I	RBC	CG	AQ-II	Grth	Eff-II	IS	No Name
G4	Prof	Sh-t liq	M(Y)-I	M(C)-II	Ln&Ls	AQ-I	RBC	CG	AQ-II	Grth	Eff	IS	-

* Refer to Table 5.8 for full names of the components.

6.3.3 Analyses for all groups in years 2001-2004

In this subsection, the financial patterns are identified for each of the four asset-size groups in the years 2001-2004. The relevant results are summarised in Table 6.8 and Appendix 6.3 and 6.4. Since the two earlier subsections (Subsections 6.3.1 and 6.3.2) reported the results for the groups in year 2005, Table 6.8 is best explained on a year-by-year basis.

Financial patterns for the four asset-size groups in year 2001. The first part of Table 6.8 reports the statistics of the initial tests for the factorability of the data in year 2001. The overall correlations amongst variables in the four groups could be considered as significant given the results of the BTS test. Moreover, the KMO statistics could be described as 'middling' for G2, G3 and G4 whereas, for G1, the KMO statistic (.699) fell slightly below the 'middling' into the 'mediocre' range. Also from Table 6.8, the latent root criterion suggested retaining 16 components for G1, and 15 components for each of the other groups. According to the scree plot method, extracting 12 components seemed to be sufficient for each of the four groups. Nevertheless, the results of PA suggested retaining 12 components for G1, G3 and G4, and 13 components for G2. The solutions suggested by PA accounted for 74.58%, 78.00%, 76.34%, and 76.06% of the variance in the four groups, respectively.

Table 6.8: Initial results for all groups (2001-2004)

	Group 1	Group 2	Group 3	Group 4
2001				
KMO	0.699	0.771	0.770	0.771
BTS: Approx. χ^2	92,989.467	225,290.6	197,340.3	169,705.3
df	1540	1540	1540	1540
Sig.	.000	.000	.000	.000
<u>Number of factors</u>				
Eigenvalue >1	16	15	15	15
Cattell's scree plot	12	12	12	12
PA	12	13	12	12
% of variance explained	74.580%	78.001%	%76.336%	76.056%

	Group 1	Group 2	Group 3	Group 4
2002				
KMO	0.728	0.723	0.764	0.772
BTS: Approx. χ^2	102,502.4	223,447.5	195,752.3	166,952.9
df	1540	1540	1540	1540
Sig.	.000	.000	.000	.000
Number of factors				
Eigenvalue >1	14	16	15	15
Cattell's scree plot	13	12	13	11
PA	12	12	13	11
% of variance explained	75.408%	75.137%	78.348%	74.816%
2003				
KMO	0.721	0.719	0.762	0.777
BTS: Approx. χ^2	116,172.1	208,750.6	184,705.8	151,545.8
df	1540	1540	1540	1540
Sig.	.000	.000	.000	.000
Number of factors				
Eigenvalue >1	14	15	14	15
Cattell's scree plot	13	13	11	11
PA	13	13	13	13
% of variance explained	77.667%	77.701%	77.899%	78.123%
2004				
KMO	0.730	0.771	0.757	0.778
BTS: Approx. χ^2	124,118.8	230,950.8	163,721.0	130,525.4
df	1540	1540	1540	1540
Sig.	.000	.000	.000	.000
Number of factors				
Eigenvalue >1	15	14	15	15
Cattell's scree plot	11	12	11	12
PA	13	12	13	12
% of variance explained	76.533%	75.994%	77.90%	75.763%

The rotated component matrices for the four groups in year 2001 are given in Appendix 6.4. Ratio X40 failed to have any significant loadings onto any of the components in G1, G2 and G3; this also applied to ratio X37 in G4. Only C10 in G4 could not be successfully labelled. The names assigned to the components are given in Table 6.9 (further descriptions of these labels are given in Table 5.8).

Table 6.9: Labels assigned to components of the four asset-size groups (2001)*

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
G1	M(Y)-I	Prof	Fnd	Sh-t liq	M(C)-II	AQ-I	RBC	Eff	Grth	AQ-II	CG	IS	-
G2	Prof	M(C)-II	M(Y)-I	Ln&Ls	Sh-t liq	RBC	Fnd-II	AQ-I	CG	AQ-II	Eff-II	Grth	IS
G3	Prof	M(Y)-I	M(C)-II	Sh-t liq	Eff	AQ-I	RBC	CG	Fnd-II	AQ-II	Grth	IS	-
G4	Prof	Sh-t liq	M(Y)-I	M(C)-II	Ln&Ls	RBC	AQ-I	CG	AQ-II	No Name	IS	Grth	-

* Refer to Table 5.8 for full names of the components.

Financial patterns for the four asset-size groups in year 2002. The statistics from the KMO and BTS factorability tests, shown in Table 6.8, indicated that the four datasets in this year appeared to have different dimensions and thus PCA was appropriate to uncover these patterns. The number of components with an eigenvalue in excess of unity was 14 for G1, 16 for G2, and 15 for both G3 and G4. The scree plots, however, pointed to the existence of 13 components in G1 and G3, 12 in G2 and 11 in G4. Yet, PA suggested 12 components for G1 and G2, 13 for G3 and only 11 for G4. The different factor solutions accounted for 75.41%, 75.14%, 78.35% and 74.82% of the variance in the four groups, respectively.

Appendix 6.4 gives the rotated component matrices for the four groups in year 2002. Only in G3 did all ratios load significantly onto the components. Ratios with insignificant loadings were X37 and X40 in G1 and G2 and ratios X40 and X52 in G4 (see Table 4.4 for the list of ratio names). Table 6.10 summarises the labels that were assigned to the components of the four groups in year 2002. As can be seen from the table, the components of all the groups, except for C13 in G3, were labelled successfully.

Table 6.10: Labels assigned to components of the four asset-size groups (2002)*

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
G1	Prof	M(Y)-I	Sh-t liq	AQ-I	fnd	M(C)-II	RBC	CG	Eff	AQ-II	IS	Grth	-
G2	Prof	M(C)-II	M(Y)-I	Sh-t liq	Ln&Ls	AQ-I	RBC	CG	AQ-II	Eff-II	Grth	IS	-
G3	Prof	Sh-t liq	M(C)-II	Ln&Ls	M(Y)-I	AQ-I	CG	RBC	Eff	AQ-II	Grth	IS	No Name
G4	Prof	M(Y)-I	Sh-t liq	M(C)-II	Ln&Ls	RBC	AQ-I	CG	AQ-II	IS	Grth	-	-

* Refer to Table 5.8 for full names of the components.

Financial patterns for the four asset-size groups in year 2003. All groups in this year successfully passed the two statistical tests concerning the factorability of the data. As Table 6.8 shows, the KMO statistics for the four groups were all greater than .7, *i.e.* fell in the ‘middling’ range, and the BTS statistics were also significant. The number of components with an eigenvalue in excess of unity was 14 for G1 and G3, and 15 for G2 and G4. Cattell's scree plot, however, suggested keeping 13 components for G1 and G2, and 11 for G3 and G4. Given the outputs of PA, solutions of 13 components were suggested for all the four groups. These solutions accounted for over 77-78% of the variance in the four groups.

Appendix 6.4 shows the rotated component matrices for the four asset-size groups of commercial banks in year 2003. Ratios X37 and X40 generally failed to have significant loadings onto any of the components for the different groups. Table 6.11 gives the names of the components for the different groups in year 2003. The table clearly shows that all 13 components were successfully labelled in G3. C13 in all groups except for G3 could not be assigned any name, as the table shows.

Table 6.11: Labels assigned to components of the four asset-size groups (2003)*

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
G1	Prof	M(Y)-I	Sh-t liq	Fnd	M(C)-II	AQ-I	RBC	CG	Eff	AQ-II	Grth	IS	No Name
G2	Prof	M(Y)-I	Sh-t liq	M(C)-II	RBC	AQ-I	Fnd	CG	Eff	AQ-II	IS	Grth	No Name
G3	Prof	M(Y)-I	M(C)-II	Sh-t liq	RBC	AQ-I	CG	AQ-II	Fnd-II	Eff-II	Grth	Eff-I	IS
G4	Prof	Sh-t liq	M(C)-II	M(Y)-I	Ln&Ls	RBC	CG	AQ-I	AQ-II	IS	Grth	Fnd-II	No Name

* Refer to Table 5.8 for full names of the component.

Financial patterns for the four asset-size groups in year 2004. The factorability statistics for all groups in year 2004 implied that PCA could be used to uncover the different patterns that existed in the datasets. In regard to the number of these patterns, the latent root criterion suggested that there were 14 components in G2 and 15 in the other groups. Cattell's scree plot suggested keeping only 11 components for G1 and G3, and 12 for the other two groups. PA, on the other hand, showed that retaining 13 components would be sufficient for G1 and G3 whereas 12 components would be adequate for G2 and G4. The percentage of variance accounted for by the solutions suggested by PA for the four groups ranged between 75.76% (G4) and 77.90% (G3).

The rotated component matrices for the four groups in year 2004 are given in Appendix 6.4. In these matrices, the following ratios had no significant loadings: X40 in G1; X37, X40 and X52 in G2; X40 and X30 in G3; and X44 in G4. The names assigned to the components are given in Table 6.12. As can be seen from the table, C12 in G1 and C11 in G4 could not be successfully labelled.

Table 6.12: Labels assigned to components of the four asset-size groups (2004)*

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
G1	Prof	M(Y)-I	Sh-t liq	Fnd	M(C)-II	CG	AQ-I	RBC	Eff	AQ-II	Grth	No Name	IS
G2	Prof	Sh-t liq	M(Y)-I	M(C)-II	Ln&Ls	AQ-I	CG	Eff	RBC	AQ-II	IS	Sh-t inv	-
G3	Prof	M(Y)-I	M(C)-II	Sh-t liq	RBC	CG	AQ-I	Ln&Ls	Fnd-II	AQ-II	AQ-III	Eff-II	IS
G4	Prof	Sh-t liq	M(Y)-I	Ln&Ls	M(C)-II	AQ-I	CG	AQ-II	RBC	Grth	No Name	IS	-

* Refer to Table 5.8 for full names of the components.

6.4 Cross-sectional stability of financial patterns of banks in the four asset-size groups

Up to this point, the financial patterns of ratios for four asset-size groups of commercial banks were identified over five successive years. The practical steps followed in deriving the patterns were identical for all groups over the period between 2001 and 2005. Having accomplished this, the question to be answered in this section is to what extent are the financial patterns of ratios for commercial banks in different asset-size groups similar? In other words, this section looks at the cross-sectional stability of financial patterns extracted for the different groups. Similar to Chapter 5, various methods were employed in checking the stability: first, visual comparisons were carried out; this was followed by examining the correlation and congruence analyses; finally, transformation analysis was used. Since this study covered a period of five years, five cross-sectional comparisons were thus conducted using each of the above-mentioned methods.

6.4.1 Visual comparison

In visual factor comparison, many areas were tackled. These included: the number of components extracted in each group; the proportion of variance explained by the different factor solutions; and whether the same patterns were identified in all groups. To facilitate carrying out the comparison, Table 6.13 offers some of the results reported in the previous sections.

Table 6.13: Number of components identified, % variance explained and ratios with insignificant loadings in all groups (2001-2005)

		G1	G2	G3	G4
2001	components	12	13	12	12 (11)
	% variance	74.58	78.00	76.34	76.06
	insig. loading	X40	X40	X40	X37- X40
2002	components	12	12	13 (12)	11
	% variance	75.41	75.14	78.35	74.82
	Insig. loading	X37- X40	X37- X40	-	X40- X52
2003	components	13 (12)	13 (12)	13	13 (12)
	% variance	77.67	77.70	77.90	78.12
	Insig. loading	X37	X37- X40	X37	X40
2004	components	13 (12)	12	13	12 (11)
	% variance	76.53	75.99	77.90	75.76
	Insig. loading	X40	X37- X52- X40	X30- X40	-
2005	components	13	12	13 (12)	12
	% variance	76.26	76.23	77.58	75.92
	Insig. loading	-	X40	X40	X40- X52

1. Numbers in brackets represent the number of meaningful components (that is, those that were successfully labelled).
2. The proportion of variance explained by all the extracted components, not only those which were successfully labelled.

Number of components and proportion of variance explained. As Table 6.13 shows, different numbers of financial patterns were identified for commercial banks in the different asset-size groups. In year 2001, 12 components were successfully labelled for G1 and G3, 13 for G2, and only 11 for G4. The solution for G2 accounted for the highest proportion of the variance (78.00%) whereas the solution for G1 explained the lowest proportion (74.58%). In year 2002, 11 meaningful components were identified for G4 whereas 12 components were identified for each of the other asset-size groups. The components extracted for G3 accounted for the highest proportion of the variance (78.35%) and those for G4 explained the least variance (74.82%). In year 2003, 13 components were derived and successfully named for G3 whereas 12 were labelled for the other groups. The highest proportion of the variance was explained by G4 (78.12%) and the least by G1 (77.67%). In year 2004, different components were found for the different groups: 13 components were successfully labelled in G3, 12 in G1 and G2, and only 11 in G4. The factor solution for G3 explained the largest proportion of variance (77.9%) whereas the solution for G4 explained the least (75.76%). Finally, as for year 2005, 13 meaningful components were found for G1 whereas the other three groups of smaller asset-size banks each had 12 components. In terms of the proportion of variance accounted for by the different factor solutions, the highest explained proportion was for the solution of G3 (77.58%) whereas the least was by the solution of G4 (75.92%).

Table 6.13 also reports the ratios that failed to load significantly onto any of the components (i.e. ratios with loadings of less than |0.30|[111]). For all groups over the five years, these ratios were four in total: X30, X37, X40 and X52. However, the insignificant loadings for these ratios did not seem to be related to the asset size of the groups of banks. In other words, these four ratios could not be grouped under any of the identified ratio patterns for commercial banks, regardless of their asset-size class.

Thus, the visual inspection conducted at this point revealed some dissimilarity in the results of the four asset-size groups, both in the number of meaningful components and in the proportion of variance explained. Broadly, the number of identified components tended to be smaller for G4 compared to other groups (e.g. G4 in 2001, 2002, 2004 and 2005 in Table 6.13). In addition, it appeared that solutions with 11-12 components tend to explain less proportion of variance compared to the 13-factor solutions (see, for example, G2 and G4 in 2001 in Table 6.13).

Proportion of total variance explained by components. The visual inspection was further enhanced by following Martikainen et al. (1995a) who compared the cumulative variance explained by different factor solutions. Table 6.14 gives the cumulative proportions of variance explained by each of the extracted components for the four groups over the five-year period. As can be seen from the table, the solutions for G1 seemed to account for the least proportion of variance compared to the other groups over the period. For example, the percentage of variance accounted for by the first five components was the lowest for G1 and highest for G4 in each of the five years (row C5 in Table 6.14). This also applies, to some extent, to the percentage of variance explained by the 12 components (row C12) where the solutions for G1 explained the least amount of variance compared to other groups in most of the years covered in the study.

[111] This was decided given the size of the different samples used in this chapter with reference to Table 3.2 in Hair et al. (1998, p. 112).

Table 6.14: Cumulative proportion of total variance explained for all groups of commercial banks (2001-2005)

	2001				2002				2003				2004				2005			
	G1	G2	G3	G4	G1	G2	G3	G4	G1	G2	G3	G4	G1	G2	G3	G4	G1	G2	G3	G4
C1	15.18	16.89	17.10	16.84	14.16	14.99	15.62	16.72	14.55	14.45	16.08	17.54	14.74	16.08	16.46	18.10	14.40	16.70	17.52	17.48
C2	27.55	30.02	30.11	32.46	27.97	28.09	30.85	32.53	27.18	28.24	30.56	32.94	27.15	29.81	30.54	33.02	28.24	30.31	31.42	32.76
C3	36.78	40.12	40.85	41.90	37.61	38.08	40.46	41.76	36.93	37.82	40.34	42.04	37.43	39.39	40.03	42.43	37.82	40.64	41.85	42.78
C4	44.16	47.24	48.05	48.53	44.34	46.11	48.07	48.80	43.78	46.18	47.75	48.69	44.92	47.80	48.09	48.66	45.04	47.54	48.55	48.79
C5	49.96	52.77	53.98	54.45	50.70	52.25	54.01	54.55	49.73	52.36	53.73	54.08	50.54	53.75	53.73	54.18	51.04	53.45	54.03	54.22
C6	55.20	57.46	58.48	58.53	55.90	56.75	58.27	58.77	54.89	57.26	58.14	58.40	55.47	58.04	58.00	58.48	55.41	57.99	58.06	58.78
C7	59.11	61.61	62.45	62.16	60.29	60.69	62.38	62.65	59.55	61.18	61.79	62.04	59.53	61.73	61.77	61.96	59.38	61.92	61.58	62.30
C8	62.86	65.03	65.53	65.37	64.31	64.15	65.64	66.09	63.76	64.41	65.06	65.35	62.97	65.17	64.95	65.17	62.62	65.46	65.05	65.48
C9	66.37	68.01	68.49	68.37	67.78	67.22	68.63	69.42	67.33	67.56	68.05	68.29	66.28	68.23	68.07	68.07	65.75	68.48	67.96	68.35
C10	69.41	70.77	71.26	71.02	70.69	69.96	71.27	72.25	70.33	70.33	70.80	70.99	69.15	71.04	70.89	70.87	68.69	71.20	70.75	71.11
C11	72.05	73.36	73.92	73.60	14.16	14.99	15.62	16.72	72.88	73.01	73.42	73.67	71.93	73.57	73.49	73.47	71.53	73.86	73.26	73.59
C12	74.58	75.80	76.34	76.06	27.97	28.09	30.85	32.53	75.35	75.45	75.73	75.97	74.29	76.00	75.76	75.76	74.06	76.23	75.43	75.92
C13	-	78.00	-	-	37.61	38.08	40.46	41.76	77.67	77.70	77.90	78.12	76.53	-	77.90	-	76.26	-	77.58	-

Components' relative position in solutions. Another point which could be also uncovered by visual comparison is the relative position of components in the different solutions. The order in which components are extracted reflects the decreasing contribution of these components to the total proportion of the variance explained[112]. This makes the relative position of a component in the solution an indicator of its contribution to the amount of variance explained by the whole solution. Thus, if a component has the same position in two solutions, the relative importance of this particular component to the two solutions is thus expected to be similar. As can be seen from Tables 6.7, and 6.9-6.12, no component maintained the same position across all the four groups in the five years studied. However, the Prof component was the first to be extracted for almost all the groups over the period.

Labels of components. Regardless of the order in which the components were extracted, Tables 6.7, and 6.9-6.12 also show that nine components were identified in all four groups over the five-year period. With reference to Table 5.8 for the full names, these components were the following: Prof, Sh-t liq, M(Y)-I, M(C)-II, AQ-I, AQ-II, RBC, CG and IS. Others, such as Fnd, Ln&Ls, Grth, Eff, Eff-II, and Fnd-II, were less consistent as they were not identified for all groups in all the years. Also, two components, Sh-t inv and the AQ-III, were identified for one group only (G2 and G3 in year 2004, respectively).

Ratios forming components. Identifying the same components for the different groups was not enough to consider these components as similar; so, a closer look at the variables that loaded onto the factors was essential. Thus, all the variables in the rotated component matrices (Table 6.6, Appendix 6.2 and 6.4) were subjected to greater scrutiny in order to uncover any peculiar differences in the components they loaded onto across the different groups. This was done visually in this section whereas some statistical techniques were used subsequently. In the following

[112] As mentioned in Chapter 5 (Subsection 5.5.1), after rotating the solution, the first component does not necessarily account for the largest proportion of the variance. Nevertheless, even after rotation, the order in which components appear in SPSS output is based on the decreasing amount of variance accounted for by each of the components. Thus, the order of components can still imply the importance of the different components to the solution.

paragraphs, ratios are referred to only by their number; further descriptions of these ratios are given in Table 4.4.

First, in regard to the Prof component, ratio X25 tended to load significantly onto this component for all the groups except for G1 in which it loaded instead onto CG. As for the M(Y)-I component, in groups with smaller asset-size it can be seen that some efficiency ratios (such as X4, X5, X 11, and X35) had rather significant loadings onto the factor. Actually, in G4 of all years except 2005, it seemed that Eff has merged into M(Y)-I because of the significant loadings the efficiency ratios had onto the factor. Also, it is worth mentioning that the Ln&Ls ratios (X23, X48 and X49) loaded significantly onto M(Y)-I in one case (G3 in 2001). In regard to the M(C)-II component, it was noticeable that ratio X12 had significant loadings onto this factor in all groups except for G1 for which it loaded instead onto RBC; this applied to all years except 2005. Furthermore, similar to what was observed for M(Y)-I, some efficiency ratios also had some significant loadings onto the M(C)-II factor for some of the groups. In the case of G2 (in 2001 and 2002), however, the Eff component had clearly merged into M(C)-II. Last but not least, concerning the nine components consistently identified for all the groups, it can be noticed that the Ln&Ls ratios loaded significantly onto RBC in G3 (2003). Other than what has been mentioned above, the visual checking revealed nothing peculiar in regard to Sh-t liq, AQ-I, AQ-II, CG and, IS.

The visual checking of the less consistent components began with Fnd and Ln&Ls. The Fnd component was identified for G1 in all years except 2005; also, it was found for G2 in year 2003. However, for the other groups, the formation of Fnd has changed as some Ln&Ls ratios dominated with their high loadings; therefore, this component was labelled as Ln&Ls instead of Fnd for these groups. Nevertheless, recalling earlier paragraphs, Ln&Ls appeared to merge into RBC in G3 (2003) and also into M(Y)-I in G3 (2001); this appeared to cause this component to be somewhat inconsistent.

As for the two efficiency factors, Eff-I and Eff-II, the former consisted of ratios X4, X5 and X11, while the latter was formed from X34 and X35. When any of the two ratios of Eff-II loaded onto the other factor, the factor was labelled ‘Eff’. As can be seen from the rotated component matrices, the two Eff components were identified for the same group only in two cases: G1 (2005) and G3 (2003). Furthermore, with the exception of year 2005, neither of the two Eff components was identified for banks with the smallest asset size (i.e. G4); for this group, the Eff ratios loaded instead onto the M(Y)-I, as mentioned earlier. In the case of other groups (G1-G3), only one of the two Eff components was identified.

Thus, the preliminary findings of the visual comparisons conducted above enabled the broad conclusion to be drawn that the financial patterns for the different asset-size groups of commercial banks did not appear to be similar. The extent to which this conclusion is valid is examined in the following sections using different mathematical methods.

6.4.2 Correlation coefficients

Following the visual comparisons made for the components in the different asset-size groups, the first part of the technical comparisons were made using correlation coefficients to assess the cross-sectional stability of the components. Correlation analysis in this sense was carried out by assessing the absolute size of the correlation coefficients where the higher the coefficient, the more stable the component. Table 6.15 shows the correlation coefficients between components of the four groups over the study period. Note that, since this study is interested in the cross-sectional similarities in the patterns of different groups, the correlation coefficients were calculated between all possible pairs of groups; this returned the six pairs listed in the table. Also, the components in the table are given in a specific order to ease the interpretation process where the first nine components are those which were consistently found in all the groups and the last six were the less consistent components.

By closely examining the first nine factors in Table 6.15, the smallest correlation coefficients (in an absolute sense) were generally found for the M(Y)-I component whereas the highest correlations were found for the Sh-t liq component. Over all six pairs, for the five years covered, the correlations of M(Y)-I ranged between .554 for G3-G4 (2001) and .978 for the same pair (2004). On the other hand, the correlation coefficients for Sh-t liq ranged between .881 for G2-G3 (2004) and .992 for G2-G3 and G3-G4 (2002). High correlations were also found, as shown in Table 6.15, for the Prof component. The correlation coefficients for the rest of the nine components were reasonably good for most of the pairs over the years.

As for the inconsistent components, starting with Fnd and Ln&Ls, it may be recalled from the previous section that Fnd was identified for G1 in all years except 2005, and also identified for G2 in 2003. Ln&Ls, however, was found for the rest of the groups over the five years, with the exception of G3 in 2003 and 2001. It may also be recalled that these two components are formed by the almost same ratios. For this reason, from this point in this chapter, the two components will be considered as counterparts; thus their cross-sectional stability can be checked by correlating the two components in different groups, and also by using other factor comparison techniques. As Table 6.15 shows, the correlation coefficients between Fnd and Ln&Ls were in their smallest absolute size whenever G1 was compared with G3 and G4; the correlations between G1 and G2 could be also considered to be of a small size. However, larger correlation coefficients were found between Ln&Ls in different groups. Thus, correlating Fnd and Ln&Ls returns smaller correlation coefficients (see, for example, the correlations for the first three pairs in year 2004), whereas correlating Ln&Ls in different groups yields higher correlation coefficients (see, for example, the correlations for the last three pairs of groups in year 2004).

In regard to Grth, the absolute size of its correlation coefficients were relatively small, especially for the pairs involving G1 (i.e. the first three pairs) over the five years. The correlation coefficients of this component were also small for G2, G3 and G4 over the years 2003-2005, with the exception of the pair G2-G3 in 2003 where the correlation coefficient was fairly high (.958). As for the years 2001-2002, the correlations for the pairs consisting of G2, G3 and G4 were also high (the smallest correlation was .922 for G2-G4 in 2002).

Table 6.15: Correlation coefficients between components of different asset-size groups (2001-2005)

	Prof	Sh-t liq	M(Y)-I	M(C)-II	AQ-I	AQ-II	RBC	CG	IS	Ln&Ls/Fnd	Grth	Eff	Eff-II	Fnd-II	No Name
	2001														
G1-G2	0.952	-0.964	0.851	0.776	0.959	0.866	-0.962	0.822	0.837	0.582	0.871	-	-	-	-
G1-G3	0.932	-0.974	0.709	0.943	0.937	0.873	0.941	0.888	0.832	-	0.829	-0.793	-	-	-
G1-G4	0.908	0.971	0.802	0.916	0.880	0.824	-0.945	0.839	0.865	0.772	0.819	-	-	-	-
G2-G3	0.988	0.980	0.682	0.881	0.970	0.986	-0.975	0.925	0.977	-	0.938	-	-	0.974	-
G2-G4	0.968	-0.952	0.869	0.878	0.886	0.964	0.979	0.965	0.949	0.930	0.961	-	-	-	-
G3-G4	0.960	-0.982	0.554	0.966	0.912	0.976	-0.971	0.937	0.961	-	0.925	-	-	-	-
	2002														
G1-G2	0.967	0.972	0.924	0.901	0.947	0.968	-0.956	0.763	0.862	0.819	0.767	-	-	-	-
G1-G3	0.942	0.972	0.919	0.932	0.932	0.971	-0.957	0.799	0.911	0.790	0.750	-0.898	-	-	-
G1-G4	0.921	0.968	0.734	0.848	0.839	0.881	-0.939	0.737	0.841	0.818	0.766	-	-	-	-
G2-G3	0.989	0.992	0.967	0.964	0.981	0.969	0.986	0.965	0.947	0.977	0.967	-	-	-	-
G2-G4	0.964	0.987	0.871	0.909	0.885	0.925	0.975	0.959	0.938	0.949	0.922	-	-	-	-
G3-G4	0.971	0.992	0.882	0.918	0.903	0.945	0.970	0.967	0.908	0.963	0.965	-	-	-	-
	2003														
G1-G2	0.972	0.989	0.965	0.935	-0.957	0.932	-0.950	0.971	-0.882	0.944	0.849	-0.919	-	-	0.862
G1-G3	0.940	0.983	0.913	0.887	-0.948	0.933	-0.921	0.948	0.920	-	0.798	-0.678	-	-	-
G1-G4	0.898	0.976	0.809	0.868	-0.945	0.892	0.963	0.935	0.937	0.722	0.894	-	-	-	-0.694
G2-G3	0.985	0.990	0.975	0.970	0.991	0.982	0.983	0.979	-0.960	-	0.958	0.802	-	-	-
G2-G4	0.946	0.982	0.881	0.955	0.972	0.957	-0.924	0.918	-0.902	0.642	0.779	-	-	-	-0.637
G3-G4	0.981	0.990	0.933	0.983	0.971	0.959	-0.921	0.940	0.942	-	0.745	-	-	0.776	-
	2004														
G1-G2	0.959	0.897	0.936	0.951	-0.961	0.903	0.963	0.978	0.907	0.862	-	-0.874	-	-	-
G1-G3	0.944	0.982	0.893	0.908	-0.935	0.934	-0.953	0.957	0.911	0.769	-	-	-	-	-
G1-G4	0.929	0.978	0.835	0.885	0.939	0.899	0.719	0.913	0.941	0.817	0.844	-	-	-	-0.568
G2-G3	0.975	0.881	0.941	0.965	0.957	0.932	-0.978	0.978	0.956	0.902	-	-	-	-	-

	Prof	Sh-t liq	M(Y)-I	M(C)-II	AQ-I	AQ-II	RBC	CG	IS	Ln&Ls/Fnd	Grth	Eff	Eff-II	Fnd-II	No Name
G2-G4	0.963	0.925	0.878	0.944	-0.959	0.935	0.715	0.934	0.936	0.940	-	-	-	-	-
G3-G4	0.991	0.960	0.978	0.968	0.972	-0.968	-0.666	0.956	0.961	0.892	-	-	-	-	-
	2005														
G1-G2	0.933	0.977	0.805	0.920	-0.967	0.922	0.954	0.962	0.919	0.810	0.776	-0.839	-	-	-
G1-G3	0.952	0.980	0.668	0.948	0.932	0.937	0.954	0.933	0.928	0.650	0.821	-	-0.902	-	-
G1-G4	0.922	0.973	0.848	0.944	0.945	0.922	0.918	0.927	0.926	0.701	0.835	-0.609	-	-	-
G2-G3	0.953	0.992	0.736	0.945	-0.935	0.957	0.973	0.949	0.966	0.918	0.556	-	-	-	-
G2-G4	0.960	0.983	0.858	0.927	-0.946	0.953	0.944	0.951	0.947	0.938	0.840	0.765	-	-	-
G3-G4	0.986	0.926	0.926	0.980	0.962	0.941	0.938	0.971	0.958	0.967	0.776	-	-	-	-

1. Refer to Table 5.8 for the full names of the components.
2. All correlations are significant at 0.05 level (2-tailed).
3. When no component appeared in either group, a (-) sign is shown instead.

As for Eff, the correlation coefficients calculated for this component were generally small in absolute size. One of the few exceptions to this was the .919 correlation coefficient calculated between G1 and G2 in 2003 which was the highest for the component over the years. Regarding Eff-II, as can be seen from Table 6.15, calculating the correlation coefficient for this component was only feasible between G1-G2 in year 2005 where the component showed a fairly good level of similarity.

As for the Fnd-II component, its correlation coefficient was small (.776) between G3 and G4 in 2003, whereas a larger correlation (.974) was found for this component between G2 and G4 in 2001.

Finally, the last column in Table 6.15 shows that the correlations between the unlabelled components were in general the smallest (in absolute terms) compared to others (these ranged between -.568 and .862).

Now, since the Sh-t inv and AQ-III were identified for one group only (G2 and G3 in year 2004, respectively), it was not possible to check their cross-sectional stability. However, it is worth mentioning that Sh-t inv had fairly substantial correlations (in absolute terms) with Sh-t liq (-0.658, -0.716, and -0.601 in the pairs G1-G2, G2-G3 and G3-G4, respectively). AQ-III, however, seemed to have quite significant correlations with many components, such as AQ-I, AQ-II and Grth.

In summary, given the correlation coefficients results, Sh-t liq and Prof were the most similar components for the different asset-size groups of commercial banks. M(Y)-I, although found for all groups over the study period, showed the lowest similarity level compared to the other eight consistent components. A low level of similarity was also exhibited by Fnd and Ln&Ls when compared to each other on the basis that they were both made up of the same ratios. Ln&Ls, nevertheless, could be considered as fairly similar between the different groups. Furthermore, Grth showed a low level of similarity, especially when G1 was compared to the other groups. In addition, the two Eff components did not appear similar across the groups. Also, the level of similarity exhibited by Fnd-II was inconsistent as the component could be considered as similar in one period (2001) and dissimilar in another (2003). Finally, the unlabelled components were considered as dissimilar.

6.4.3 Congruency coefficients

In this part of the technical factor comparison, the congruency coefficients were used to check the cross-sectional stability of components. The formula used in calculating the congruency coefficient was summarised in Chapter 3 (Subsection 3.4.3) and the significance of the congruency coefficients was assessed using Table 3.1 given in Richman and Lamb (1985, Appendix). Table 6.16 reports the congruency coefficients for the components which are set out in the same order used in Table 6.15 where the nine consistent components come first followed by other, less consistent components. For each year over the period, the four asset-size groups were put into six pairs and the coefficients of congruency were calculated wherever the same component was identified in the two groups under comparison. The last row for each year in the table shows the mean value of the congruency coefficients calculated for all six pairs of groups. In calculating the means, the absolute values of the coefficients were considered, following Ketz et al. (1990, p. 71).

The congruency analysis commenced by assessing the mean values of the congruency coefficients in Table 6.16. Following the criteria given in Table 3.1, Sh-t liq had ‘excellent’ matches in most of the years covered (2002, 2003 and 2005), whereas it had ‘good’ matches in the rest of the years. The Prof and AQ-I components each had ‘good’ matches between the different groups across the five years. Matches of M(C)-II, AQ-II, CG and IS ranged between ‘good’ and ‘excellent’, and hence, could be considered as similar components over the different groups. Also, using the congruency coefficient method, M(Y)-I appeared to be the least similar component across the different groups given the size of its coefficients which fluctuated between ‘poor’ and ‘good’.

A closer look at the congruency coefficients of the nine consistent components in the different pairs of groups was then taken to identify any peculiar findings that were not identified by the correlation coefficients. It was first noticed that M(Y)-I clearly had a poor level of cross-sectional stability in 2001 and 2005. Between these two points in time, this component was still the least stable of the nine consistent components; nevertheless, its stability level was higher. Also, it can be noticed that AQ-II in year 2002 had ‘poor’ matches, mainly when G1 was compared to the other groups. However, the cross-sectional correlation coefficients calculated for this component were weak only for the G1-G4 pair, as Table 6.15 shows. Another point to add in this context is regarding the RBC component which had some ‘poor’ and some ‘terrible’ matches in year 2004, mainly when G4 was compared to the other groups; this was also reflected in the small correlation coefficients summarised in Table 6.15.

In regard to the Fnd/Ln&Ls inconsistent components, similar to the findings of the correlation coefficients; Fnd had a ‘good’ match when compared in G1-G2 (2003), the two groups in which it was identified. Also, Ln&Ls had ‘good’ matches when compared over the different groups. However, when Fnd and Ln&Ls were compared to each other, their matches could be considered as ‘borderline’, ‘poor’ and ‘terrible’. Furthermore, the findings of the congruency coefficients, in regard to the Grth component, confirmed those of the correlation coefficients. Grth had ‘borderline’, ‘poor’ and ‘terrible’ matches in all the pairs of groups involving G1. However, the matches concerning the other pairs were ‘good’ in 2001 and 2002, and bordered between ‘borderline’ and ‘poor’ in almost all the pairs in the following years. In addition, the matches of the Eff component were a mixture of ‘borderline’, ‘poor’ and ‘terrible’, which can be clearly interpreted as a low level of cross-sectional stability for that component. As for Eff-II, its congruency coefficient, calculated for G2-G3 in 2005, could be considered as ‘borderline’. Additionally, Fnd-II had a ‘good’ match in G2-G3 of year 2001, and a ‘poor’ match in G3-G4 in 2003, confirming the findings of the correlation coefficients presented in the previous subsection. The unlabelled component had a ‘borderline’ match for G1-G2 in 2003, and other ‘terrible’ and ‘poor’ matches for the rest of the pairs.

Table 6.16: Serial congruency coefficients between components of different asset-size groups (2001-2005)

	Prof	Sh-t liq	M(Y)-I	M(C)-II	AQ-I	AQ-II	RBC	CG	IS	Ln&Ls/Fnd	Grth	Eff	Eff-II	Fnd-II	No Name
	2001														
G1-G2	0.955	-0.964	0.873	0.772	-0.959	0.828	0.959	0.863	0.836	0.613	0.872	-	-	-	-
G1-G3	0.937	-0.973	0.752	0.943	0.941	0.890	0.935	0.873	0.825	-	0.837	-0.791	-	-	-
G1-G4	0.916	0.971	0.828	0.920	-0.941	0.844	0.879	0.826	0.862	0.794	0.828	-	-	-	-
G2-G3	0.988	0.980	0.737	0.879	-0.971	0.929	0.969	0.986	0.976	-	0.938	-	-	0.976	-
G2-G4	0.968	-0.951	0.883	0.866	0.979	0.967	0.884	0.966	0.949	0.933	0.960	-	-	-	-
G3-G4	0.963	-0.979	0.615	0.963	-0.965	0.940	0.912	0.978	0.960	-	0.929	-	-	-	-
Mean	**0.955**	**0.970**	**0.781**	**0.891**	**0.959**	**0.900**	**0.923**	**0.915**	**0.901**	**-**	**0.894**	**-**	**-**	**-**	**-**
	2002														
G1-G2	0.970	0.971	0.934	0.904	-0.949	0.771	0.945	0.970	0.862	0.835	0.785	-	-	-	-
G1-G3	0.947	0.971	0.930	0.935	-0.952	0.806	0.932	0.972	0.910	0.808	0.771	-0.897	-	-	-
G1-G4	0.928	0.965	0.773	0.853	-0.934	0.744	0.836	0.890	0.841	0.831	0.787	-	-	-	-
G2-G3	0.990	0.992	0.973	0.964	0.985	0.966	0.980	0.972	0.946	0.979	0.970	-	-	-	-
G2-G4	0.967	0.986	0.894	0.900	0.975	0.960	0.885	0.931	0.938	0.953	0.928	-	-	-	-
G3-G4	0.974	0.992	0.902	0.916	0.970	0.967	0.901	0.949	0.908	0.966	0.968	-	-	-	-
Mean	**0.963**	**0.980**	**0.901**	**0.912**	**0.961**	**0.869**	**0.913**	**0.947**	**0.901**	**0.895**	**0.868**	**-**	**-**	**-**	**-**
	2003														
G1-G2	0.973	0.989	0.969	0.938	-0.957	0.933	-0.946	0.974	-0.882	0.948	0.852	-0.919	-	-	0.847
G1-G3	0.945	0.983	0.925	0.894	-0.947	0.932	-0.915	0.953	0.920	-	0.798	-0.676	-	-	-
G1-G4	0.909	0.976	0.834	0.877	-0.944	0.898	0.963	0.940	0.937	0.755	0.890	-	-	-	-0.685
G2-G3	0.986	0.990	0.980	0.971	0.991	0.982	0.982	0.981	-0.960	-	0.954	0.802	-	-	-
G2-G4	0.951	0.982	0.895	0.956	0.972	0.958	-0.919	0.926	-0.900	0.679	0.784	-	-	-	-0.589
G3-G4	0.983	0.988	0.936	0.984	0.970	0.959	-0.912	0.946	0.942	-	0.734	-	-	0.775	-
Mean	**0.958**	**0.985**	**0.923**	**0.936**	**0.964**	**0.944**	**0.940**	**0.953**	**0.924**	**-**	**0.835**	**-**	**-**	**-**	**-**

	Prof	Sh-t liq	M(Y)-I	M(C)-II	AQ-I	AQ-II	RBC	CG	IS	Ln&Ls/Fnd	Grth	Eff	Eff-II	Fnd-II	No Name
	2004														
G1-G2	0.959	0.893	0.945	0.950	-0.958	0.904	0.959	0.979	0.906	0.874	-	-0.870	-	-	-
G1-G3	0.948	0.981	0.909	0.915	-0.930	0.929	-0.947	0.960	0.911	0.769	-	-	-	-	-
G1-G4	0.936	0.978	0.854	0.894	0.939	0.906	0.723	0.920	0.940	0.833	0.839	-	-	-	-0.564
G2-G3	0.977	0.872	0.952	0.965	0.957	0.933	-0.978	0.980	0.956	0.899	-	-	-	-	-
G2-G4	0.966	0.923	0.888	0.944	-0.955	0.936	0.708	0.941	0.936	0.945	-	-	-	-	-
G3-G4	0.992	0.976	0.959	0.970	-0.963	0.952	-0.657	0.974	0.961	0.888	-	-	-	-	-
Mean	**0.963**	**0.937**	**0.918**	**0.940**	**0.950**	**0.927**	**0.829**	**0.959**	**0.935**	**0.868**	**-**	**-**	**-**	**-**	**-**
	2005														
G1-G2	0.931	0.977	0.841	0.927	-0.964	0.922	0.953	0.965	0.917	0.816	0.788	-0.837	-	-	-
G1-G3	0.957	0.980	0.707	0.952	0.932	0.941	0.953	0.940	0.926	0.662	0.831	-	-0.887	-	-
G1-G4	0.930	0.973	0.872	0.949	0.945	0.924	0.917	0.934	0.926	0.711	0.843	-0.596	-	-	-
G2-G3	0.950	0.992	0.765	0.947	-0.933	0.958	0.973	0.953	0.966	0.920	0.597	-	-	-	-
G2-G4	0.959	0.983	0.882	0.933	-0.945	0.955	0.944	0.955	0.947	0.941	0.856	0.760	-	-	-
G3-G4	0.987	0.989	0.932	0.979	0.961	0.945	0.938	0.974	0.958	0.970	0.796	-	-	-	-
Mean	**0.952**	**0.983**	**0.833**	**0.948**	**0.947**	**0.941**	**0.946**	**0.953**	**0.940**	**0.837**	**0.785**	**-**	**-**	**-**	**-**

1. Refer to Table 5.8 for the full names of the components.
2. Mean values are calculated using the coefficients in absolute terms (Ketz et al., 1990, p. 71).
3. When no component appeared in either group, a (-) sign is shown instead.

6.4.4 Transformation Analysis

Transformation analysis was the final test applied to ascertain the cross-sectional stability of components. As explained in Chapter 3 (Subsection 3.4.4), transformation analysis not only measures the correlation and congruence between two factor solutions, it also identifies the factors and variables standing behind any divergence which might be found between the two solutions. Using the software SURVO 2.51, transformation analysis was carried out for the three pairs of successive groups in every year covered. The transformation matrices obtained for the pairs of groups in year 2005 are given in Table 6.17 whereas the transformation matrices between the groups in years 2001-2004 are summarised in Appendix 6.5.

In regard to the transformation matrices, note that the original order in which the components appeared in the PCA outputs was maintained while performing the analysis. Thus, if the two groups have the same number of components, a close-to-unity diagonal item in the transformation matrix would mean that both the practical meaning of the component and its relative position or importance in the solution have not changed between the two groups. Also, note that when the two groups have a different number of components, the group with the larger number of components should be considered as the first group when running the analysis, otherwise the software does not execute the analysis, and a message saying ‘incompatible dimensions’ is shown.

Transformation matrices 2005. As explained in Chapter 3 (Subsection 3.4.4), following previous research, if the element for two factors is equal to or larger than .95, the two factors are then considered to be similar. In Table 6.17, the elements for five components were persistently equal to or larger than .95 in all the pairs of groups, which means that the meaning of these five components did not change for the different asset-size groups. These components were Prof, Sh-t liq, CG, RBC, and IS; these were all amongst the nine components consistently found for all the groups over the study period.

Furthermore, the two AQ components could be also considered to have a considerable level of similarity between the groups although their elements were slightly lower than .95 in one case for each of them (-.933[113] for AQ-I in G2-G3 and .944 for AQ-II in G1-G2). Also, the practical meaning of M(C)-II did not change between G3 and G4, whereas a slight change was observed in the first two pairs of groups given that the size of the elements was just below .95, as Table 6.17 shows. Furthermore, the M(Y)-I had rather sizeable elements with other components such as Ln&Ls in G1-G2, Eff-II in G2-G3 and Eff in G3-G4 (elements are .311, .411 and -.382, respectively). This indicated that a practical change had occurred for M(Y)-I over the different groups.

In regard to the inconsistent components, it can be seen from Table 6.17, the two Eff components (Eff-I and Eff-II) identified for G1 transferred into on component (Eff) identified in G2. Eff-I had an element of -.776 with Eff, and Eff-II had an element of -.602 with the Eff; besides these, Eff-I and Eff-II had other sizeable elements with the rest of the components. Eff in G2, however, had clearly transferred into different components of G3. The highest elements it manifested were -.674 and .603 with M(Y)-I and Eff-II, respectively. Finally, Eff-II in G3 had fairly sizeable elements with many components of G4, the highest elements being .490 and .423 with Eff and Grth, respectively. As for Ln&Ls, a high degree of similarity was found for this component between the solutions of G3 and G4 (.951). This component, however, showed an unsatisfactory level of invariance between G1 and G2 (.869); it also had some sizeable elements (-.247 and .324) with M(Y)-I and Grth, respectively. Between G2 and G3, besides the relatively good element of .931, a certain amount of transference was observed between Ln&Ls and the unlabelled component (.330). Last but not least, the Grth component showed no signs of invariance between the different groups. This component demonstrated rather sizeable elements with many components, especially with M(C)-II, Ln&Ls and the unlabelled factor (elements are .255, -.254, and .757, respectively) between G2-G3.

[113] According to Martikainen et al. (1995a, p. 40), only the absolute values in the transformation matrices matter.

Table 6.17: Cross-sectional transformation matrices of components of different groups (2005)

			C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**
		G2	Prof	M(Y)-I	Sh-t liq	Ln&Ls	M(C)-II	CG	Eff	RBC	AQ-I	AQ-II	Grth	IS	-
G1	**C1**	M(Y)-I	0.026	0.888	-0.097	0.311	0.010	0.024	-0.067	0.002	0.023	0.015	-0.167	-0.049	
	C2	Prof	**0.961**	0.079	0.026	-0.034	0.006	-0.047	0.037	0.035	-0.038	-0.025	0.136	0.023	
	C3	Sh-t liq	0.006	0.012	**0.976**	0.171	-0.055	0.001	0.005	-0.023	0.018	0.005	-0.113	-0.004	
	C4	M(C)-II	-0.086	0.069	0.069	0.096	0.937	0.024	0.119	0.070	0.007	-0.011	0.196	0.049	
	C5	AQ-I	-0.069	0.091	0.044	-0.087	-0.028	0.011	0.008	-0.013	**-0.982**	0.015	0.105	0.020	
	C6	CG	0.059	-0.042	-0.010	0.022	-0.007	**0.995**	-0.020	-0.039	-0.003	0.003	-0.044	0.007	
	C7	RBC	-0.018	-0.001	0.029	-0.065	-0.055	0.043	-0.015	**0.990**	-0.003	0.041	0.015	-0.019	
	C8	Eff-I	-0.125	0.170	0.056	-0.093	-0.062	-0.000	-0.776	0.028	0.055	-0.111	0.107	0.087	
	C9	AQ-II	-0.036	0.123	0.049	-0.192	-0.045	0.014	0.030	-0.050	0.071	0.944	0.178	0.003	
	C10	Ln&Ls	-0.001	-0.247	-0.113	0.867	-0.127	-0.018	-0.097	0.045	-0.066	0.150	0.324	-0.099	
	C11	Eff-II	0.198	-0.256	-0.021	-0.042	0.290	-0.034	-0.602	-0.051	-0.080	0.168	-0.167	-0.163	
	C12	Grth	-0.053	0.132	0.107	-0.208	-0.096	0.054	-0.038	-0.063	0.121	-0.202	0.845	-0.038	
	C13	IS	0.026	-0.040	-0.021	0.094	-0.009	-0.011	-0.054	0.006	0.001	0.045	0.004	**0.974**	
		G2	Prof	M(Y)-I	Sh-t liq	Ln&Ls	M(C)-II	CG	Eff	RBC	AQ-I	AQ-II	Grth	IS	**-**
G3	**C1**	Prof	**0.967**	0.151	0.006	-0.029	0.005	-0.065	0.189	-0.006	-0.008	-0.010	0.031	-0.007	
	C2	Sh-t liq	0.001	-0.010	**0.996**	0.027	-0.006	-0.019	-0.021	0.006	-0.010	0.029	-0.035	0.005	
	C3	M(Y)-I	0.016	0.707	-0.009	-0.039	-0.036	-0.018	-0.674	0.034	0.071	-0.013	0.143	0.005	
	C4	M(C)-II	-0.054	0.120	0.016	0.074	0.944	0.024	0.132	0.044	0.007	-0.022	0.255	0.012	
	C5	Ln&Ls	-0.006	0.195	-0.021	0.931	-0.034	0.041	0.071	-0.065	0.006	0.006	-0.254	0.004	
	C6	AQ-I	-0.091	0.271	0.003	-0.072	-0.053	-0.030	0.184	-0.036	-0.933	-0.004	0.015	-0.009	
	C7	RBC	-0.011	0.039	0.003	0.031	-0.056	0.012	0.064	**0.987**	-0.006	-0.007	-0.016	-0.008	
	C8	CG	0.085	-0.046	0.001	-0.008	-0.001	**0.969**	-0.048	0.019	-0.074	0.043	-0.032	0.013	
	C9	AQ-II	-0.042	0.161	-0.011	-0.082	-0.001	0.011	0.130	-0.024	0.087	**0.958**	-0.029	-0.001	
	C10	Grth	-0.077	0.191	0.082	-0.048	-0.173	0.214	0.187	-0.116	0.161	-0.179	0.488	-0.052	
	C11	Eff-II	-0.181	0.411	-0.007	-0.016	-0.212	-0.016	0.603	0.002	0.243	-0.098	0.183	0.125	
	C12	IS	0.025	-0.048	0.000	-0.001	0.003	-0.002	-0.062	0.001	-0.033	0.006	0.011	**0.990**	
	C13	No Name	0.070	-0.337	-0.017	0.330	-0.161	-0.081	-0.167	0.053	-0.157	0.191	0.757	-0.014	

			C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
		G4	Prof	Sh-t liq	M(Y)-I	M(C)-II	Ln&Ls	AQ-I	RBC	CG	AQ-II	Grth	Eff	IS	-
G3	**C1**	Prof	**0.988**	-0.004	0.128	-0.002	-0.037	0.010	-0.012	-0.023	-0.019	-0.006	0.071	-0.006	
	C2	Sh-t liq	0.016	**0.985**	-0.037	0.033	0.027	0.002	0.039	-0.025	0.056	0.094	-0.064	-0.004	
	C3	M(Y)-I	-0.091	-0.001	0.901	-0.101	-0.069	-0.062	0.022	-0.017	0.010	0.071	-0.382	0.023	
	C4	M(C)-II	-0.011	-0.012	0.103	**0.984**	-0.064	-0.014	-0.030	0.017	-0.028	-0.051	-0.036	0.027	
	C5	Ln&Ls	-0.000	0.018	0.171	0.027	**0.951**	0.028	-0.050	0.018	-0.041	-0.141	0.157	-0.014	
	C6	AQ-I	-0.034	0.007	0.097	0.009	-0.055	**0.982**	-0.002	-0.017	-0.084	0.031	0.101	-0.021	
	C7	RBC	0.010	-0.007	0.013	-0.001	0.000	0.016	**0.968**	0.044	-0.008	-0.110	0.006	-0.014	
	C8	CG	0.037	-0.009	-0.038	0.008	0.039	0.026	0.002	**0.975**	0.037	0.071	-0.101	0.004	
	C9	AQ-II	-0.008	-0.016	0.087	0.000	-0.041	0.065	-0.042	0.019	**0.960**	-0.073	0.174	-0.000	
	C10	Grth	-0.028	0.016	0.105	-0.035	-0.042	-0.038	-0.060	0.089	-0.107	0.731	0.256	-0.032	
	C11	Eff-II	-0.042	-0.084	0.103	0.112	0.074	-0.105	0.207	-0.098	0.072	0.423	0.490	0.013	
	C12	IS	0.017	-0.007	-0.045	-0.019	0.039	0.034	0.017	-0.015	0.015	0.060	-0.049	**0.994**	
	C13	No Name	0.099	-0.144	-0.297	0.077	0.266	0.109	0.095	-0.166	0.217	0.472	-0.679	-0.095	

1. Elements above .950 are in bold (Martikainen et al., 1994, p. 63).
2. Refer to Table 5.8 for the full names of the components.

Transformation matrices (2001-2004). Separate transformation analysis was carried out between the successive groups in each of the years 2001-2004; the resulting transformation matrices are given in Appendix 6.5. As can be seen from these matrices, some components appeared to be dissimilar across the different groups and also a considerable amount of transference had occurred; so, in a way, these matrices appeared very similar to those for year 2005 discussed in detail earlier.

By considering the .95 criterion, some components in Appendix 6.5 showed a significant level of similarity across the different asset-size groups on the basis of the year; amongst these components were Prof, Sh-t liq, and AQ-I in year 2001, and components Sh-t liq, AQ-I and CG in year 2002 [see Table 5.8 for further descriptions of the components). However, regardless of the results according to the year, it is believed that a better way of interpreting the figures summarised in the transformation matrices would be by looking at each of the components in the different matrices reported for the years examined in this study. This commenced by analysing the nine consistent components (that is, those identified for all groups over all the years).

Over the period 2001-2004, only five components showed a satisfactory level of similarity between the different groups; these were Prof, AQ-I, Sh-t liq, CG and IS although the coefficients of coincidence for some of these components fell below the .95 criterion in a few cases. In such cases, sizeable elements were found between these components and others, as in the case of AQ-I in year 2004 where this component in G2 had an element of -.303 with AQ-III in G3. As for Sh-t liq, a certain amount of transference seemed to occur in year 2004 in the pairs G1-G2 and G2-G3; in G1-G2 this component had sizeable elements with Sh-t liq and Sh-t inv (.779 and -.577, respectively). In G2-G3, however, Sh-t liq had sizeable elements with Sh-t liq and Fnd-II (.700 and .706, respectively). Furthermore, CG between G1 and G2 in year 2001 had some high elements with Eff-II (.383), in addition to some significant elements with the other components. However, in G3-G4 (2003), the CG coefficient of coincidence was .947 and its next highest element below this was .223 with Grth. Moreover, the similarity level for the IS component was lowest between G1 and G2 in 2001, and between G3 and G4 in 2002; its coefficients of coincidence were .854 and .949, respectively. In these two cases, IS showed some transference with the Eff-II and the unlabelled component (the elements were .295 and .176 in the two cases, respectively).

Nevertheless, regardless of the few cases where there was discrepancy, these five components (Prof, AQ-I, Sh-t liq, CG and IS) showed the highest levels of similarity across the different groups over the years. In regard to the other four consistent components [RBC, AQ-II, M(C)-II and M(Y)-I], the following paragraphs report on their level of cross-sectional similarity in the period covered in the study.

RBC. This component showed a satisfactory level of invariance in all cases except the following: G2-G3 (2001) and G3-G4 in all four years. In these cases, RBC had transferred into Ln&Ls and the unlabelled component; the elements it had with Ln&Ls ranged between .155 and .333 whereas the elements with the undefined components ranged between .349 and .415. [These figures are in absolute terms; see footnote 113]

AQ-II. Similar to RBC, this component showed a satisfactory level of similarity in most cases; however, its coefficients of coincidence fell below the .95 criterion between some groups. This was the case with G1-G2 (2001, 2002 and 2004) and with G2-G3 (2001 and 2004) where, for this component, a certain amount of transference occurred into other components, such as Ln&Ls, Eff-II, M(Y)-I, M(C)-II, Grth, Sh-t liq and AQ-III.

M(C)-II. The elements of this component were above the criterion of .95 in half of the cases shown in the transformation matrices. The coefficients of coincidence below .95 for M(C)-II ranged between 0.690 and 0.949. In most cases, sizeable elements were found with the two Eff components whereas slightly smaller elements were reported with M(Y)-I, Fnd-II, Sh-t inv, RBC and AQ-III.

M(Y)-I. This component showed a low level of similarity across the different asset-size groups in the different years. Its coefficients of coincidence were lower than .95 in the majority of the cases. In such cases, the coefficients of coincidence for M(Y)-I were smaller in the pairs of groups in year 2001 (.450, .477, .759), higher for year

2004 (.928, .929), and moderate in years 2002 and 2003 (over .8). In these cases, M(Y)-I had sizeable elements with different components such as Eff, Ln&Ls and M(C)-II, amongst others.

As for the less consistent components (Fnd/Ln&Ls, Grth, Eff, Eff-II, Fnd-II and the undefined component), the results indicated obvious transference occurring to these components between the different groups in years 2001-2004. To begin with, a dissimilarity between Fnd and Ln&Ls was observed given the small coefficients of coincidence these two components had; in addition, each of these two components had generally sizeable elements with other different, mainly inconsistent, components such as Fnd-II, Eff, Eff-II, Grth, AQ-III, and also with M(Y)-I. Fnd, however, showed a satisfactory level of invariance between G1 and G2 (2003), and also was the level shown by Ln&Ls between G2 and G3 (2002) and between G3 and G4 (2004).

Grth. Although this component could not be considered as stable, given the results of correlation and congruency analyses, the results of transformation analysis implied that it had a satisfactory level of invariance between the different groups in some years. In the few cases where dissimilarity was found, its coefficients of coincidence ranged between .748 and .940. The elements found with other components were generally of a moderate to small size, with the exception of G3-G4 (2003) where it had sizeable elements (in absolute terms) with Ln&Ls and Fnd-II (-.497 and 0.345, respectively).

Eff. The two Eff components showed a clear pattern of instability across the different groups over the years. The size of their coefficients of coincidence was relatively small in absolute terms (ranging between -.558 and .833) for almost all the pairs of groups with one exception only: the case of Eff in G1-G2 in 2003 (with a coefficient of coincidence in excess of .95 in absolute terms). Also, it is worth mentioning that since no Eff components were identified in G4 in any of the years 2001-2004, and given that the transformation matrices were estimated between the successive groups, whenever Eff was found in G3 it had the highest elements with the unlabelled component, M(Y)-I, M(C)-II, and with Ln&Ls of G4. Similarly, the Eff component tended to manifest such sizeable elements with these components in the different pairs of groups over the years.

Fnd-II. The coefficient of coincidence for this component was greater than .95 between G2 and G3 (2001); however, it fell below .95 between G3 and G4 (2003) which means that Fnd-II could not be considered as similar to the previous case. In other cases, where Fnd-II was found in only one group under comparison, it had sizeable elements with Ln&Ls, RBC and the undefined component.

The unlabelled component. This component had its highest elements with the two Eff factors and with Fnd-II, amongst others.

AQ-III and Sh-t inv. These two components were identified in only one group over the years; thus, measuring their cross-sectional stability was not possible. Nevertheless, checking the size of their elements with other components could offer some interesting insights into the nature of these two factors. AQ-III in G3 (2004) had its highest elements, in absolute terms, with the following components of G4: Grth, unlabelled, and AQ-I (elements -.538, -.409 and .230, respectively). On the other hand, Sh-t inv in G2 (2004) had its highest elements in absolute terms with the Sh-t liq (-.700), Fnd-II (.654) and Ln&Ls (-.254).

Residual Matrices (2005). As mentioned in Chapter 3 (Subsection 3.4.4), transformation analysis identifies the factors which have their practical meaning changed between two solutions; these factors are uncovered through the transformation matrices. However, transformation analysis also identifies the variables/ratios which have their interpretative meaning changed between the two solutions; this can be achieved by examining the residual matrix. This matrix has close-to-zero elements if the meaning of the ratios is maintained between the two factor solutions. By squaring and adding up the residual elements for every ratio, the abnormal transformation is obtained; the size of the abnormal transformation points out those ratios that have their meaning changed where, according to previous research, an abnormal / unexplained transformation exceeding .20 should be closely examined.

The residual matrices are not shown here due to space limitations; however, the abnormal transformations are summarised in Table 6.18 for the three pairs of groups in each of the five years. Also, following previous research (Martikainen et al., 1995a, p. 42), the last two lines of the table show the cumulative abnormal transformation for each pair of groups and the average figure for each year.

As can be seen from Table 6.18, and using the .20 criterion, for year 2005, ratios X34 and X52 had their practical meaning changed between G1 and G2, and similarly X40 between G3 and G4. A closer look at the relevant residual matrices (not shown) revealed that the abnormal transformation of X34 could be tied to the M(Y)-I in G2; for X52, it could be tied to Ln&Ls and M(Y)-I in G2. The abnormal transformation of X40 between G3 and G4 could be tied to Eff, Ln&Ls, AQ-II and RBC in G4.

Residual matrices (2001-2004). By looking at the abnormal transformations of the 56 ratios shown in Table 6.18, and considering the .20 criterion, with a few exceptions, most ratios maintained their practical meaning across the different groups, particularly between the solutions of G2 and G3.

In regard to the ratios with high abnormal transformations, X4, X46, X48 and X52 were identified in year 2001 to have changes in their meaning between G1 and G2, and X34 was identified between G3 and G4. Further investigations into the relevant residual matrices (not shown) were carried out and revealed that such abnormal transformations could be attributed to the following: M(Y)-I (X4 and X46); Eff (X46); AQ-II, Eff, Fnd, and M(Y)-I (X52). As for X34, the abnormal transformation could be tied to the unlabelled and M(Y)-I components as the relevant residual matrix implies.

Table 6.18: Cumulative abnormal transformations between components of different groups (2001-2005)

	2001			2002			2003			2004			2005		
	G1-G2	**G2-G3**	**G3-G4**	**G1-G2**	**G2-G3**	**G3-G4**	**G1-G2**	**G2-G3**	**G3-G4**	**G1-G2**	**G2-G3**	**G3-G4**	**G1-G2**	**G2-G3**	**G3-G4**
X1	0.053	0.014	0.013	0.015	0.032	0.033	0.026	0.011	0.013	0.028	0.015	0.009	0.080	0.089	0.016
X2	0.029	0.006	0.010	0.041	0.007	0.056	0.038	0.009	0.014	0.028	0.007	0.017	0.036	0.047	0.007
X3	0.143	0.008	0.014	0.057	0.017	0.066	0.055	0.013	0.019	0.040	0.022	0.007	0.078	0.046	0.024
X4	**0.228**	0.040	0.032	**0.283**	0.082	0.129	0.097	0.067	0.075	0.055	0.036	0.037	0.056	0.041	0.070
X5	0.056	0.019	0.025	0.159	0.015	0.085	0.046	0.031	0.022	0.039	0.013	0.013	0.053	0.016	0.029
X6	0.092	0.015	0.046	0.102	0.028	0.035	0.137	0.035	0.063	0.131	0.019	0.017	0.129	0.070	0.058
X7	0.045	0.005	0.020	0.043	0.003	0.049	0.043	0.007	0.009	0.035	0.007	0.008	0.077	0.039	0.005
X8	0.045	0.004	0.019	0.044	0.003	0.011	0.036	0.008	0.009	0.035	0.006	0.009	0.074	0.040	0.007
X9	0.037	0.006	0.015	0.047	0.007	0.009	0.020	0.014	0.008	0.031	0.012	0.010	0.096	0.043	0.005
X10	0.041	0.006	0.015	0.046	0.007	0.008	0.021	0.013	0.008	0.030	0.012	0.011	0.098	0.043	0.005
X11	0.146	0.052	0.055	0.194	0.113	0.023	0.140	0.040	0.045	0.094	0.062	0.050	0.188	0.055	0.091
X12	0.106	0.019	0.022	0.180	0.029	0.019	0.142	0.022	0.022	0.099	0.054	0.042	0.118	0.026	0.029
X13	0.040	0.012	0.011	0.016	0.027	0.021	0.030	0.009	0.014	0.024	0.010	0.011	0.081	0.073	0.016
X14	0.043	0.006	0.011	0.058	0.010	0.057	0.044	0.010	0.016	0.028	0.009	0.019	0.047	0.043	0.010
X15	0.119	0.006	0.010	0.038	0.012	0.064	0.040	0.014	0.017	0.035	0.015	0.008	0.074	0.035	0.018
X16	0.073	0.009	0.030	0.164	0.034	0.025	0.097	0.026	0.040	0.098	0.011	0.015	0.131	0.067	0.030
X17	0.035	0.010	0.018	0.029	0.006	0.046	0.011	0.015	0.029	0.018	0.019	0.031	0.026	0.039	0.041
X18	0.030	0.006	0.035	0.115	0.009	0.015	0.024	0.007	0.012	0.017	0.014	0.015	0.021	0.025	0.018
X19	0.030	0.015	0.010	0.097	0.012	0.005	0.090	0.013	0.022	0.038	0.016	0.008	0.068	0.019	0.009
X20	0.024	0.015	0.009	0.115	0.012	0.006	0.088	0.009	0.021	0.032	0.015	0.008	0.066	0.019	0.010
X21	0.032	0.016	0.081	**0.235**	0.034	0.023	0.091	0.143	**0.364**	0.071	0.024	0.073	0.045	0.008	0.026
X22	0.036	0.007	0.012	0.014	0.013	0.011	0.021	0.013	0.009	0.016	0.010	0.007	0.023	0.031	0.009
X23	0.078	0.007	0.035	0.088	0.014	0.030	0.037	0.008	0.030	0.054	0.013	0.011	0.092	0.032	0.007
X24	0.048	0.018	0.040	0.069	0.015	0.012	0.078	0.022	0.018	0.090	0.011	0.038	0.106	0.023	0.031
X25	0.066	0.030	0.031	0.050	0.049	0.022	0.055	0.071	0.076	0.031	0.025	0.105	0.076	0.071	0.055
X26	0.100	0.006	0.005	0.036	0.013	0.014	0.011	0.027	0.018	0.022	0.015	0.022	0.040	0.010	0.024
X27	0.034	0.029	0.056	**0.298**	0.047	0.031	0.121	0.122	**0.333**	0.072	0.019	0.053	0.054	0.032	0.031
X28	0.030	0.037	0.030	0.040	0.022	0.067	0.043	0.053	0.126	0.050	0.043	0.037	0.060	0.055	0.060
X29	0.090	0.014	0.024	0.054	0.012	0.020	0.016	0.026	0.043	0.028	0.016	0.019	0.013	0.027	0.016
X30	0.078	0.019	0.105	0.104	0.004	0.046	0.075	0.078	0.058	0.059	0.026	0.075	0.129	0.053	0.040

	2001			2002			2003			2004			2005		
	G1-G2	**G2-G3**	**G3-G4**	**G1-G2**	**G2-G3**	**G3-G4**	**G1-G2**	**G2-G3**	**G3-G4**	**G1-G2**	**G2-G3**	**G3-G4**	**G1-G2**	**G2-G3**	**G3-G4**
X31	0.092	0.020	0.025	0.019	0.032	0.053	0.059	0.049	0.058	0.114	0.052	0.064	0.066	0.065	0.056
X32	0.054	0.011	0.022	0.021	0.041	0.039	0.024	0.049	0.125	0.035	0.066	0.065	0.075	0.020	0.019
X33	0.065	0.014	0.036	0.113	0.161	0.043	0.046	0.037	0.024	0.030	0.013	0.020	0.031	0.011	0.039
X34	0.103	0.042	**0.267**	**0.320**	0.049	**0.244**	0.129	0.105	0.070	0.140	0.051	0.054	**0.331**	0.110	0.071
X35	0.113	0.010	0.058	0.087	0.017	0.043	0.066	0.025	0.022	0.059	0.015	0.034	0.057	0.021	0.019
X36	0.121	0.032	0.040	0.094	0.052	0.049	0.123	0.018	0.065	0.040	0.056	0.052	0.125	0.132	0.049
X37	0.139	0.076	0.127	**0.212**	0.137	0.068	0.132	0.014	0.168	0.090	0.028	0.052	0.184	0.100	0.048
X38	0.065	0.015	0.015	0.062	0.006	0.080	0.064	0.013	0.023	0.042	0.011	0.018	0.075	0.040	0.012
X39	0.050	0.011	0.009	0.075	0.011	0.019	0.049	0.012	0.018	0.029	0.006	0.024	0.024	0.009	0.014
X40	0.045	0.071	0.045	0.131	0.095	0.027	0.176	0.152	0.115	**0.220**	0.048	0.127	0.159	0.136	**0.388**
X41	0.083	0.021	0.065	0.165	0.025	0.047	0.019	0.050	0.090	0.061	0.011	0.067	0.057	0.039	0.056
X42	0.095	0.009	0.025	0.047	0.018	0.028	0.081	0.018	0.037	0.053	0.008	0.012	0.073	0.024	0.022
X43	0.067	0.004	0.012	0.037	0.006	0.007	0.033	0.012	0.008	0.026	0.009	0.005	0.021	0.018	0.005
X44	0.145	0.005	0.062	0.052	0.019	0.043	0.085	0.027	0.065	0.056	0.043	0.067	0.098	0.033	0.056
X45	0.020	0.011	0.014	0.027	0.009	0.004	0.025	0.012	0.013	0.011	0.005	0.023	0.013	0.010	0.007
X46	**0.207**	0.012	0.042	0.056	0.013	0.030	0.082	0.020	0.028	0.066	0.033	0.060	0.069	0.028	0.045
X47	0.050	0.019	0.035	0.021	0.023	0.028	0.043	0.031	0.031	0.020	0.024	0.045	0.020	0.029	0.048
X48	**0.235**	0.011	0.031	0.094	0.015	0.025	0.158	0.012	0.020	0.052	0.013	0.011	0.101	0.039	0.011
X49	0.193	0.017	0.037	0.096	0.017	0.020	0.076	0.039	0.033	0.070	0.017	0.008	0.082	0.039	0.011
X50	0.014	0.014	0.026	0.021	0.015	0.003	0.009	0.016	0.030	0.016	0.010	0.010	0.017	0.015	0.020
X51	0.052	0.012	0.018	0.028	0.004	0.007	0.016	0.014	0.031	0.022	0.007	0.009	0.016	0.008	0.023
X52	**0.357**	0.050	0.064	**0.294**	0.041	0.098	0.153	0.065	0.099	0.151	0.047	0.017	**0.215**	0.063	0.073
X53	0.050	0.011	0.020	0.020	0.004	0.004	0.011	0.008	0.014	0.017	0.006	0.007	0.035	0.012	0.008
X54	0.084	0.021	0.018	0.063	0.017	0.024	0.025	0.016	0.040	0.025	0.015	0.028	0.061	0.016	0.018
X55	0.018	0.009	0.023	0.037	0.014	0.021	0.031	0.011	0.028	0.028	0.003	0.030	0.016	0.013	0.012
X56	0.016	0.008	0.024	0.030	0.014	0.022	0.028	0.011	0.029	0.016	0.003	0.029	0.012	0.012	0.011
Cumulative abnormal transformation	4.543	0.990	1.995	5.052	1.544	2.112	3.516	1.773	2.835	2.920	1.181	1.721	4.269	2.261	1.939
Average		**2.509**			**2.903**			**2.708**			**1.940**			**2.823**	

1. Figures over .20 are in bold (Martikainen et al., 1995a, p. 41).
2. Refer to Table 4.4 for the full names of ratios.

Similar investigations into the residual matrices were carried out to discuss the components to which the abnormal transformation of the ratios could be tied in the following years. In year 2002, six ratios: X4, X21, X27, X34, X37 and X52 exhibited abnormal transformations between G1 and G2. The abnormal transformations were attributed mainly to AQ-II and Eff-II. Between G3 and G4, ratio X34 had the highest significant abnormal transformation, which could be mainly tied to M(Y)-I. Between G3 and G4 in year 2003, two ratios were identified, X21 and X27, and the abnormal transformations were tied largely to the unlabelled component, Grth and Fnd-II. Finally, in year 2004, X40 was identified between G1 and G2 and its abnormal transformations were tied to Sh-t inv and IS. Interestingly, three of the ratios with abnormal transformations, X37, X40 and X52, were among the ratios that failed to load significantly on any factor.

Overall assessment. An overall assessment of the similarity of the 56 ratios over the different asset-size groups was gained by assessing the cumulative abnormal transformations; these are shown at the end of Table 6.18 for all the pairs of groups over the study period. The table shows that the highest cumulative abnormal transformation (5.052) occurred between G1 and G2 in year 2002, whereas the lowest (.990) occurred between G2 and G3 in year 2001. The table also shows that, in general, the abnormal transformation was the highest between G1 and G2 and the lowest between G2 and G3. Between G3 and G4, however, there was still a considerable level of abnormal transformation, although it was far less than that found between G1 and G2. Moreover, by averaging the cumulative abnormal transformations over all pairs of groups for each year, in general, the least amount of abnormal transformation (1.940) happened in year 2004 and the highest (2.903) in year 2002. The abnormal transformations for the rest of the years were relatively high.

Significance test for transformation matrices. The significance test for the transformation matrices introduced in Chapter 3 (Subsection 3.4.4.1) requires the diagonals of the matrices to be close to unity. In other words, it requires the components in the two solutions under comparison to be in the same order; this, in turn, assumes that the two solutions have the same number of factors. Given that the different solutions in this study had different numbers of components which were also derived in a different order; it was decided to apply the test using the nine components consistently identified in the four groups over the period 2001-2005. Thus, in order to estimate the transformation matrices for the purpose of this test, the loadings (eigenvectors) of the nine components were taken from the rotated component matrices, and then set up in the same order. Transformation analysis was then performed so that the diagonal elements in the resulting transformation matrices could be expected to have high (close to unity) values and the test could be then undertaken.

As explained in Chapter 3 (Subsection 3.4.4.1), let (M) be the transformation matrix. The transpose of this matrix was then calculated (M^T) and multiplied by (M) which returns the matrix ($B = M.M^T$). Thus, under the null hypothesis, (B) would have a unit determinant like (M), the transformation matrix. The determinant of (B) was then calculated and averaged over the three pairs of different groups and the standard deviation was also computed. The Z-score was then calculated as follows:

$$z = \frac{\overline{\det(B)} - 1}{\hat{\sigma}}.\sqrt{n}$$

where $\overline{\det(B)}$ is the average of the determinants, (n) is the number of transformation matrices on which the test is based, and $\hat{\sigma}$ is the estimated standard deviation. The Z-scores were calculated for each of the years 2001-2005; the results are shown in Table 6.19. In year 2005, $\overline{\det(B)}$ = 0.999838 and $\hat{\sigma}$ =0.001288. This returned a z-score of -0.217753. This is insignificant at any reasonable level and therefore could be interpreted as meaning that no significant differences exist among the transformation matrices which, in turn, indicates that the nine components are similar across the different asset-size groups in year 2005. The null hypotheses of no significance differences in the matrices of the years 2001-2003 also could not be rejected, given the z-scores that were obtained. However, with the z-score statistic of -1.873783 obtained for year 2004, the difference observed between mean of the determinants and unity was statistically significant at the .10 significance level. This leads one to reject the null hypothesis of no differences in the transformation matrices for the year 2004. It is unclear, however, whether this result is due to the existence of instability in the factor structure between groups or to the limitations of the testing procedure.

Table 6.19: Results of transformation matrices' significance test (2001-2005)

Year	$\overline{\det(B)}$	$\hat{\sigma}$	z-score
2001	0.999894	0.000364	-0.506604
2002	0.999386	0.001170	-0.908902
2003	0.999723	0.002438	-0.196797
2004	0.998665	0.001234	-1.873783
2005	0.999838	0.001288	-0.217753

In this respect, it should be noted that, with only three observations for each year (i.e. three transformation matrices), whatever the results of this test, they should be interpreted with caution and other techniques should therefore be allowed to contribute to the conclusion in regard to the cross-sectional stability of the components. Here we would refer in particular to the visual comparisons, correlation tests and congruency coefficients which were summarised in previous sections.

6.5 Short-term stability of financial patterns for banks in different asset-size groups

After checking the cross-sectional stability of the components identified for the different asset-size groups, the same methods were used in this section to check the stability of the components over a period of five years. However, it was decided not to carry out a visual comparison of the components over time as Subsection 6.4.1 covered this extensively; thus, only the technical methods were used in the current section.

6.5.1 Correlation coefficients

The components identified for each of the four asset-size groups were correlated with their counterparts in the same groups over the different years. Thus, given the five-year period covered in this study, for each asset-size group there were ten pairs of years. For each of these pairs, the correlation coefficients were calculated; the results are summarised in Table 6.20[114].

[114] Note that in Chapter 5 (Subsection 5.5.2); Table 5.13 reports the correlation coefficients between the components for commercial banks only in the adjacent years and between components at the beginning

This analysis began by checking the short-term stability of the components in G1. As Table 6.20 shows, most of the nine consistent components had a very good level of stability over the ten pairs of years; the most stable components were RBC, Prof and Sh-t liq. On the other hand, AQ-II exhibited the lowest level of stability over the period. As for the inconsistent components, starting off with the Fnd/Ln&Ls factors, Fnd was identified for G1 in all the years except 2005 where Ln&Ls was found instead. Thus, in the pairs made of the years 2001-2004, the short-term stability of Fnd was measured, whereas for the pairs involving year 2005, the relationship between Fnd and Ln&Ls was measured instead. As can be seen from Table 6.20, Fnd showed a good level of short-term stability, especially for the pairs of successive years (i.e. 2001-2002, 2002-2003 and 2003-2004). However, when Ln&Ls in year 2005 was considered, the stability level clearly declined. Moving on to Grth, in general, this component did not exhibit a good level of short-term stability although it appeared more stable in the period 2003-2005. As for Eff, G1 had only one Eff component identified over the five years; the time stability for this component could be considered as good given the sizeable correlation coefficients (in absolute terms) this component had. Lastly, for G1, the undefined component seemed to be stable between 2003 and 2004, as the last column of Table 6.20 indicates.

In regard to the components of G2, all nine consistent ones showed a very good level of stability over the period. The least stable amongst these components was M(Y)-I whereas Prof, CG and RBC were the most stable over time. Also for G2, Ln&Ls was identified in all years except 2003 where Fnd was found instead; thus large correlations were reported for the pairs of years not including 2003. Nevertheless, similar to G1, a weak relationship was found between Fnd and Ln&Ls in the pairs of years involving 2003. Moreover, Grth for G2 seemed unstable in the short-term whereas Eff exhibited a better level of stability and even showed excellent stability between 2004 and 2005. As for Eff-II, which was identified for G2 in years 2001 and

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and end of the period (2001 and 2005). However, in the current subsection, it was decided to report the correlations between the components in all the possible pairs of years as the solutions for the asset-size groups appeared rather inconsistent. Thus, such a representation would allow components identified in non-adjacent years to be compared to each other. This also applies to the congruency analysis discussed in the following subsection (6.5.2) and to the correlation and congruency analysis conducted in the following chapter (seven).

2002, given its relatively small correlation coefficient in the absolute term, this component could be considered as unstable over the two years.

Out of the nine consistent components in G3, M(Y)-I showed the poorest level of stability. As can be seen from the G3 section in Table 6.20, M(Y)-I was actually very stable in the period between 2002 and 2004. However, the structure of the component seemed to differ considerably between 2001 and 2005 given the low correlation coefficient (.465) reported between the two years. Furthermore, Ln&Ls for G3 showed an average level of stability over the years in which it was identified (2002, 2004 and 2005). As for the Grth component, given its small correlation coefficients, it was clearly unstable, although between 2001 and 2005 a fairly good level of stability was reported. The two Eff factors also did not exhibit an acceptable stability level, except in the case of Eff-II between 2003 and 2004. In addition, Fnd-II, which was identified only in 2001, 2003 and 2004, was fairly stable when compared across those years. Finally for G3, the unlabelled component in 2003 and 2005 was clearly dissimilar between the two years given the reported insignificant correlation.

In regard to the time stability of consistent components in G4, RBC was the most unstable. This component, however, showed an average level of stability when years 2001, 2003 and 2005 were compared. However, for the pairs involving year 2002 or 2004, the dissimilarity was noticeable. In regard to Ln&Ls, this component in G4 showed it highest stability level over time compared to the other groups. As Table 6.20 shows, the correlation coefficients for Ln&Ls were of a good absolute size (all above 0.9). The stability level of Grth was clearly unsatisfactory, although some stability was reported between 2001-2003 and 2004-2005. Last but not least, as the table shows, the unlabelled component in G4 was very similar between 2001 and 2004 whereas since none of the Eff components were identified for G4 over the period; no correlation results were reported for the Eff components.

Table 6.20: Correlation coefficients between components of the same group over time (2001-2005)

	Prof	Sh-t liq	M(Y)-I	M(C)-II	AQ-I	AQ-II	RBC	CG	IS	Ln&Ls/Fnd	Grth	Eff	Eff-II	Fnd-II	No Name
	G1														
2001-2002	0.974	0.965	0.973	0.977	0.965	0.947	0.974	0.863	0.944	0.969	0.801	-0.978	-	-	-
2001-2003	0.971	0.974	0.966	0.982	0.954	0.869	0.980	0.902	0.853	0.966	0.877	-0.971	-	-	-
2001-2004	0.959	0.968	0.944	0.968	0.948	0.868	0.967	0.859	0.858	0.922	0.766	-0.963	-	-	-
2001-2005	0.960	0.940	0.916	0.903	0.955	0.864	0.967	0.865	0.882	0.636	0.791	-0.951	-	-	-
2002-2003	0.980	0.979	0.984	0.984	0.927	0.876	0.986	0.953	0.937	0.988	0.811	0.993	-	-	-
2002-2004	0.964	0.981	0.961	0.969	0.929	0.890	0.978	0.957	0.946	0.976	0.818	0.981	-	-	-
2002-2005	0.961	0.962	0.906	0.884	0.940	0.864	0.972	0.966	0.963	0.734	0.872	0.968	-	-	-
2003-2004	0.986	0.981	0.986	0.976	0.972	0.929	0.986	0.965	0.983	0.972	0.923	0.986	-	-	0.922
2003-2005	0.981	0.959	0.955	0.893	0.962	0.934	0.981	0.968	0.957	0.751	0.926	0.969	-	-	-
2004-2005	0.991	0.974	0.971	0.948	0.984	0.979	0.987	0.983	0.974	0.811	0.926	0.975	-	-	-
	G2														
2001-2002	0.984	-0.941	0.941	0.954	0.984	0.955	0.975	0.987	0.962	0.965	0.610	-	-0.837	-	-
2001-2003	0.976	-0.942	0.901	0.858	0.987	0.957	-0.929	0.958	-0.930	0.624	0.759	-	-	-	-
2001-2004	0.986	-0.800	0.938	0.872	0.988	0.938	0.957	0.957	0.938	0.962	-	-	-	-	-
2001-2005	0.970	-0.920	0.888	0.820	0.971	0.952	0.959	0.933	0.930	0.946	0.548	-	-	-	-
2002-2003	0.985	0.987	0.951	0.961	0.988	0.972	-0.962	0.965	-0.963	0.747	0.847	-	-	-	-
2002-2004	0.988	0.939	0.959	0.967	0.988	0.967	0.983	0.962	0.969	0.971	-	-	-	-	-
2002-2005	0.966	0.983	0.851	0.929	0.975	0.963	0.976	0.938	0.954	0.946	0.937	-	-	-	-
2003-2004	0.985	0.916	0.949	0.984	0.990	0.962	-0.965	0.991	-0.979	0.750	-	0.896	-	-	-
2003-2005	0.951	0.980	0.825	0.977	0.978	0.962	-0.957	0.980	-0.967	0.733	0.827	0.906	-	-	-
2004-2005	0.976	0.956	0.924	0.966	0.980	0.988	0.986	0.987	0.972	0.958	-	0.986	-	-	-
	G3														
2001-2002	0.984	-0.956	0.639	0.975	-0.969	0.912	0.948	0.964	0.983	-	0.616	-0.874	-	-	-
2001-2003	0.977	-0.981	0.762	0.951	-0.970	0.927	-0.955	0.944	0.974	-	0.781	-0.644	-	0.902	-

	Prof	Sh-t liq	M(Y)-I	M(C)-II	AQ-I	AQ-II	RBC	CG	IS	Ln&Ls/Fnd	Grth	Eff	Eff-II	Fnd-II	No Name
2001-2004	0.962	-0.986	0.729	0.942	-0.968	0.930	-0.957	0.965	0.976	-	-	-	-	0.905	-
2001-2005	0.970	-0.958	0.465	0.914	0.983	0.940	0.969	0.970	0.962	-	0.936	-	-	-	-
2002-2003	0.986	0.985	0.959	0.979	**0.991**	0.984	-0.934	0.961	0.969	-	0.774	0.811	-	-	-
2002-2004	0.972	0.976	0.944	0.962	0.952	0.961	-0.960	0.975	0.976	0.925	-	-	-	-	-
2002-2005	0.971	0.983	0.788	0.939	-0.963	0.967	0.953	0.953	0.953	0.929	0.570	-	-	-	(-0.201)
2003-2004	0.990	0.986	0.987	0.985	0.969	0.970	0.964	0.979	0.982	-	-	-	0.940	0.865	-
2003-2005	0.988	0.978	0.839	0.941	-0.967	0.973	-0.931	0.976	0.988	-	0.689	-	0.848	-	-
2004-2005	0.990	0.973	0.888	0.950	-0.982	0.960	-0.974	0.984	0.975	0.913	-	-	0.819	-	-
	G4														
2001-2002	0.994	0.977	0.959	0.937	0.982	0.925	0.898	0.984	0.927	0.958	0.699	-	-	-	-
2001-2003	0.994	0.992	0.981	0.967	0.977	0.971	0.944	0.974	0.958	0.956	0.920	-	-	-	0.521
2001-2004	0.989	0.984	0.983	0.962	-0.986	0.961	0.853	0.972	0.953	0.950	0.856	-	-	-	0.905
2001-2005	0.986	0.982	0.978	0.958	-0.982	0.949	0.946	0.950	0.949	0.929	0.855	-	-	-	-
2002-2003	0.990	0.978	0.943	0.957	0.972	0.915	0.881	0.971	0.902	0.925	0.638	-	-	-	-
2002-2004	0.987	0.984	0.927	0.946	-0.977	0.938	0.715	0.971	0.934	0.950	0.756	-	-	-	-
2002-2005	0.986	0.976	0.946	0.901	-0.982	0.919	0.910	0.935	0.918	0.940	0.836	-	-	-	-
2003-2004	0.991	0.990	0.981	0.976	-0.986	0.971	0.787	0.976	0.974	0.963	0.865	-	-	-	0.509
2003-2005	0.986	0.986	0.970	0.952	-0.973	0.924	0.964	0.954	0.975	0.962	0.800	-	-	-	-
2004-2005	0.994	0.993	0.972	0.954	0.987	0.946	0.810	0.982	0.982	0.973	0.917	-	-	-	-

1. Refer to Table 5.8 for the full names of the components.
2. All correlations are significant at 0.05 level (2-tailed) except those in brackets.
3. When no component appeared in either year, a (-) sign is shown instead.

6.5.2 Congruency coefficients

The congruency coefficients were calculated for the 10 pairs of years for each of the four asset-size groups; the results are shown in Table 6.21. These results confirmed those of the time-series correlation coefficients; the following paragraphs elaborate on this.

The stability for the nine consistent components was first assessed for G1. As can be seen from Table 6.21, the mean values of the congruency coefficients for these components could be considered as 'good' for all except AQ-II which showed a 'borderline' mean. A further look at the congruency coefficients of AQ-II over the years showed that it had a 'good' match between 2001 and 2002; however, in the pairs involving either of these two years, the matches were 'borderline'. In the three recent years, however, the goodness of the matches for AQ-II was higher. Also, it could be noticed that M(C)-II, CG and IS had a few 'borderline' matches in addition to many 'good' matches over the years. In addition, Fnd had 'good' matches over the period between 2001 and 2004. When Fnd, however, was compared to Ln&Ls in 2005, the matches could be described as 'poor' and 'terrible'. Grth had 'borderline' and 'poor' matches whenever the first two years were part of the comparison; yet, in the last three years, the matches of this component were 'good'. Also, Eff showed 'excellent' and 'good' matches over the years whereas the two unlabelled components in 2003 and 2004 had a 'good' match.

As for G2, almost all of the nine consistent components had 'good' matches over the years; however, the components with a few 'borderline' and 'poor' matches were Sh-t liq, M(Y)-I and M(C)-II. Ln&Ls in G2 had 'good' matches in all the pairs except those involving year 2003; in such pairs of years, Ln&Ls was compared to Fnd and the reported matches were 'poor' and 'terrible'. Last for this group, the matches for Grth ranged between 'good' and 'terrible' whereas for the two Eff components the matches were 'borderline' and 'excellent'.

Table 6.21: Serial congruency coefficients between components of the same group over time (2001-2005)

	Prof	Sh-t liq	M(Y)-I	M(C)-II	AQ-I	AQ-II	RBC	CG	IS	Ln&Ls/Fnd	Grth	Eff	Eff-II	Fnd-II	No Name
	G1														
2001-2002	0.976	0.964	0.977	0.978	0.965	0.949	0.974	0.865	0.941	0.972	0.814	-0.977	-	-	-
2001-2003	0.972	0.973	0.971	0.983	0.953	0.871	0.978	0.899	0.848	0.969	0.878	-0.970	-	-	-
2001-2004	0.960	0.965	0.952	0.969	0.948	0.868	0.962	0.861	0.854	0.929	0.767	-0.960	-	-	-
2001-2005	0.962	0.936	0.928	0.907	0.955	0.862	0.964	0.862	0.883	0.650	0.802	-0.949	-	-	-
2002-2003	0.981	0.979	0.986	0.984	0.925	0.879	0.986	0.957	0.936	0.989	0.811	0.993	-	-	-
2002-2004	0.965	0.981	0.966	0.970	0.929	0.891	0.975	0.960	0.946	0.978	0.813	0.981	-	-	-
2002-2005	0.964	0.961	0.918	0.889	0.939	0.864	0.970	0.967	0.962	0.742	0.878	0.968	-	-	-
2003-2004	0.987	0.980	0.988	0.977	0.972	0.934	0.985	0.967	0.983	0.974	0.924	0.986	-	-	0.922
2003-2005	0.983	0.958	0.961	0.900	0.961	0.937	0.980	0.971	0.954	0.756	0.925	0.969	-	-	-
2004-2005	0.992	0.974	0.974	0.952	0.984	0.980	0.987	0.984	0.972	0.814	0.923	0.975	-	-	-
Mean	**0.974**	**0.967**	**0.962**	**0.951**	**0.953**	**0.904**	**0.976**	**0.929**	**0.928**	**0.877**	**0.853**	**0.973**			
	G2														
2001-2002	0.984	-0.937	0.951	0.951	0.984	0.956	0.972	0.989	0.962	0.967	0.621	-	-0.835	-	-
2001-2003	0.977	-0.940	0.921	0.853	0.987	0.958	-0.929	0.962	-0.928	0.651	0.765	-	-	-	-
2001-2004	0.986	-0.783	0.951	0.868	0.988	0.940	0.957	0.961	0.937	0.964	-	-	-	-	-
2001-2005	0.972	-0.915	0.910	0.808	0.972	0.954	0.959	0.939	0.930	0.949	0.562	-	-	-	-
2002-2003	0.987	0.987	0.960	0.961	0.988	0.973	-0.957	0.968	-0.962	0.768	0.849	-	-	-	-
2002-2004	0.989	0.934	0.967	0.968	0.988	0.968	0.981	0.966	0.968	0.973	-	-	-	-	-
2002-2005	0.966	0.983	0.878	0.927	0.975	0.964	0.975	0.943	0.954	0.948	0.941	-	-	-	-
2003-2004	0.986	0.909	0.959	0.984	0.990	0.963	-0.964	0.992	-0.979	0.770	-	0.896	-	-	-
2003-2005	0.952	0.979	0.859	0.976	0.977	0.963	-0.956	0.982	-0.966	0.750	0.826	0.906	-	-	-
2004-2005	0.975	0.952	0.939	0.964	0.980	0.988	0.986	0.988	0.972	0.960	-	0.986	-	-	-
Mean	**0.977**	**0.932**	**0.929**	**0.926**	**0.983**	**0.963**	**0.964**	**0.969**	**0.956**	**0.870**					

	Prof	Sh-t liq	M(Y)-I	M(C)-II	AQ-I	AQ-II	RBC	CG	IS	Ln&Ls/Fnd	Grth	Eff	Eff-II	Fnd-II	No Name
	G3														
2001-2002	0.985	-0.949	0.697	0.975	-0.966	0.916	0.948	0.966	0.983	-	0.637	-0.870	-	-	-
2001-2003	0.979	-0.979	0.803	0.951	-0.964	0.928	-0.950	0.949	0.974	-	0.778	-0.641	-	0.907	-
2001-2004	0.965	-0.983	0.774	0.940	-0.962	0.929	-0.955	0.968	0.975	-	-	-	-	0.910	-
2001-2005	0.971	-0.951	0.528	0.903	0.982	0.943	0.968	0.972	0.961	-	0.936	-	-	-	-
2002-2003	0.988	0.984	0.966	0.980	0.991	0.984	-0.929	0.965	0.969	-	0.762	0.812	-	-	-
2002-2004	0.974	0.975	0.954	0.962	0.952	0.961	-0.959	0.978	0.976	0.920	-	-	-	-	-
2002-2005	0.973	0.984	0.810	0.932	-0.962	0.966	0.953	0.958	0.952	0.934	0.606	-	-	-	-0.194
2003-2004	0.991	0.986	0.989	0.986	0.970	0.971	0.963	0.980	0.982	-	-	-	0.941	0.880	-
2003-2005	0.989	0.976	0.851	0.940	-0.965	0.969	-0.927	0.979	0.987	-	0.680	-	0.853	-	-
2004-2005	0.991	0.972	0.895	0.950	-0.979	0.955	-0.974	0.985	0.975	0.904	-	-	0.823	-	-
Mean	**0.981**	**0.974**	**0.827**	**0.952**	**0.969**	**0.952**	**0.953**	**0.970**	**0.974**	**0.920**					
	G4														
2001-2002	0.995	0.974	0.962	0.940	0.982	0.926	0.897	0.985	0.928	0.959	0.716	-	-	-	-
2001-2003	0.994	0.991	0.983	0.969	0.977	0.973	0.944	0.975	0.958	0.959	0.923	-	-	-	0.524
2001-2004	0.990	0.982	0.984	0.965	-0.982	0.962	0.851	0.973	0.952	0.954	0.863	-	-	-	0.906
2001-2005	0.988	0.981	0.981	0.961	-0.980	0.952	0.945	0.954	0.949	0.935	0.861	-	-	-	-
2002-2003	0.991	0.978	0.948	0.958	0.972	0.916	0.881	0.973	0.902	0.926	0.670	-	-	-	-
2002-2004	0.988	0.984	0.932	0.949	-0.974	0.936	0.720	0.973	0.934	0.953	0.777	-	-	-	-
2002-2005	0.987	0.975	0.954	0.910	-0.981	0.920	0.906	0.940	0.918	0.944	0.852	-	-	-	-
2003-2004	0.992	0.990	0.983	0.977	-0.985	0.973	0.787	0.978	0.973	0.963	0.875	-	-	-	0.511
2003-2005	0.987	0.986	0.973	0.955	-0.973	0.928	0.962	0.958	0.975	0.962	0.818	-	-	-	-
2004-2005	0.994	0.993	0.973	0.957	0.986	0.949	0.803	0.983	0.981	0.975	0.923	-	-	-	-
Mean	**0.991**	**0.984**	**0.967**	**0.954**	**0.979**	**0.943**	**0.870**	**0.969**	**0.947**	**0.953**	**0.828**				

1. Refer to Table 5.8 for the full names of the components.
2. Mean values are calculated using the coefficients in absolute terms (Ketz et al., 1990, p. 71).
3. When no component appeared in either year, a (-) sign is shown instead.

In G3, amongst the nine consistent factors, M(Y)-I had the worst matches; not only this, these matches were the poorest in G3 compared to its matches in the other groups. The only 'good' matches for M(Y)-I, however, were found in the period between 2002 and 2004 where high correlation coefficients were also reported (see Subsection 6.5.1). Similarly, all the findings concerning the inconsistent factors in G3 were in agreement with those of the correlation coefficient analysis. The matches of Ln&Ls were 'good' and 'borderline', and for Grth they were 'poor' and 'terrible' except between 2001 and 2005 where there was a 'good' match. The two Eff components had 'borderline', 'poor' and 'terrible' matches, and the only 'good' match was found for Eff-II between 2003 and 2004. Last but not least, Fnd-II had 'borderline' matches where the unlabelled component had a 'terrible' match.

Finally, in regard to the time stability of the components of G4, most of the nine consistent ones had 'good' and 'excellent' matches over the years. However, RBC had mixed matches ranging between 'good' and 'poor'; all its 'good' matches appeared when years 2001, 2003 and 2005 were under comparison. Also, Ln&Ls had 'good' matches over the short period whereas Grth was very unstable with matches described as 'poor' and 'terrible' over the years. Finally, the matches for the unlabelled factor were 'terrible', except between 2001 and 2003 when it had a 'borderline' match.

6.5.3 Transformation analysis

Following the previous relevant literature, transformation analysis was carried out only for the pairs of successive years (i.e. four pairs for each group). The resulting transformation matrices for G1 are given in Table 6.22 whereas Appendix 6.6 gives those for the rest of the groups.

Transformation matrices (G1). As can be seen from Table 6.22, six of the nine consistent components had their coefficients of coincidence in excess of .95 over the different pairs of years, and thus could be considered as stable over the short-time period. With reference to Table 5.8 for the full names of the components, the six components were Prof, Sh-t liq, M(Y)-I, M(C)-II, RBC and IS. The two AQ factors, however, showed a satisfactory level of stability over all years except between 2002 and 2003 as their coefficients of coincidence fell below .95 (.869 and .830 for AQ-I and AQ-II, respectively). AQ-I in 2002 had three sizeable elements with the unlabelled factor, AQ-II, and Grth of year 2003, whereas AQ-II had a sizeable element with the unlabelled factor; the rest of the elements were very small. Similarly, CG showed a satisfactory level of stability over the period between 2002 and 2005. Nevertheless, between 2001 and 2002, it had a certain amount of transference into Grth and AQ-II. Among the less consistent components, Eff was the only component to show a satisfactory level of short-term stability. Also, not surprisingly, Fnd exhibited a high level stability over the first four years of the period; however, it had a coefficient of coincidence of .847 with Ln&Ls in the transformation matrix of 2004-2005 besides some sizeable elements with Eff-II and Sh-t liq, amongst other factors.

Transformation matrices (G2-G4). The level of short-term stability shown by the nine consistent factors in each of the groups G2, G3 and G4 was approximately similar to G1. However, two interesting points need to be mentioned. The first is regarding Sh-t liq which showed its lowest level of time stability for G2 where its coefficient of coincidence was above .95 only between 2002 and 2003; in the rest of the pairs of years, however, Sh-t liq's coefficients of coincidence ranged between .803 and .903 in absolute terms, and sizeable elements were found between this factor and both Grth and Sh-t inv. The second point to be mentioned is concerning RBC. As mentioned earlier, RBC for G1 was stable over the five years; however, its level of time stability decreased (in absolute terms) through the rest of the groups until it clearly became unstable for G4. A closer look at RBC in the transformation matrices showed that its coefficients of coincidence were above .95 for all pairs of years in G1 whereas they fell below .95 in one pair of years for G2; they also ranged between .907 and .988 for G3 and between .799 and .856 for G4 (all in absolute terms). The sizeable elements found for RBC were with the unlabelled component, Grth and M(C)-II for G4; and Ln&Ls, M(Y)-I, Fnd-II and Grth for groups G3.

Table 6.22: Time-series transformation matrices between components of G1 (2001-2005)

			C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
		2002	Prof	M(Y)-I	Sh-t liq	AQ-I	Fnd	M(C)-II	RBC	CG	Eff	AQ-II	IS	Grth	-
2001	**C1**	M(Y)-I	0.021	**0.988**	-0.042	0.026	0.125	0.040	-0.025	-0.001	0.050	0.012	-0.013	-0.010	
	C2	Prof	**0.995**	-0.018	0.012	0.015	-0.017	-0.037	-0.005	0.073	-0.004	-0.003	-0.017	-0.037	
	C3	Fnd	0.022	-0.121	0.075	0.033	**0.971**	0.019	0.038	-0.039	-0.015	0.114	-0.034	0.131	
	C4	Sh-t liq	-0.022	0.049	**0.973**	-0.038	-0.034	-0.067	-0.027	0.010	-0.011	-0.033	0.018	-0.200	
	C5	M(C)-II	0.034	-0.031	0.084	0.028	-0.041	**0.991**	0.017	0.039	-0.009	0.017	-0.015	0.062	
	C6	AQ-I	-0.024	-0.021	0.026	**0.991**	-0.028	-0.031	-0.007	0.048	-0.004	-0.035	-0.089	-0.046	
	C7	RBC	0.003	0.031	0.021	0.003	-0.032	-0.019	**0.998**	0.006	-0.011	-0.027	-0.015	-0.011	
	C8	Eff	-0.006	0.049	-0.028	-0.006	0.005	0.000	-0.012	0.007	**-0.996**	-0.021	0.008	-0.064	
	C9	Grth	-0.011	0.034	0.156	-0.004	-0.096	-0.088	-0.007	0.468	-0.054	-0.082	-0.105	0.847	
	C10	AQ-II	0.010	0.012	0.052	0.043	-0.137	-0.032	0.022	-0.082	-0.030	**0.975**	0.057	0.117	
	C11	CG	-0.075	-0.019	-0.092	-0.049	0.087	0.006	0.001	0.874	0.034	0.144	0.053	-0.433	
	C12	IS	0.020	0.009	0.007	0.092	0.025	0.006	0.015	0.012	0.002	-0.071	**0.986**	0.112	
	C13	-													
		2002	Prof	M(Y)-I	Sh-t liq	AQ-I	Fnd	M(C)-II	RBC	CG	Eff	AQ-II	IS	Grth	-
2003	**C1**	Prof	**0.996**	-0.008	0.027	-0.016	-0.008	-0.002	0.007	0.040	-0.005	0.024	-0.015	0.005	
	C2	M(Y)-I	0.006	**0.996**	-0.026	0.010	0.054	0.001	-0.001	0.019	-0.020	0.018	0.015	-0.039	
	C3	Sh-t liq	-0.016	0.025	**0.980**	-0.003	0.022	-0.058	-0.032	0.001	-0.010	-0.018	0.026	-0.121	
	C4	Fnd	0.009	-0.052	-0.012	0.036	**0.995**	0.032	0.006	-0.023	0.010	-0.009	0.001	0.056	
	C5	M(C)-II	-0.001	0.004	0.072	0.036	-0.037	**0.993**	-0.001	-0.004	0.003	-0.023	0.015	0.071	
	C6	AQ-I	-0.023	-0.022	0.065	0.869	-0.026	-0.049	0.015	0.077	0.020	-0.012	-0.163	-0.016	
	C7	RBC	-0.006	0.005	0.033	-0.012	-0.006	-0.002	**0.999**	-0.019	-0.004	-0.002	-0.016	0.025	
	C8	CG	-0.018	-0.014	-0.046	0.066	0.020	0.019	0.019	**0.956**	-0.001	0.011	0.061	-0.063	
	C9	Eff	0.007	0.022	0.008	-0.007	-0.009	-0.004	0.003	-0.004	**0.999**	-0.008	0.017	0.012	
	C10	AQ-II	0.017	0.010	-0.016	0.257	-0.018	0.007	-0.010	-0.132	-0.006	0.830	0.054	0.221	
	C11	Grth	-0.045	0.026	0.152	-0.219	-0.029	-0.074	-0.023	0.184	-0.002	0.052	-0.132	0.865	
	C12	IS	-0.003	-0.023	0.016	0.051	-0.005	-0.029	0.018	0.007	-0.010	0.034	**0.965**	0.054	
	C13	No Name	0.065	0.047	-0.045	0.348	-0.044	-0.035	-0.018	-0.160	-0.025	-0.553	0.130	0.413	

			C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
		2004	Prof	M(Y)-I	Sh-t liq	Fnd	M(C)-II	CG	AQ-I	RBC	Eff	AQ-II	Grth	No Name	IS
2003	**C1**	Prof	**0.997**	-0.000	0.030	-0.036	-0.010	-0.019	0.019	-0.005	0.030	-0.025	0.017	0.017	0.003
	C2	M(Y)-I	0.006	**0.987**	-0.009	0.066	0.004	0.034	-0.070	0.005	-0.023	0.032	-0.090	0.080	0.015
	C3	Sh-t liq	-0.029	0.004	**0.997**	0.016	-0.066	0.004	-0.001	-0.008	-0.021	0.012	-0.017	0.014	0.012
	C4	Fnd	0.037	-0.042	-0.003	**0.972**	0.097	-0.010	0.027	0.030	0.022	0.046	0.093	-0.170	-0.018
	C5	M(C)-II	-0.001	0.000	0.067	-0.077	**0.981**	-0.021	0.027	0.032	0.043	-0.070	0.033	0.129	0.001
	C6	AQ-I	-0.023	0.085	0.001	-0.029	-0.031	-0.015	**0.987**	-0.027	0.002	-0.087	0.066	-0.046	-0.013
	C7	RBC	0.002	0.007	0.008	-0.035	-0.037	-0.017	0.016	**0.995**	-0.028	-0.036	0.061	-0.022	-0.012
	C8	CG	0.022	-0.043	-0.003	0.010	0.028	**0.991**	0.031	0.026	-0.003	0.033	-0.108	-0.012	0.008
	C9	Eff	-0.032	0.014	0.015	0.002	-0.056	0.004	-0.000	0.029	**0.993**	-0.014	-0.022	0.084	0.017
	C10	AQ-II	0.019	-0.026	-0.008	-0.043	0.047	-0.032	0.092	0.034	0.008	**0.985**	0.049	0.107	0.012
	C11	Grth	-0.018	0.086	0.014	-0.077	-0.038	0.118	-0.079	-0.062	0.018	-0.035	**0.979**	0.008	0.021
	C12	IS	-0.003	-0.019	-0.013	0.025	-0.003	-0.011	0.016	0.013	-0.020	-0.016	-0.015	0.027	**0.998**
	C13	No Name	-0.011	-0.084	-0.024	0.180	-0.115	0.013	0.045	0.016	-0.088	-0.097	0.012	**0.962**	-0.037
		2005	M(Y)-I	Prof	Sh-t liq	M(C)-II	AQ-I	CG	RBC	Eff-I	AQ-II	Ln&Ls	Eff-II	Grth	IS
2004	**C1**	Prof	-0.003	**0.999**	-0.010	0.016	-0.014	0.027	-0.006	-0.011	0.012	-0.031	0.009	-0.006	0.013
	C2	M(Y)-I	**0.979**	0.001	0.001	-0.057	0.007	-0.025	0.007	-0.000	-0.002	-0.100	0.150	0.064	-0.016
	C3	Sh-t liq	-0.037	0.002	**0.969**	0.004	0.004	0.004	0.008	0.011	0.002	-0.227	0.089	-0.012	-0.030
	C4	Fnd	0.161	0.030	0.241	0.178	0.011	-0.004	0.003	0.029	-0.030	0.847	-0.392	-0.054	0.083
	C5	M(C)-II	0.020	-0.020	-0.046	**0.979**	-0.017	-0.023	0.012	-0.004	-0.019	-0.127	0.147	0.010	-0.008
	C6	CG	0.029	-0.027	-0.005	0.024	0.002	**0.998**	0.021	0.007	-0.005	-0.019	-0.032	0.005	-0.004
	C7	AQ-I	0.004	0.013	-0.010	0.026	**0.986**	-0.007	-0.032	0.007	-0.004	-0.072	-0.131	0.038	-0.030
	C8	RBC	-0.012	0.007	-0.007	-0.013	0.033	-0.020	**0.998**	-0.015	-0.014	0.007	0.006	0.043	0.014
	C9	Eff	-0.016	0.011	-0.016	-0.009	0.008	-0.002	0.012	**0.993**	-0.003	0.025	0.109	0.031	0.015
	C10	AQ-II	0.015	-0.012	0.002	0.027	-0.002	0.002	0.017	0.012	**0.996**	-0.002	-0.056	-0.052	-0.004
	C11	Grth	-0.043	0.006	0.024	0.013	-0.057	-0.007	-0.040	-0.015	0.045	0.005	-0.133	**0.986**	-0.021
	C12	No Name	-0.098	0.006	0.022	-0.066	0.147	0.042	-0.021	-0.113	0.061	0.429	0.862	0.115	0.080
	C13	IS	0.009	-0.016	0.007	-0.001	0.016	-0.000	-0.014	-0.008	0.002	-0.117	-0.039	0.016	**0.992**

1. Elements above .950 are in bold (Martikainen et al., 1994, p. 63).
2. Refer to Table 5.8 for the full names of the components.

In regard to the short-term stability exhibited by the inconsistent components for groups G2-G4, Ln&Ls' time stability could be described as average in the different groups. However, since Fnd was identified for G2 in year 2003, the coefficients of coincidence for the two factors (Ln&Ls and Fnd) in the pairs 2002-2003 and 2003-2004 were below .7 (in absolute terms). Sizeable elements were found with the unlabelled factor and Grth between 2002 and 2003, and with Sh-t inv, Eff and RBC between 2003 and 2004.

The two Eff components did not exhibit a consistent level of stability over the short period for the groups G2-G4. When Eff-II was identified in consecutive years, its coefficients of coincidence ranged between .895 and .991. Similarly, when Eff was identified in adjacent years, its coefficients of coincidence ranged between 0.807 and 0.991. Nevertheless, when the two Eff factors were compared to each other, the elements were -0.671 or under (in absolute terms). In addition, in regard to Eff, sizeable elements were found mainly with M(C)-II, M(Y)-I, and the unlabelled factor, whereas smaller elements were found with Sh-t inv, Grth and AQ (I and II). Note that the results outlined above concern G2 and G3 because, as stated earlier, for G4 there was only one Eff factor identified in year 2005; this component, nevertheless, had sizeable elements with the unlabelled factor, RBC, Grth, AQ-II and M(Y)-I.

Last but not least, Fnd-II for G3 had a coefficient of coincidence of .838 between 2003 and 2004. In these two years, and also for G4 in 2003 where it was identified, Fnd-II had high elements with the unlabeled factor, Grth, RBC and Ln&Ls, amongst others. Finally, Sh-t inv (identified for G2 in 2004) had its largest elements in absolute terms with Grth (.892) and Sh-t liq (-.420) in 2004-2005. Between 2003 and 2004, however, sizeable elements were also found with Fnd (.325) and Eff (-.243). As for AQ-III (identified for G3 in 2004), this component had a relatively large element in absolute terms with Grth (-0.889); also, some sizeable elements were found with the unlabelled component (.279) and M(Y)-I (.201). In the period between 2003 and 2004, the sizeable elements were found between AQ-III and a few factors such as Eff-I (-.616), Grth (-.600), amongst others. As for the component that could not be identified for some groups in some periods, it had it sizeable elements with the Eff, Ln&Ls, the two margin factors [M(Y)-I and M(C)-II], and RBC.

Residual matrices. The residual matrices, which help in identifying those ratios with abnormal transformations between the solutions, are not reported in this study due to space limitations. However, Table 6.23 summarises the abnormal transformations for each of the 56 ratios in the four groups over the years 2001-2005. As can be seen from the table, only a few ratios could be considered to have significant abnormal transformations (i.e. in excess of .20). These are X37 for G1 between 2001 and 2002; and X21, X27, X30 and X32 for G3 between 2004 and 2005 (refer to Table 4.4 for descriptions of these ratios). The residual matrices (not shown) were subjected to further investigations to identify the components to which the observed abnormal transformations could be tied. The results were as follows. The unexplained changes in X37 could be tied mostly to AQ-II and RBC, whereas the changes in the other ratios in G3 could be tied mainly to Grth and Eff. Also, it can be noted from Table 6.23, that the abnormal transformations for some ratios were of a considerable size (over .10) at least for one group over the period. These ratios are X11, X28, X31, X32, X33, X34, X37, X40 and X54 (see Table 4.4 for the names of the variables).

Overall assessment. The last two lines of Table 6.23 show the cumulative abnormal transformations for all 56 ratios between the different factor solutions and the overall averages for these figures in the four groups. As can be seen from the table, the highest abnormal transformations were found for G1 and G4 whereas the smallest occurred for G2. In addition, on a single group level, the highest abnormal transformation was for G3 between 2004 and 2005 (2.323) and the lowest for G2 between 2003 and 2004 (0.835).

Table 6.23: Cumulative abnormal transformations between components of the same group over time (G1-G4)

	G1				G2				G3				G4			
	01-02	**02-03**	**03-04**	**04-05**	**01-02**	**02-03**	**03-04**	**04-05**	**01-02**	**02-03**	**03-04**	**04-05**	**01-02**	**02-03**	**03-04**	**04-05**
X1	0.016	0.016	0.013	0.025	0.014	0.010	0.008	0.008	0.019	0.010	0.006	0.021	0.026	0.041	0.008	0.003
X2	0.016	0.005	0.009	0.030	0.021	0.004	0.004	0.004	0.017	0.004	0.006	0.019	0.073	0.053	0.003	0.010
X3	0.007	0.011	0.017	0.023	0.030	0.013	0.008	0.008	0.033	0.018	0.008	0.019	0.071	0.034	0.012	0.009
X4	0.008	0.008	0.007	0.012	0.063	0.017	0.024	0.024	0.081	0.033	0.032	0.017	0.055	0.092	0.022	0.050
X5	0.017	0.005	0.018	0.007	0.005	0.006	0.008	0.008	0.002	0.011	0.007	0.007	0.050	0.065	0.006	0.015
X6	0.020	0.030	0.047	0.027	0.016	0.013	0.021	0.021	0.016	0.025	0.015	0.022	0.028	0.066	0.030	0.030
X7	0.012	0.010	0.010	0.004	0.005	0.004	0.003	0.003	0.007	0.004	0.001	0.002	0.019	0.029	0.006	0.004
X8	0.013	0.013	0.010	0.003	0.004	0.004	0.003	0.003	0.006	0.004	0.001	0.002	0.003	0.002	0.007	0.005
X9	0.012	0.008	0.010	0.005	0.004	0.008	0.003	0.003	0.008	0.007	0.002	0.004	0.006	0.004	0.011	0.006
X10	0.018	0.008	0.010	0.005	0.004	0.008	0.003	0.003	0.008	0.007	0.002	0.005	0.006	0.004	0.011	0.006
X11	0.041	0.022	0.045	0.051	0.110	0.034	0.062	0.062	0.048	0.023	0.028	0.029	0.027	0.065	0.051	0.023
X12	0.050	0.021	0.020	0.017	0.011	0.008	0.007	0.007	0.037	0.016	0.039	0.063	0.013	0.003	0.009	0.011
X13	0.027	0.015	0.008	0.030	0.010	0.009	0.006	0.006	0.022	0.007	0.008	0.020	0.026	0.036	0.005	0.004
X14	0.019	0.003	0.011	0.041	0.027	0.004	0.006	0.006	0.023	0.005	0.008	0.022	0.073	0.058	0.005	0.011
X15	0.009	0.013	0.013	0.020	0.029	0.011	0.008	0.008	0.020	0.016	0.007	0.015	0.066	0.024	0.008	0.009
X16	0.020	0.017	0.012	0.034	0.010	0.014	0.004	0.004	0.036	0.010	0.018	0.023	0.009	0.011	0.020	0.007
X17	0.029	0.018	0.011	0.009	0.012	0.012	0.010	0.010	0.017	0.013	0.013	0.004	0.017	0.006	0.012	0.018
X18	0.013	0.008	0.006	0.007	0.004	0.005	0.008	0.008	0.011	0.007	0.009	0.010	0.008	0.006	0.009	0.016
X19	0.027	0.011	0.049	0.012	0.012	0.005	0.014	0.014	0.012	0.003	0.006	0.010	0.009	0.013	0.015	0.011
X20	0.026	0.010	0.051	0.011	0.010	0.005	0.016	0.016	0.011	0.004	0.006	0.010	0.007	0.012	0.015	0.012
X21	0.013	0.029	0.040	0.015	0.010	0.022	0.010	0.010	0.013	0.024	0.057	**0.251**	0.054	0.057	0.039	0.035
X22	0.015	0.016	0.021	0.018	0.007	0.004	0.008	0.008	0.009	0.008	0.012	0.012	0.010	0.009	0.011	0.007
X23	0.025	0.009	0.021	0.028	0.013	0.011	0.016	0.016	0.015	0.006	0.008	0.007	0.044	0.057	0.008	0.002
X24	0.028	0.014	0.016	0.010	0.006	0.008	0.004	0.004	0.029	0.010	0.004	0.011	0.008	0.017	0.033	0.029
X25	0.046	0.036	0.042	0.036	0.024	0.029	0.008	0.008	0.010	0.012	0.011	0.023	0.010	0.025	0.009	0.024
X26	0.058	0.020	0.023	0.014	0.010	0.019	0.012	0.012	0.006	0.003	0.010	0.014	0.007	0.008	0.011	0.009
X27	0.026	0.025	0.024	0.016	0.008	0.012	0.007	0.007	0.019	0.020	0.039	**0.252**	0.033	0.039	0.034	0.015
X28	0.031	0.014	0.032	0.039	0.018	0.033	0.051	0.051	0.068	0.034	0.051	0.187	0.019	0.023	0.050	0.048
X29	0.036	0.017	0.022	0.013	0.007	0.016	0.010	0.010	0.007	0.003	0.003	0.018	0.009	0.008	0.016	0.007
X30	0.028	0.037	0.083	0.082	0.019	0.033	0.015	0.015	0.099	0.019	0.029	**0.246**	0.058	0.013	0.021	0.026

	G1				G2				G3				G4			
	01-02	**02-03**	**03-04**	**04-05**	**01-02**	**02-03**	**03-04**	**04-05**	**01-02**	**02-03**	**03-04**	**04-05**	**01-02**	**02-03**	**03-04**	**04-05**
X31	0.081	0.078	0.146	0.123	0.061	0.020	0.020	0.020	0.142	0.045	0.107	0.074	0.107	0.047	0.076	0.068
X32	0.104	0.049	0.064	0.044	0.046	0.025	0.031	0.031	0.053	0.059	0.070	**0.243**	0.070	0.018	0.029	0.035
X33	0.034	0.018	0.014	0.005	0.113	0.109	0.007	0.007	0.013	0.019	0.012	0.013	0.015	0.029	0.006	0.028
X34	0.139	0.054	0.050	0.021	0.018	0.015	0.033	0.033	0.010	0.017	0.032	0.005	0.149	0.172	0.049	0.070
X35	0.030	0.013	0.020	0.019	0.011	0.004	0.009	0.009	0.006	0.009	0.006	0.008	0.038	0.026	0.008	0.012
X36	0.057	0.040	0.025	0.038	0.040	0.023	0.021	0.021	0.030	0.014	0.041	0.052	0.051	0.060	0.013	0.033
X37	**0.240**	0.147	0.070	0.123	0.096	0.073	0.073	0.073	0.077	0.028	0.127	0.080	0.094	0.168	0.068	0.026
X38	0.025	0.004	0.015	0.038	0.038	0.006	0.007	0.007	0.033	0.008	0.010	0.034	0.067	0.075	0.007	0.017
X39	0.006	0.012	0.019	0.022	0.008	0.007	0.005	0.005	0.007	0.006	0.011	0.011	0.017	0.015	0.015	0.013
X40	0.066	0.060	0.041	0.041	0.034	0.038	0.097	0.097	0.070	0.040	0.086	0.116	0.014	0.036	0.091	0.139
X41	0.028	0.023	0.023	0.010	0.005	0.014	0.050	0.050	0.006	0.009	0.022	0.019	0.038	0.010	0.036	0.035
X42	0.018	0.014	0.024	0.034	0.020	0.011	0.007	0.007	0.030	0.005	0.005	0.024	0.009	0.009	0.017	0.052
X43	0.017	0.018	0.028	0.019	0.009	0.004	0.005	0.005	0.009	0.004	0.003	0.009	0.008	0.002	0.008	0.005
X44	0.051	0.032	0.021	0.068	0.029	0.015	0.013	0.013	0.032	0.015	0.035	0.036	0.066	0.034	0.068	0.020
X45	0.009	0.009	0.015	0.014	0.008	0.005	0.004	0.004	0.007	0.005	0.009	0.013	0.006	0.003	0.013	0.008
X46	0.079	0.010	0.036	0.052	0.021	0.014	0.009	0.009	0.038	0.013	0.020	0.029	0.028	0.015	0.025	0.023
X47	0.046	0.015	0.062	0.047	0.033	0.012	0.013	0.013	0.032	0.015	0.012	0.032	0.020	0.008	0.021	0.024
X48	0.037	0.011	0.036	0.043	0.010	0.009	0.004	0.004	0.013	0.005	0.004	0.009	0.034	0.055	0.008	0.005
X49	0.027	0.009	0.011	0.014	0.009	0.017	0.007	0.007	0.012	0.004	0.003	0.012	0.020	0.041	0.010	0.007
X50	0.014	0.008	0.004	0.006	0.007	0.008	0.002	0.002	0.010	0.012	0.011	0.014	0.010	0.013	0.004	0.009
X51	0.034	0.014	0.015	0.007	0.004	0.008	0.006	0.006	0.007	0.003	0.008	0.005	0.006	0.010	0.009	0.005
X52	0.042	0.060	0.061	0.075	0.026	0.031	0.032	0.032	0.027	0.031	0.041	0.079	0.034	0.080	0.026	0.043
X53	0.022	0.007	0.019	0.006	0.006	0.015	0.006	0.006	0.007	0.006	0.004	0.006	0.004	0.008	0.008	0.003
X54	0.034	0.036	0.016	0.015	0.011	0.107	0.005	0.005	0.023	0.152	0.010	0.042	0.015	0.116	0.013	0.024
X55	0.008	0.014	0.006	0.006	0.007	0.007	0.001	0.001	0.009	0.008	0.005	0.007	0.006	0.010	0.021	0.007
X56	0.008	0.014	0.008	0.006	0.007	0.008	0.002	0.002	0.010	0.010	0.004	0.007	0.006	0.010	0.024	0.008
Cumulative abnormal transformation	1.963	1.236	1.550	1.540	1.199	0.987	**0.835**	1.897	1.425	0.904	1.145	**2.323**	1.774	1.947	1.171	1.177
Average	**1.572**				**1.230**				**1.449**				**1.517**			

1. Figures over .20 are in bold (Martikainen et al., 1995a, p. 41).
2. Refer to Table 4.4 for the full names of ratios.

Significance test for the transformation matrices. This chapter concludes by applying the significance test for the transformation matrices as the final check regarding the stability of the components over the period. Following the same approach as in Subsection 6.4.4, this test was performed over the nine factors consistently identified for the different groups over the years; the results are summarised in Table 6.24. As can be seen from the table, given the values of the z-scores, the null hypotheses of no significant differences between the components over time could not be rejected for G1, G2 and G3. This implied that the nine components in each of the three asset-size groups were all similar over the period 2001-2005. However, the z-score value for G4 (-1.620369) is *almost* significant at the .10 significance level, which casts some doubt over the decision to accept the null hypothesis of no significance differences between the components of G4 over the years. However, since the significance test applied here is based on the Central Limit Theorem which requires a minimum sample size of 30, and given that only four observations were used (four transformation matrices for each group), the results of the test should be interpreted with caution.

Table 6.24: Results of transformation matrices' significance test (G1-G4)

Group	$\overline{\det(B)}$	$\hat{\sigma}$	z-score
G1	1.000824	0.002075	0.794530
G2	1.000277	0.001720	0.322601
G3	1.000608	0.001541	0.789650
G4	0.999436	0.000696	-1.620369

6.6 Summary

This chapter aimed to answer questions regarding the extent to which the classification patterns of financial ratios for commercial banks in different asset-size groups are similar, and whether the patterns of the different asset-size groups exhibit a similar level of stability over time.

In answering these research questions, the study used four asset-size groups for each year between 2001 and 2005. The smallest sample consisted of 880 commercial banks whereas the largest sample comprised 1,941 banks. The financial patterns were derived using PCA with a varimax rotation, and PA was used to decide on the final number of components to be interpreted. In checking the cross-sectional and short-term stability of the derived patterns, the study used the following techniques: visual checking, correlation analysis, congruency coefficients, and transformation analysis.

Different numbers of financial patterns, ranging between 11 and 13, were found for the different groups of banks over the five years covered. However, the differences in the number of financial patterns could not be related to either the year or the asset-size class. Nevertheless, it was found that the factor solutions for G1 tended to explain a smaller proportion of variance than that accounted for by the solutions for other groups of smaller asset sizes. Also, it was reported that the solutions for G4 tended to explain the highest proportion of the variance.

The financial patterns identified for banks in the different asset-size groups over the years were slightly dissimilar. However, nine of these patterns were identified consistently across the four groups over the period. These were: Prof, Sh-t liq, M(Y)-I, M(C)-II, AQ-I, AQ-II, RBC, CG and IS. The less consistent patterns included Ln&Ls, Fnd, Grth, Eff, Eff-II, and Fnd-II; also, Sh-t inv and AQ-III were identified only once. Furthermore, for some groups, it was not possible to assign any label for one of the derived factors; thus, these were left without any name.

Given the results of the different comparison methods applied in checking the cross-sectional and time stability of the financial patterns, the two patterns showing highest stability were Prof and Sh-t liq. M(Y)-I, however, was the least stable amongst the nine patterns consistently identified. Interestingly, Fnd was identified for G1 (the group of banks with the largest asset size) over the five years whereas Ln&Ls was found for the groups of banks with smaller asset size. This implied that, in general, ratios for banks with an asset size in excess of $300 million tended to have a Fnd pattern whereas ratios for banks with an asset size less that $300 million tended to form up a Ln&Ls pattern instead. Also, it could be said that, in general, the Eff ratios for banks with a smaller asset size (less than $50 million) tended to cluster together with the M(Y)-I ratios: i.e. the Eff pattern tended to merge into the M(Y)-I for banks with a smaller asset size whereas these ratios formed a unique Eff pattern for banks with larger asset sizes. Finally, it was apparent that the level of short-term stability of the financial patterns was higher than that of the cross-sectional stability between the different asset-size groups.

In the following chapter (Chapter 7), using a sample of savings banks, a study was carried out to check whether the same 56 ratios could be grouped into the same financial patterns as turned out to be the case with the commercial banks investigated in Chapter 5. The time stability of the financial patterns for the saving banks was also investigated.

Chapter 7 The Classification Patterns of Financial Ratios: A Comparison between Savings and Commercial Banks

7.1 Introduction

Chapter 5 empirically identified the financial patterns for a set of bank ratios and checked the stability of these patterns over time. Next, Chapter 6 answered, also empirically, the questions of whether similar financial patterns could be identified for different asset-size groups of commercial banks and whether the patterns for each asset-size group exhibited similar levels of stability over time. The two previous chapters used a set of 56 ratios; Chapter 5 used a large sample of U.S. commercial banks and covered the period between 2001 and 2005. As for Chapter 6, the large sample of commercial banks was divided into four sub-samples according to the asset size of the banks. Given that the two chapters only used data for commercial banks, their findings are thus specific to that type of bank.

In order to answer the general question of whether the type of bank influences the identified financial patterns, the current chapter aims to investigate the financial patterns for U.S. savings banks and to check their stability over the period between 2001 and 2005. The chapter also compares the identified patterns for savings banks with the patterns found for the commercial banks in Chapter 5. In doing so, this study uses the same set of 56 ratios and employs the same methodology for deriving and comparing the patterns.

The rest of the chapter is organised as follows. The methodology and data are given in Section 7.2. The results of the steps leading to the derivation of the patterns for the savings banks are explained in Section 7.3, first for year 2005, followed by the preceding years. The time stability of the identified patterns is then verified in Section 7.4. Next, in Section 7.5, various comparisons are made between the patterns for the savings and commercial banks. Finally, in Section 7.6, the results are summarised and highlights are given of the issues to be investigated in Chapter 8.

7.2 Methodology and data

Methodology. The current chapter aims to derive the financial patterns of ratios for a group of savings banks and to check the short-term stability of the patterns; it also aims to compare the identified patterns with the patterns found for commercial banks. Similar to the previous chapters (Chapters 5 and 6), Principal Component Analysis (PCA) was used to extract the components; a varimax rotation method was performed to facilitate their interpretation. Also, Parallel Analysis (PA) was employed to decide on the number of components to keep. Besides PA, the number of components suggested by some common methods such as the ‘eigenvalue >1’ and Cattell’s scree plot were reported for comparison purposes only.

To assess the time stability of the savings banks’ patterns and to compare the patterns to those for the commercial banks, this chapter applied all the comparison methods used earlier in Chapters 5 and 6. These methods included conducting visual comparisons, examining the correlation and congruency coefficients, and performing transformation analysis.

The statistical software package SPSS 15.00 and Microsoft Excel spreadsheets were used to carry out most of the analysis, except for transformation analysis which was performed entirely using SURVO 2.51 software. Since the methodology used in this chapter was identical to that used in the previous two chapters, and also to avoid any unnecessary repetition, details about the steps followed to derive the patterns is kept to a minimum and, whenever necessary, reference are made to relevant chapters.

Data. The current chapter uses a sample of the Federal Deposit Insurance Corporation (FDIC)-insured savings banks. As clarified in Chapter 4 (Section 4.3.3), the Uniform Bank Performance Report (UBPR), the main source of data in this study, was also available for this type of bank. Data regarding savings banks are given separately from those of commercial banks in the UBPR. According to the UBPR’s manual

(FFIEC, 2006, p. II-2), such separation has proved to be useful since the two types of bank perform differently.

In regard to the criteria used by the UBPR to classify banks, bank asset size, location and the number of offices were used for commercial banks, as previously mentioned in Chapters 4 (Subsection 4.3.1). The UBPR, however, grouped savings banks only by their asset size using 90-day average assets[115]; accordingly, savings banks were set into four asset-size groups. Table 7.1 gives some relevant details relating to the number of banks in each of these groups over the period 2001-2005. The figures in this table were collected either from the different UBPRs downloaded for this study or from the FFIEC website.

Table 7.1: Description of U.S. savings bank groups and number of banks (Q4, 2001-2005)

Number	Assets	2001	2002	2003	2004	2005
101	More than $1 billion	47	48	50	48	48
102	$300 million - $1 billion	136	144	149	143	143
103	$100 - $300 million	181	174	165	153	143
104	Less than $100 million	150	126	119	115	110
Total number		514	492	483	459	444
Obtained/Collected		444	444	444	444	444
Complete observations		274	287	284	286	277
Cases-to-variable ratios		4.89	5.13	5.07	5.11	4.95

Source: FFIEC (2006, p. II-2) and Researcher.

As can be seen from the first part of Table 7.1, the four asset-size groups of savings banks were numbered 101-104, where group 101 consists of banks with asset sizes in excess of $1 billion. Banks of group 102 ranged in sizes between $300 million and $1 billion. Banks in group 103 had asset sizes ranging between $100 million and $300 million whereas the last group, 104, comprised banks with less than $100 million in assets. Savings banks were assigned to the matching group based on their average asset size in the fourth quarter of each year. It is important to note, however, the relatively small number of savings banks in the different asset size groups. As mentioned in Chapter 4 (Subsection 4.3.2), given that the general aim of the chapter is to investigate the financial patterns of savings banks with no reference being made to the size of the banks, it was decided to combine the four groups of savings banks in

[115] See footnote 86 in Chapter 4 (Subsection 4.3.1), for further explanations on calculating 90-day average assets.

each year into one group of a more adequate size in order to run PCA. Accordingly, the total number of savings banks over the specified period ranges between 444 banks in 2005 and 514 in 2001, as Table 7.1 shows.

However, similar to the explanations given in Chapter 4 (at the end of Section 4.2), at the time when data were being collected (December 2006 - January 2007), lists of savings banks in the four groups were available only for year 2005. Since each UBPR contains data for a standard period of five years, downloading the reports for all the banks on the list of year 2005 gave access to these banks' data for year 2005 and the four preceding years. Therefore, the total number of banks whose reports were accessed was slightly different from the number of U.S. savings banks actually operating in the fourth quarter of each of the years 2001-2004; the related figures are reported in the second part of Table 7.1. Hence, given this, the maximum number of savings banks covered by this study was 444. Nevertheless, this number did not make up the final sample; this is because the study is only interested in banks with a complete set of ratios available for any given year.

In regards to the ratios used in this study, given that one purpose of the current chapter is to compare the financial patterns of savings and commercial banks, it was crucial to use the same set of 56 ratios which were used to derive the financial patterns for commercial banks (Chapter 5). These 56 ratios are listed in Table 4.4 and full descriptions of their components are provided in Appendix 4.1. Consequently, after deleting banks with incomplete information (that is, banks for which any of the 56 ratios were not available), the number of usable banks varied from 274 in 2001 to 287 in 2002, as Table 7.1 shows. So, the question that needed to be answered next was whether the size of the sample satisfied the requirements for the application of PCA.

In deciding on the adequacy of the sample size for PCA, what is important is the ratio of cases-to-variable where the minimum ratio that is generally accepted is 5-to-1, although a 10-to-1 ratio is preferable (Hair et al., 1998, p. 98). The cases-to-variable ratios shown in the last row of Table 7.1 are above the least acceptable ratio in years 2002-2004 whereas the ratios fell slightly below the standard of 5-to-1 in years 2001

(274/56= 4.89) and 2005 (277/56= 4.95). Notwithstanding the two rather low ratios, it was decided to carry on with the analysis as planned using the available sample size. This decision was based on the following two grounds. First, emphasis is placed by some references on the absolute sample size rather than the ratio of cases-to-variable. Generally, a sample size of 100 or larger is preferred (Hair et al., 1998, p. 98). Second, a number of studies in the relevant literature used considerably smaller sample sizes: for example, Laurent (1979): 45 ratios for 63 companies; Yli-Olli and Virtanen (1989): 12 ratios for 42 firms; Salmi et al. (1990): 28 ratios for 32 firms, amongst others. Clearly, the cases-to-variable ratios reported for the current study appear healthier than the ratios in some of the previous literature.

Data transformation. The last point to make in regard to the data is that an arcsinh transformation was carried out for all 56 ratios for the samples in each year. Although this transformation could not bring the distribution to normality, the results reported in Chapter 5 (Section 5.3), showed that the arcsinh transformation method succeeded in significantly reducing the skewness and kurtosis measures of the data.

7.3 Financial patterns of U.S. saving banks (2001-2005)

In this section, the financial patterns of a set of 56 ratios for the U.S. savings banks were uncovered using PCA with a varimax rotation. A separate PCA was carried out for the savings banks data in each of the years 2001-2005. As explained in Chapter 3 (Section 3.3), performing PCA involves a series of steps starting with testing the factorability of the correlation matrix followed by deciding on the number of components to retain. The process ends by assigning appropriate labels to the components after rotating the solution. A detailed description of these steps is given for year 2005 in Subsection 7.3.1, whereas Subsection 7.3.2 briefly reports the results for years 2001-2004.

7.3.1 Financial patterns of U.S. savings banks in 2005

In year 2005, all 56 ratios were available for 277 U.S. savings banks; this gives a 4.95-to-1 cases-to-variable ratio, deemed as satisfactory in the previous section. The starting point in PCA is the correlation matrix where it is preferable to have a substantial number of correlation coefficients larger than |0.30| if the analysis is to be reliable. Visual examination of the matrix[116] revealed that this starting condition of PCA was satisfied. This was followed by two statistical tests: Bartlett's Test of Sphericity (BTS) and Kaiser-Meyer-Olkin's (KMO) measure of sampling adequacy (MSA); the statistics from these two tests for year 2005 are reported in Table 7.2. As the table shows, the KMO statistic describing the common variance shared by the 56 ratios was .744 which could be described as 'middling' using the guidelines of Sharma (1996, p. 116). Also, the BTS statistic was significant at the .000 level which indicated the existence of sufficiently significant correlations in the correlation matrix to conduct further analysis. Thus, given the results of this stage, it was evident that the data contained different dimensions; these could be identified by employing PCA.

Table 7.2: KMO and BTS for savings banks (2005)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.744
Bartlett's Test of Sphericity	Approx. χ^2	33,514.576
	df	1540
	Sig.	.000

The following step in PCA involved evaluating the initial solution and then deciding on the number of factors to be extracted. Table 7.3 summarises the initial solution for the data of year 2005; this includes the amount and percentage of variance accounted for by each component and the cumulative percentage of variance explained by consecutive components. As can be seen from the table, the first component accounts for the highest proportion of variance (17.77%), the second for less variance (14.97%) and so on, until the last components account for only a trivial proportion of variance. So, as can be seen, the first few components explain over half of the total variance in percentage terms; a number of these components should then be kept and interpreted in the final solution.

[116] Correlation matrix is not given due to space limitations.

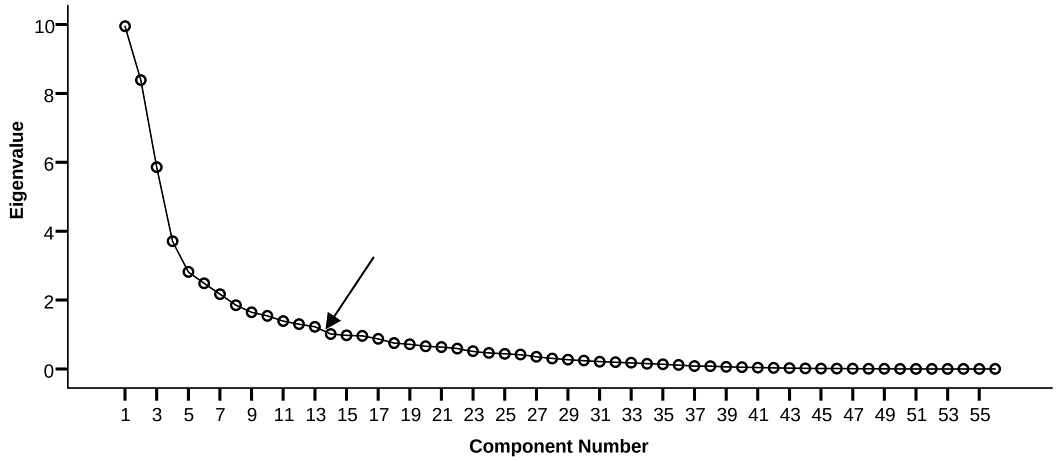
Table 7.3: Initial solution for savings banks (2005)*

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	9.949	17.767	17.767
2	8.383	14.970	32.737
3	5.859	10.462	43.200
4	3.710	6.625	49.825
5	2.817	5.031	54.856
6	2.483	4.435	59.291
7	2.172	3.879	63.170
8	1.855	3.312	66.482
9	1.649	2.944	69.427
10	1.540	2.750	72.177
11	1.389	2.480	74.657
12	1.300	2.321	76.978
13	1.227	2.191	79.169
14	1.016	1.814	80.983
15	.980	1.750	82.733
16	.961	1.716	84.449
17	.875	1.563	86.011
18	.754	1.346	87.357
19	.717	1.280	88.637
20	.658	1.175	89.813
.	.	.	.
.	.	.	.
.	.	.	.
50	.001	.001	99.999
51	.001	.001	100.000
52	.000	.000	100.000
53	5.44E-005	9.71E-005	100.000
54	1.96E-005	3.50E-005	100.000
55	1.77E-005	3.16E-005	100.000
56	3.22E-008	5.74E-008	100.000

* The eigenvalues of components 21 to 49 inclusive not shown due to space limitations.

For deciding on the number of components forming the final solution, various methods could be used. One of these methods, ‘eigenvalue >1’, keeps the components with an eigenvalue in excess of unity. By reference to Table 7.3, this method suggested retaining 14 components. Another method, Cattell’s scree plot in Figure 7.1, suggested keeping 13 components for the data in year 2005 as the line started to straighten at around component 14.

Figure 7.1: Cattell's scree plot for U.S. savings banks (2005)



In addition to these two methods, Parallel Analysis (PA) was performed. By applying PA, 1,000 random datasets, each with 56 variables and 277 cases (the sample size in 2005), were generated and a separate PCA was performed using each of the datasets. The output of PA for year 2005 is given in Table 7.4; for each of the 56 variables, the table gives the eigenvalues for the actual dataset, mean eigenvalues for the 1,000 random datasets and for the 95th percentile. As can be seen from the table, the mean eigenvalues and the 95th percentile started to exceed the actual eigenvalues at component 11, which indicated that the precise number of components to retain was ten.

Table 7.4: Parallel analysis output for savings banks (2005)*

Root	Actual eigenvalue	Average eigenvalue	95th percentile eigenvalue
1	9.94938	2.00902	2.10528
2	8.38345	1.90642	1.98107
3	5.85892	1.83494	1.90012
4	3.71025	1.77301	1.82594
5	2.81737	1.71905	1.77039
6	2.48347	1.66909	1.71788
7	2.17243	1.62046	1.66769
8	1.85479	1.57572	1.61726
9	1.64890	1.53387	1.57225
10	1.53998	1.49324	1.52942
11	1.38901	1.45539	1.49443
12	1.29991	1.41781	1.45268
13	1.22681	1.38325	1.42035
14	1.01588	1.34767	1.38116
15	.97972	1.31518	1.34744
16	.96096	1.28211	1.31279
17	.87505	1.25089	1.28081
18	.75381	1.22041	1.24961

Root	Actual eigenvalue	Average eigenvalue	95th percentile eigenvalue
19	.71689	1.18999	1.21786
20	.65827	1.16070	1.18919
.	.	.	.
.	.	.	.
.	.	.	.
50	.00073	.47040	.49228
51	.00052	.44921	.47249
52	.00011	.42778	.45122
53	.00005	.40555	.42892
54	.00002	.38238	.40777
55	.00002	.35708	.38404
56	.00000	.32447	.35405

* The results of components 21 to 49 inclusive not shown due to space limitations.

Clearly, the different factor retention methods suggested keeping a different number of components. However, as stated in earlier chapters, the ultimate number of components in this study was decided only by PA. Given this, the 56 ratios of the savings banks could be grouped into ten financial patterns. With reference to Table 7.3, the 10-factor solution explains 72.18% of the variability of the 56 ratios.

In order to assign appropriate names to the ten components retained, a varimax rotation was carried out over the initial solution[117]. The rotated component matrix for year 2005 is given in Table 7.5. The loadings of the 56 ratios in this matrix were then evaluated; this was followed by assigning names to the components based on the ratios with high loadings in absolute terms. How high a loading should be in order to be considered significant is based on the size of the sample used. Here it can be recalled that in Chapters 5 and 6, where the samples used consisted of 350+ banks, loadings equal to or greater than .30 in the absolute sense were considered significant (Table 3.2 in Hair et al., 1998, p. 112). In this chapter, however, given the size of the sample (277 banks), loadings equal to or greater than |.35| were considered to be significant according to Table 3.2 in Hair et al. (1998, p. 112).

[117] See Chapter 3 (Subsection 3.3.3.1) for explanations about the available methods of rotation and justification for choosing the varimax method for this study.

Table 7.5: Rotated component matrix for savings banks (2005)

Variable Number	Ratio	Component									
		1	2	3	4	5	6	7	8	9	10
X8	PRETAX NET OPER INC (TE) \ AVR AST	0.961									
X7	PRETAX OPER INC (TE) \ AVR AST	0.943									
X10	NET INC \ AVR AST	0.934									
X9	NET OPER INC \ AVR AST	0.934									
X53	NET INC \ AVR TOT EQ	0.882									
X33	EFFICIENCY RATIO	-0.871									
X54	G R TOT EQCAP	0.690								0.520	
X29	G R TIER ONE CAP	0.686								0.540	
X26	RETAIN EARNS \ AVR TOT EQ	0.672								0.562	
X38	COST OF ALL INT-BEARING FUNDS		0.845								
X14	INT EXP \ AVR EARN AST		0.834								
X2	INT EXP \ AVR AST		0.830								
X41	CORE DEP \ TOT AST		-0.794								
X42	S T NCORE FUNDING \ TOT AST		0.574				-0.395				
X44	BROK DEP \ DEP		0.531								
X28	G R AST		0.479			0.405					
X23	NET LN&LS \ AST			0.837							
X1	INT INC (TE) \ AVR AST			0.711	0.397						
X48	NET LS&LS \ DEP			0.696							
X3	**NET INT INC (TE) \ AVR AST**	0.352		0.694				0.399			
X13	INT INC (TE) \ AVR EARN AST			0.693	0.409						
X49	NET LN&LS \ CORE DEP		0.501	0.675							
X15	NET INT INC-TE \ AVR EARN AST			0.668				0.472			
X18	LN&LS ALLOW \ NET LOSSES				-0.795						
X16	NET LOSS \ AVR TOT LN&LS				0.747						
X17	EARN COV OF NET LOSS	0.432			-0.693						
X21	NON-CUR LN&LS \ GRS LN&LS				0.657						
X27	RESTR+NONAC+RE ACQ \ EQCAP+ALLL				0.621						

Variable Number	Ratio	Component									
		1	2	3	4	5	6	7	8	9	10
X34	AVR PERSONNEL EXP PER EMPL($000)				-0.475						
X6	PROVISION: LN&LS LOSSES \ AVR AST				0.473						
X36	**YIELD ON TOT LN&LS (TE)**			0.416	0.435			0.366			
X30	G R NET LN&LS				-0.367						
X55	TIER ONE RBC \ RISK-WGT AST					-0.875					
X56	TOT RBC \ RISK-WGT AST					-0.875					
X24	TIER ONE LEVERAGE CAP					-0.871					
X52	PLEDGED SEC \ TOT SEC					0.435					
X45	S T INV \ S T NCORE FUND						0.810				
X39	S T INV \ TOT AST						0.792				
X46	S T AST \ S T LIABS						0.717				
X43	NET S T NCORE FUND DEPENDENCE		0.399				-0.706				
X47	NET S T LIAB \ TOT AST						-0.582				
X22	NET NCORE FUND DEPENDENCE		0.475				-0.549				
X31	G R S T INV						0.399				
X5	NONINT EXP \ AVR AST			0.430				0.726			
X4	NONINT INC \ AVR AST							0.709			
X35	AST PER EMPLOYEE ($MILLION)							-0.669			
X11	AVR EARN AST \ AVR AST							-0.609			
X12	AVR INT-BEARING FUNDS \ AVR AST					0.353		-0.391			
X19	LN&LS ALLOW \ LN&LS NOT HFS								0.902		
X20	LN&LS ALLOW \ TOT LN&LS								0.901		
X25	CASH DIV \ NET INC									-0.653	
X51	TOT AFS SEC \ TOT SEC										0.840
X50	TOT HTM SEC \ TOT SEC										-0.784
X40	MARKETABLE EQ SEC \ TOT AST										0.447
X32	G R S T NON CORE FUNDING										
X37	YIELD ON TOT INV SEC (TE)										

1. Loadings smaller than |.35| are suppressed (Table 3.2 in Hair et al., 1998, p. 112).
2. Ratios loading significantly onto three or more components are in bold.

As seen at the bottom of Table 7.5, two ratios (X32 and X37) failed to load significantly onto any of the ten components (refer to Table 4.4 for the full names of ratios). Also, in Table 7.5 a number of ratios had significant loadings onto two or more components; for example, X3 and X36 (shown in bold) had significant loadings onto three factors. Some references (Hair et al., 1998, p. 113) suggest that variables with relatively high cross-loadings are candidates for deletion; however, as previously explained (Chapter 6, Subsection 6.3.1), since one aim of this study is to compare the patterns of the 56 ratios across different samples, to enable a sound comparison to be made, it was decided to resume the analysis using all 56 ratios without any omission. So, the interpretation process was continued by focusing only on the ratios with the highest significant loadings when choosing suitable labels for the components.

After studying carefully the ratios loading significantly onto the ten components in year 2005, the components were assigned the following labels: C1: Prof, C2: Ln&Ls, C3: M(C)-II, C4: Sh-t liq, C5: Eff, C6: RBC, C7: AQ-I, C8: AQ-II, C9: CG, and C10: Grth. Table 5.8 gives a full description of the abbreviations used for all the components identified in this study. Here, it is worth mentioning that, since a considerable part of this study was devoted to making comparisons between components, it was important to use the same label for factors with similar content across all the chapters. For example, the Efficiency factor identified in this chapter was labelled as Eff as it appeared (to the researcher) to have the characteristics of both the Eff-I and Eff-II factors identified in Chapters 5 and 6. Also, the Funding (Fnd) component identified later in this chapter was labelled as Fnd-II to distinguish it from the Fnd component found in Chapter 6, given the different content of the two components. More discussion on the content of the factors is given in later sections.

Labelling the patterns extracted for year 2005 was rather straightforward. However, attention must be drawn to the case of CG (C9). On looking at the C9 column in Table 7.5, only one ratio (X25) had its highest loading onto this component. However, whilst three other ratios (X54, X26 and X29) had significant loadings onto CG (C9), their highest loadings were actually onto Prof (C1). This means that CG is a one-variable component; this is the first example in this study when only one ratio loaded highly onto a component.

A factor with only a few loadings is ‘not much of a factor’ according to Stevens (2002, p. 395) who considers such a factor as variable specific. To check whether the CG component could be defined by more than one ratio, two different trials of PCA were performed using a different number of components: 9 and 11. Interestingly, in both trials, X25 was the only ratio with the highest loading onto this component and similar to what was seen in the 10-factor solution, the other three ratios also had significant loadings onto the CG component whereas their highest loadings were onto Prof. Given this, it was decided not to discard this component and, accordingly, to label it as the CG factor based on all the ratios that loaded highly onto it.

Thus, the 56 ratios of the U.S. savings banks in 2005 were grouped into ten financial patterns which explained 72.18% of the variance in the data; appropriate labels were then assigned to these patterns. The following subsection identifies the patterns of the 56 ratios for the savings banks in years 2001-2004.

7.3.2 Financial patterns of U.S. savings banks in 2001-2004

By following the same steps given in the previous subsection, a separate PCA was conducted for each of the datasets in years 2001-2004. The size of the samples ranged between 274 and 287 banks in years 2001 and 2002, respectively (Table 7.1). In Table 7.6, a summary of the initial results shows that the KMO statistics were all ‘middling’ and that BTS statistics were significant for all years. This indicated that the correlation matrices for all four years contained a sufficient number of significant correlation coefficients to proceed with further analysis.

The second part of Table 7.6 summarises the outcomes of the three methods used to decide on the number of components to retain. Cattell’s scree plots and the outputs of PAs for years 2001-2004 are given in Appendices 7.1. The different methods suggested a different number of factors, as Table 7.6 shows. The ‘eigenvalue >1’ method suggested keeping 15 components in years 2001-2003 and 14 in 2004. Plotting the eigenvalues against the number of components (Cattell’s scree plot) suggested keeping 13 components in 2001, 12 in 2002, 15 in 2003 and 16 in 2004.

Table 7.6: Initial results for savings banks (2001-2004)

	2001	2002	2003	2004
KMO	0.719	0.707	0.719	0.734
BTS: Approx. χ^2	34,496.2	34,306.9	34,496.2	34,002.2
df	1540	1540	1540	1540
Sig.	.000	.000	.000	.000
Number of factors				
Eigenvalue >1	15	15	15	14
Cattell's scree plot	13	12	15	16
PA	11	11	11	11
% of variance explained	73.796%	74.114%	74.813%	75.952%

In regard to the scree plot method, deciding on the point at which the plot starts to straighten and thus the number of factors to keep, is not straightforward and involves a fair amount of subjectivity. This is because many major breaks may appear in the line, which suggests retaining different numbers of components. In the absence of any clear-cut rule, it is the researcher's responsibility to decide on how many components to retain. For instance, in the scree plots of years 2001-2004 (Appendix 7.1), it could be argued that the plots started to level-off at points other than those marked by the arrows. Such a bias, however, does not exist when the PA method is used as this method only requires finding the last component for which the actual eigenvalue exceeds the mean and the 95th percentile of the random datasets. As Table 7.6 shows, PA suggested keeping 11 components for each of the years covered. Retaining 11 components explained a percentage of variance ranging between 73.80% in 2001 and 75.95% in 2004.

The rotated component matrices for years 2001-2004 are given in Appendix 7.2. Loadings of the 56 ratios in each matrix were examined in order to find the appropriate labels to describe the patterns of the ratios. First, the ratios with insignificant loadings were identified, i.e. ratios loading below |.35|, given that the sizes of the datasets used were all above 250 and below 350 [see Table 7.1 and Table 3.2 in Hair et al., (1998, p. 112)]. All ratios loaded significantly onto the components in 2001; in 2002 and 2003, however, X40 failed to load onto any component, as did ratio X34 in 2004 (see Table 4.4 for the ratio descriptions). Second, ratios with several moderate size loadings were identified. Year 2002 had the least number of ratios with cross-loadings (13 ratios) whereas year 2001 had the largest number (17 ratios). Ratios that loaded significantly onto more than three components were X36, X15, X3 and X21 in 2001; X5 in 2002; X3, X15 and X5 in 2003; and, X15, X36 and X28 in 2004.

Table 7.7 gives the labels of all the components identified in years 2001-2004 (see Table 5.8 for the full names of the components); the table also gives labels of the factors derived in the previous section for year 2005 for comparison purposes. As the table shows, all patterns of ratios were found to be meaningful (that is, could be labelled successfully) except for one case only: C9 in year 2003 which was therefore not assigned a name.

Table 7.7: Labels assigned to components of saving banks (2001-2005)*

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
2001	Prof	Ln&Ls	M(C)-II	Sh-t liq	Eff	RBC	AQ-I	AQ-II	CG	IS	Grth
2002	Prof	Ln&Ls	M(C)-II	Sh-t liq	AQ-I	RBC	Fnd-II	CG	AQ-II	Eff	IS
2003	Prof	Ln&Ls	Sh-t liq	M(C)-II	AQ-I	RBC	AQ-II	CG	No Name	Grth	IS
2004	Prof	Ln&Ls	RBC	Sh-t liq	AQ-I	M(C)-II	Eff	Fnd-II	CG	AQ-II	IS
2005	Prof	M(C)-II	Ln&Ls	AQ-I	RBC	Sh-t liq	Eff	AQ-II	CG	IS	-

* Refer to Table 5.8 for full names of the components.

Also, it can be seen from the table that nine components appeared consistently in the solutions of all the years covered; these were Prof, Sh-t liq, M(C)-II, Ln&Ls, AQ-I, AQ-II, RBC, CG and IS. Inconsistent components (that is, those found in only some of the years) were: Eff (identified in all years except for 2003), Grth (years 2001 and 2003), and Fnd-II (years 2002 and 2004). Further details about the content of the components are given in the following section where different comparison methods were used to check the time stability of the patterns.

7.4 Short-term stability of financial patterns of saving banks over 5 years

One of the general aims of this chapter is to compare the financial patterns of savings and commercial banks. Before doing so, the short-term stability of the savings banks' patterns was investigated in order to see whether they exhibited the same level of time stability as shown by patterns for commercial banks in Chapter 5. In carrying out the stability check, the same comparison methods were used as in earlier chapters; these included: visual checking, analysing correlation and congruency coefficients, and transformation analysis.

7.4.1 Visual comparison

The first step in checking the short-term stability of the patterns involved a visual inspection of the financial patterns identified for the period 2001-2005. By using PCA with a varimax rotation, the 56 ratios of U.S. savings banks were grouped into 11 components in 2001-2004 and 10 components in 2005. These factor solutions accounted for a proportion of variance ranging from 72.18% in 2005 to 75.95% in 2004.

Cumulative proportion of variance explained. The visual check began by looking simultaneously at the cumulative proportion of variance explained by the components of the yearly solutions. If the components in the different years account for a similar proportion of variance, this could be considered as a sign of short-term stability. Table 7.8 gives the cumulative percentage of variance explained by the financial patterns of savings banks over the period from 2001 to 2005. Figures shown in the table are for the components after a varimax rotation was applied. The reason for underlining this point is that rotating the solution alters the proportion of variance explained by individual components while the total amount of variance explained by the solution remains unchanged (Stevens, 2002, p. 392). Therefore, it was more relevant to compare the factors' contribution to the total variance after rotation and not to use the figures in the initial solutions.

By looking into Table 7.8, the percentage of variance explained by the ten components of 2004 was the highest in the period covered by the study, whereas the lowest level was explained by the components of 2002. In addition, the amount of variance accounted for by each of the first six components in 2003 was fairly close to that of the components in 2005. However in 2003, after C7, the cumulative explained variance fell below 2005's numbers. As for years 2001, 2002 and 2004, the proportion of variance explained by the first three components was rather similar. However, after that, the proportion of variance explained by the 2002 components became the lowest, and the components of 2004 started to explain a higher and higher proportion of the variance until, by C10 and C11, the components accounted collectively for the highest proportion of the variance over the five years.

Table 7.8: Cumulative proportion of total variance explained for savings banks (2001-2005)

	2001	2002	2003	2004	2005
C1	12.99	11.94	12.47	11.97	13.80
C2	21.81	21.69	23.69	21.98	23.77
C3	29.63	29.86	32.76	29.48	32.44
C4	37.22	36.70	40.89	36.80	40.32
C5	44.65	43.49	47.70	44.04	47.45
C6	51.06	49.81	54.05	51.14	54.58
C7	56.81	55.74	58.74	57.76	60.60
C8	61.98	60.73	63.16	62.96	65.22
C9	66.69	65.57	67.39	68.10	68.72
C10	70.43	70.34	71.12	72.48	72.18
C11	73.80	74.14	74.81	75.95	-

Components' relative position in solutions. The visual comparison was further enriched by evaluating the relevant position of the components in the different solutions. As mentioned in earlier chapters, in the output of PCA, factors appear in a descending order according to their contribution in explaining the variance in the data. Thus, when components have the same order in the different solutions, this can be regarded as a sign of a potential degree of similarity between the solutions. Therefore, another look at Table 7.7 was taken to observe the order in which the components were extracted over the years.

As can be seen from Table 7.7, only Prof maintained its position as the first component over the period; it was followed by Ln&Ls as the second component to be extracted for the majority of years. The factors Sh-t liq, AQ-I, RBC, CG and IS held the same relative position in three of the five years. The rest of components, however, were extracted in a different order over the years. Having said that, it is important to clarify that even when two components hold the same label, their content might not be exactly the same. It is meant by the content of a component the ratios loading significantly onto the component, together with the magnitude of the loadings. While checking the ratios with significant loadings can be carried out visually, assessing the magnitude of the loadings requires the use of technical methods; the following paragraphs elaborate these points further.

Ratios forming components. Checking whether components which held the same name over the years were made up of the same ratios was carried out by closely examining the rotated component matrices. These are given in Table 7.5 and Appendix 7.2. In the following paragraphs, the ratios are referred to only by their numbers; the full names of ratios are listed in Table 4.4 and a description of their components is given in Appendix 4.1.

To start with, it should be recalled that the 56 ratios of the savings banks were grouped into different components in every year between 2001 and 2005. First, there were nine factors appearing for every year over the period 2001-2005 (Prof, Sh-t liq, M(C)-II, Ln&Ls, AQ-I, AQ-II, RBC, CG and IS). Besides this, three components could not identified for all years (Eff, Grth and Fnd-II), in addition to one component which was found to be meaningless (that is, it could not be labelled).

First, the content of the Prof Component was checked. This component consisted of six ratios (X7, X8, X9, X10, X33 and X53) loading highly in all five years. However, as mentioned in Subsection 7.3.1, in year 2005, three CG ratios (X54, X29 and X26) had their highest loadings onto Prof; at the same time, these ratios significantly loaded onto CG. Also, X25 loaded onto Prof in 2001, as did X6 in 2004.

Ln&Ls was made up of Ln&Ls ratios (X48, X49 and X23), in addition to some M(Y)-I ratios (X1, X3, X13 and X15) which, in contrast to commercial banks, did not cluster under a separate component. Although M(Y)-I ratios loaded highly onto Ln&Ls, they had significant loadings onto M(C)-II in some years. In addition, in year 2003, two Eff ratios (X5 and X35) had their highest loadings onto Ln&Ls. This could explain why no Eff component was identified in that year (2003).

Sh-t liq was generally defined by the following ratios: X45, X39, X43, X46, X22, X47 and X31. In year 2003, however, X41 and X42 loaded onto Sh-t liq, whereas X31 loaded on Grth instead and X47 loaded onto Eff.

M(C)-II was composed of ratios X38, X14 and X2. However, there were a few other ratios which loaded onto M(C)-II in different years; these, however, did not affect its label because of the moderate size of their loadings (X41, X44, X42, X36, X40, X37, X11 and X28).

As for AQ-I, it was composed of ratios X6, X16, X17, X18, X21 and X27, which defined the component in the first three years, in addition to X34 which was originally one of the Eff ratios. In year 2004, X6 left AQ-I and loaded instead onto Prof, as mentioned earlier, whereas X34 failed to load significantly onto any factor. Also, in year 2004, X36 joined AQ-I with a moderate loading. In 2005, X6 and X34 loaded back onto the factor, as did X30 with a small yet significant loading. As for the second asset quality component (AQ-II), its content appeared to be consistent over the period as it had only two ratios (X19 and X20) with high loadings.

Three main ratios contributed to the labelling of RBC: X24, X55 and X56. Other ratios with smaller sized loadings were found to be associated with the factor in some years (X12, X52 and X30). CG, on the other hand, was generally formed by X25, X29, X54 and X26. However, in year 2005, X25 was the only ratio to load highly onto CG whereas the other ratios loaded onto Prof. Nevertheless, the CG label was assigned to the factor as discussed earlier (Subsection 7.3.1). In year 2002, CG included ratios X28 and X30 with moderate loadings.

The last consistent factor to be checked was IS; it was defined primarily by X50 and X51. In years 2004 and 2005, X40 had some significant loadings onto IS; however, this ratio does not seem of much importance since it failed to load onto any factor in the years 2002 and 2003.

As for the less consistent components, Eff was identified in all years except for 2003. Ratios that largely influenced the labelling of this component were X4, X5, X11 and X35. In addition, in 2001, two M(Y)-I ratios (X3 and X15) loaded onto the Eff factor. In 2002, however, X11 loaded onto M(C)-II whereas X37 joined the Eff factor. Furthermore, in 2004, X37 and X12 loaded onto the Eff factor, as also did X12 in 2005.

Grth was another inconsistent factor identified for only two years (2001 and 2003). Ratios forming this factor were X28, X30 and X32. However, in 2003, X31 also joined the Grth component with a moderate loading.

The Fnd-II factor was identified in two years: 2002 and 2004 and comprised the ratios X41, X42, X44 and X32. Further to these ratios, X52 loaded onto this factor in 2002 and X28 also loaded onto the factor in 2004.

The undefined factor was comprised of the following ratios: X37, X4, X47 and X44. No appropriate name was found to describe these ratios as a group. Thus, this factor remained unlabelled.

Briefly, this subsection took a general look at the rotated component matrices and visually compared the content of the components over the five years. In the following subsection, the correlations between the components were checked over the study period.

7.4.2 Correlation coefficients

The starting point of the technical comparison between factor solutions over time involved checking the correlation coefficients. The stability of financial patterns was judged based on the absolute size of the correlation coefficients calculated between components of the different years where components with high correlation coefficients in absolute terms were considered as stable over time. The correlation matrices for all the components in all the possible pairs of years (10 pairs) were calculated. A summary of the results is given in Table 7.9; in the table the correlation coefficients of the nine consistent components are reported first, followed by those of the three less consistent components.

Table 7.9: Correlation coefficients between components of savings banks (2001-2005)

	Prof	Sh-t liq	Ln&Ls	M(C)-II	AQ-I	AQ-II	RBC	CG	IS	Eff	Grth	Fnd-II
2001-2002	0.973	0.976	0.944	0.779	0.926	0.953	0.956	0.854	0.913	-0.671	-	-
2001-2003	0.972	0.945	0.915	0.843	0.937	0.917	0.950	0.907	-0.859	-	0.647	-
2001-2004	0.948	0.952	0.947	0.850	0.910	0.848	-0.913	0.887	-0.793	-0.892	-	-
2001-2005	0.948	-0.928	0.917	0.841	0.920	0.899	-0.930	0.795	-0.818	0.917	-	-
2002-2003	0.970	0.931	0.960	0.960	0.963	0.919	0.965	0.883	-0.917	-	-	-
2002-2004	0.945	0.953	0.973	0.943	0.935	0.882	-0.954	0.948	-0.895	0.776	-	0.878
2002-2005	0.937	-0.944	0.936	0.719	0.933	0.892	-0.935	0.752	-0.894	-0.601	-	-
2003-2004	0.938	0.948	0.965	0.929	0.932	0.904	-0.946	0.928	0.929	-	-	-
2003-2005	0.968	-0.939	0.943	0.771	0.926	0.923	-0.942	0.804	0.862	-	-	-
2004-2005	0.907	-0.974	0.961	0.754	0.938	0.930	0.969	0.827	0.929	-0.880	-	-

1. Refer to Table 5.8 for the full names of the components.
2. All correlations are significant at 0.05 level (2-tailed).
3. When no component appeared in either year, a (-) sign is shown instead.

By considering the absolute size of the correlation coefficients in the adjacent years reported in Table 7.9, it can be seen that RBC, Ln&Ls, Sh-t liq were the most stable of the nine components constantly identified over the period. The correlation coefficients for these components ranged between -.946 and .969 for RBC, .944 and .965 for Ln&Ls, and .931 and .976 for Sh-t liq. Prof and AQ-I showed less stability as their correlation coefficients in the adjacent years ranged between .907 and .973 for Prof and between .926 and .963 for AQ-I. AQ-II and IS, on the other hand, showed a lower, yet acceptable level of stability in the short-term as the range of their correlation coefficients was between .909 and .953 for AQ-II, and between .913 and .929 for IS. The least stable over the period amongst the consistent components were CG and M(C)-II; the ranges of coefficients were .827 and .928, and .454 and .960, respectively.

A closer look was then taken at the correlation coefficients calculated between all the pairs of years for the nine consistent components. RBC had its smallest correlation coefficient in absolute terms (-.913) between 2001 and 2004; the highest correlation coefficient, however, for this component (.969) was found between 2004 and 2005. Ln&Ls and Sh-t liq had their smallest correlation coefficients and thus were the least stable between 2001 and 2005 (.917 and -.928, respectively). They exhibited their highest level of stability between 2002 and 2004 for Ln&Ls (.973) and between 2001 and 2002 for Sh-t liq (0.976).

AQ-I was most stable between 2002 and 2003 (.963) whereas the lowest stability was found between 2001 and 2004 (.910). Moving on to Prof, the pattern of changes in its stability over time was more apparent. Between 2001 and 2002, Prof showed its highest stability level (.973). In the following adjacent years, however, Prof showed a gradual decrease in its stability until it reached its lowest level between 2004 and 2005 (0.907). Furthermore, the stability level for Prof fell gradually when measured between non-adjacent years. The only exception to this was between 2003 and 2005 where the correlation coefficient reached .968.

In regard to the components that appeared to have an average stability level, namely, IS and AQ-II, although both factors showed an acceptable level of stability in adjacent years (correlations over .9), their stability seemed to fall away between non-adjacent years. The lowest coefficients were found between 2001 and 2004 (-.793 and .848 for the two factors, respectively).

CG and M(C)-II were the least stable amongst all the consistently identified factors. The best stability level for M(C)-II was found over the period 2002-2004 as the correlation coefficients for the pairs involving this period were all over .9. However, for the other pairs, the coefficients were as low as .719 (2002-2005). Regarding CG, the best level of stability was between 2002 and 2004 (.948); also, in the pairs 2003-2004 and 2001-2003 CG was fairly stable (.928 and .907). In the other pairs of years, CG was clearly unstable.

Concerning the components that were found for some years, Eff, which emerged as a significant component in all years except 2003, was clearly unstable over the period. Its highest correlation coefficient was .917 between 2001 and 2005. As for the other pairs of years, its coefficients were smallest, in absolute terms, in the pairs involving year 2002 (-.671 in 2001-2002, .776 in 2002-2004 and -.601 in 2002-2005). Furthermore, by examining Eff in the correlation matrices of the ten pairs of years[118], rather high significant correlation coefficients were found between Eff and two other components: Ln&Ls and M(C)-II.

[118] These matrices are not shown here due to space limitations.

Regarding the Grth component which was identified in two years only (2001 and 2003), in these years, the content of this component was not exactly the same given its poor correlation coefficient (.647). Also, by checking the correlation matrices involving years 2001 and 2003, some sizeable correlations were found between Grth and other factors (CG, M(C)-II, AQ-I, Fnd-II, RBC).

Similar to Grth, Fnd-II which was also identified in only two years: 2002 and 2004, showed rather unsatisfactory level of stability (.878). Over these two years, Fnd-II also had significant correlations with Sh-t liq, M(C)-II and Grth.

In regard to the undefined component in 2003, by referring to the relevant correlation matrices involving 2003 (not shown), high correlations in absolute terms were found between this factor and Eff. The absolute size of these correlations ranged from .541 (2001-2003) to -.853 (2002-2003). Also, the undefined component had significant correlations with Ln&Ls (2001, 2002, 2003), Fnd-II (2004) and RBC (2005).

To sum up, the correlation analysis revealed that RBC, Ln&Ls and Sh-t liq were the most stable components in the short-term. Other factors like Prof, AQ-I, AQ-II and IS also showed acceptable time stability levels. CG and M(C)-II were the least stable over time; however, the correlations of these components were of a good size in some of the years. Factors like Grth, Fnd-II and the undefined factor, did not show a satisfactory level of stability; however, significant correlations were found between these factors and some of the consistent ones such as Sh-t liq, CG and M(C)-II, amongst others.

In the following subsections, congruency coefficients and transformation analysis were used to strengthen the investigations into the stability of components in the short term. The findings of all these methods should be considered collectively in answering the question of the extent to which savings banks' financial patterns are stable over the short term.

7.4.3 Congruency coefficients

Congruency coefficients were calculated for components holding the same labels over the period 2001-2005. The results are summarised in Table 7.10 which first shows the coefficients between all possible pairs of years (10 pairs) for the nine consistent components, followed by those of the less consistent components; the table also gives the means of the coefficients using the absolute value of the coefficients similar to the approach followed in the previous chapters (Ketz et al., 1990, p. 71). The significance of the coefficients was assessed using Table 3.1 from Richman and Lamb (1985, Appendix).

Table 7.10: Serial congruency coefficients between components of saving banks (2001-2005)

	Prof	Sh-t liq	Ln&Ls	M(C)-II	AQ-I	AQ-II	RBC	CG	IS	Eff	Grth	Fnd-II
2001-2002	0.976	0.976	0.952	0.777	0.926	0.956	0.956	0.854	0.913	-0.665	-	-
2001-2003	0.974	0.944	0.927	0.849	0.937	0.925	0.950	0.908	-0.845	-	0.655	-
2001-2004	0.952	0.952	0.954	0.848	0.910	0.862	-0.913	0.887	-0.771	-0.888	-	-
2001-2005	0.953	-0.926	0.929	0.853	0.920	0.904	-0.930	0.795	-0.801	0.915	-	-
2002-2003	0.970	0.928	0.966	0.958	0.962	0.925	0.964	0.886	-0.908	-	-	-
2002-2004	0.950	0.953	0.978	0.944	0.934	0.890	-0.952	0.950	-0.878	0.776	-	0.889
2002-2005	0.941	-0.943	0.947	0.707	0.932	0.889	-0.934	0.749	-0.881	-0.586	-	-
2003-2004	0.939	0.945	0.970	0.929	0.932	0.913	-0.945	0.929	0.929	-	-	-
2003-2005	0.974	-0.934	0.952	0.773	0.926	0.923	-0.942	0.803	0.863	-	-	-
2004-2005	0.911	-0.973	0.968	0.744	0.939	0.931	0.970	0.824	0.930	-0.869	-	-
Mean	0.954	0.947	0.954	0.838	0.932	0.912	0.946	0.858	0.872	-	-	-

1. Refer to Table 5.8 for the full names of the components.
2. Mean values are calculated using the coefficients in absolute terms (Ketz et al., 1990, p. 71).
3. When no component appeared in either group, a (-) sign is shown instead.

The congruency analysis began by examining the mean values of the coefficients in Table 7.10. As can be seen from the table, means were calculated only for the nine consistent factors. By referring to Table 3.1, five of the nine components had 'good' overall matches: these were Ln&Ls, Prof, Sh-t liq, RBC and AQ-I. However, mean matches for the rest of the consistent factors, AQ-II, IS, CG and M(C)-II, were 'borderline'.

The congruency coefficients in the different pairs of years were then examined to see whether components maintained the same level of stability over the years. First, regarding the five components with average 'good' matches, Ln&Ls and Sh-t liq had 'good' matches in all 10 pairs of years. Matches of Prof, RBC and AQ-I, however, were all ‘good’ except for one pair that had a ‘borderline’ match; these were the cases in 2004-2005 for Prof and 2001-2004 for the other two factors. Regarding the components with ‘borderline’ mean matches, AQ-II had ‘good’ matches in five pairs of years and ‘borderline’ matches in the rest. Furthermore, IS, CG and M(C)-II had ‘terrible’ matches in some years besides other ‘good’ matches.

The last three columns in Table 7.10 were then studied to check the consistency of matches for the less consistent components (Eff, Grth and Fnd-II) over the years in which they were identified. As the table shows, Eff had ‘borderline’ matches in the pairs formed by 2001, 2004 and 2005. However, whenever year 2002 was included in the comparison, Eff matches became ‘poor’ or ‘terrible’. Lastly, Grth was compared between 2001 and 2003; its match between the two years was found to be ‘terrible’. Finally, the Fnd-II match between 2002 and 2004 could be described as ‘borderline’.

In addition, the congruency coefficients between each of the inconsistent components and all the components in other years were calculated and any sizeable coefficients were examined[119]. For Eff, the highest congruency coefficients were found with Ln&Ls and M(C)-II. However, none of these coefficients exceeded .68 which, according to Table 3.1, meant the matches could be described as ‘terrible’. Eff also had some sizeable coefficients with the undefined component in 2003; however, these matches were generally ‘terrible’. Furthermore, over the years, Grth had some sizeable yet ‘terrible’ matches with Fnd-II, CG, RBC and AQ-I, amongst others. Finally, significant coefficients were found between Fnd-II and components Sh-t liq, M(C)-II, Ln&Ls and Grth; however, these matches were generally ‘terrible’, with the highest coefficient being ‘poor’ between Fnd-II (2002) and M(C)-II (2005).

In summary, the findings of the congruency coefficients in this subsection supported those of the correlation analysis reported in Subsection 7.4.2. However, congruency analysis labels could be assigned to the relationships in order to describe the significance of the matches. This was not possible in the correlation analysis in which the relative significance of the coefficients was judged more intuitively. In the next

[119] Detailed results of this part of analysis are not reported due to space limitations.

subsection, transformation analysis was used to uncover further details regarding the short-term stability of the financial patterns for savings banks.

7.4.4 Transformation analysis

As explained earlier in this study, there are two advantages of using transformation analysis to assess the stability of financial patterns (Martikainen et al., 1995b, p. 1704). First, the 'normal' or 'explained' shifts of factors between two solutions can be uncovered through the transformation matrix. Second, the 'abnormal' or 'unexplained' transformation between two factor solutions can be revealed through the residual matrix. Thus, compared to correlation analysis and congruency coefficients, transformation analysis not only gives further insight into the degree of similarity between two factor solutions, it also uncovers the variables that stand behind any dissimilarity (Martikainen et al., 1995b).

Transformation matrices. Transformation analyses were performed between factor solutions in the adjacent years over the period 2001-2005; the software used was SURVO 2.51. This resulted in the four transformation matrices summarised in Table 7.11. Before these matrices are examined, it should be recalled that, as mentioned in Chapter 3 (Subsection 3.4.4), the two solutions under comparison in transformation analysis are considered as similar when the diagonal elements of the transformation matrix are close to unity and the off-diagonal elements are close to zero. The diagonal elements are considered to be close enough to unity when they are equal to or greater than .95, according to the relevant literature (Martikainen et al., 1994, p. 63). However, since the components in the current study were extracted in a different order over the different years, the close-to-unity elements in the transformation matrices were not necessarily the diagonal ones. This, however, should not cause any concern as the absolute size of these elements was assessed; such elements are referred to later in this chapter as the coefficients of coincidence.

As mentioned earlier, the transformation matrices were estimated between solutions for adjacent years: i.e. 2001-2002, 2002-2003, etc. Thus, rows in the transformation matrices represent components of the first solution (the first year) whereas columns represent components of the second solution (the second year). A coefficient of coincidence below .95 indicates some transference in the meaning of the component between the two periods. The observed transformation could be tied to components in the second period; these are the components with sizeable elements. Thus, for a component identified in the two periods which had a coefficient of coincidence below .95, the sizeable elements in its row lead to those components into which that particular component had transferred over time. For a component identified only in one period, one of the following two cases was considered. First, if the component was identified in the first period, the row of this component in the transformation matrix was checked to uncover, guided by the sizeable elements in absolute terms, the components of the second period which were involved in the transference. Second, if a component was identified in the second period, its column in the transformed matrix was examined to uncover those components of the first period from which the factor had evolved. Nevertheless, it should be noted that, in Subsection 7.5.4 where the similarity of the components for commercial and savings banks was checked, both the rows and columns of the transformation matrix needed to be examined for each component as the rows represented commercial banks' components and the columns represented savings banks' components in a specific year.

The transformation matrices summarised in Table 7.11 were examined, as explained in the paragraph above. In summarising the findings of this stage of analysis, the coefficients of coincidence for the consistent components (that is, those which were identified in all five years) were first reported. By considering the .95 criterion, four components showed a satisfactory stability level over the period between 2001 and 2005; these were Ln&Ls, AQ-II, RBC and IS. Furthermore, the level of stability for Prof, AQ-I and Sh-t liq was satisfactory only between certain years over the period covered in the study. Other components, CG and M(C)-II, had their coefficients of coincidence below the acceptable level of .95 in all the matrices of the adjacent years.

Regarding the less consistent components, the coefficients of coincidence of Eff in the matrices of 2001-2002 and 2004-2005 were far below .95 which clearly indicated the dissimilarity of this component over these years. In the pairs of years involving 2003, the stability of Eff could not be checked since this component was not identified in that year. For the same reason, the stability of Grth and Fnd-II could not be assessed as each of them was identified only in two non-adjacent years (2001 and 2003 for Grth, and 2002 and 2004 for Fnd-II). Also, time stability could not be assessed for the undefined factor as it was found only for 2003.

After studying the coefficients of coincidence for the components across the different years, the absolute size of the other elements in the transformation matrices was then assessed for the components that had unsatisfactory coefficients of coincidence (that is, coefficients below .95), and also for the inconsistent components.

The Prof row in the matrix for 2004-2005, where the coefficient of coincidence fell slightly below .95 (.938), contained an element of -.232 which indicated that a small amount of transference occurred between Prof and CG in year 2005[120]. Similarly, the coefficients of coincidence for AQ-I were of a good size, yet lower than .95 in the periods 2001-2002 (.918) and 2004-2005 (.943). The transference found for this factor in both periods was into Eff (the elements were .349 and .107, respectively). Furthermore, the Sh-t liq factor had low coefficients of coincidence (.787 and .746, respectively) over the periods 2002-2003 and 2003-2004. The transference observed for Prof in 2002-2003 occurred into the undefined factor (-.351), Grth (-.349) and M(C)-II (-.327), amongst others. In 2003-2004, Prof transferred into Fnd-II (.515) and M(C)-II (.320), amongst others.

Coefficients of coincidence for M(C)-II were lower than the .95 criterion in all four pairs of comparisons (.701, .934, .899 and .744, respectively). The largest transference of M(C)-II occurred between 2001 and 2002 (.588) and this could be primarily tied to Fnd-II whereas the transference that occurred over the other different years involved Eff, AQ-I and Sh-t liq, amongst others.

[120] Recall here that only the absolute values in the transformation matrices matter, according to Martikainen et al. (1995a, p. 40).

Table 7.11: Time-series transformation matrices of components of saving banks (2001-2005)

			C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**
		2002	Prof	Ln&Ls	M(C)-II	Sh-t liq	AQ-I	RBC	Fnd-II	CG	AQ-II	Eff	IS
2001	**C1**	Prof	**0.962**	0.035	-0.174	-0.037	0.021	0.037	0.182	0.030	-0.018	0.080	0.003
	C2	Ln&Ls	-0.002	**0.978**	0.088	0.019	-0.119	-0.081	-0.073	-0.038	-0.026	0.040	-0.074
	C3	M(C)-II	0.019	0.043	0.701	-0.100	0.224	0.159	0.588	0.030	0.011	-0.253	0.102
	C4	Sh-t liq	-0.010	0.002	-0.031	**0.977**	0.008	0.026	0.203	0.025	0.035	0.028	-0.001
	C5	Eff	-0.083	0.135	-0.535	-0.034	0.244	0.078	0.166	0.050	-0.066	-0.761	0.090
	C6	RBC	-0.039	0.060	-0.061	-0.008	-0.065	**0.977**	-0.112	0.039	-0.027	0.109	-0.078
	C7	AQ-I	-0.052	0.094	-0.085	-0.003	0.918	-0.010	-0.092	0.054	0.011	0.349	-0.076
	C8	AQ-II	-0.013	0.040	-0.080	-0.053	-0.018	0.023	0.063	0.044	**0.991**	-0.008	-0.015
	C9	CG	0.109	-0.008	0.226	0.074	0.016	-0.034	-0.391	0.858	0.011	-0.200	0.024
	C10	IS	-0.018	0.072	-0.052	0.005	0.002	0.046	-0.057	0.001	0.012	0.159	**0.980**
	C11	Grth	-0.227	0.051	-0.336	-0.156	-0.169	-0.046	0.605	0.500	-0.101	0.386	-0.049
		2003	Prof	Ln&Ls	Sh-t liq	M(C)-II	AQ-I	RBC	AQ-II	CG	No Name	Grth	IS
2002	**C1**	Prof	**0.987**	-0.035	0.049	0.027	-0.054	-0.051	-0.036	-0.003	0.073	-0.092	0.025
	C2	Ln&Ls	0.029	**0.989**	0.059	0.079	0.004	0.002	-0.061	-0.018	-0.075	-0.045	0.001
	C3	M(C)-II	-0.060	-0.102	0.263	0.934	-0.040	-0.128	-0.059	0.045	-0.070	-0.117	0.050
	C4	Sh-t liq	-0.051	-0.064	0.787	-0.327	-0.051	-0.108	-0.059	0.050	-0.351	-0.349	0.045
	C5	AQ-I	0.035	-0.008	0.034	0.013	**0.986**	-0.027	-0.003	0.083	0.051	-0.107	0.060
	C6	RBC	0.026	-0.022	0.129	0.083	0.006	**0.974**	-0.040	0.008	0.046	-0.135	-0.061
	C7	Fnd-II	0.046	0.022	0.488	0.018	0.090	0.021	0.135	-0.275	0.212	0.751	-0.218
	C8	CG	0.039	0.028	0.053	-0.013	-0.042	0.035	0.076	0.940	-0.073	0.311	-0.020
	C9	AQ-II	0.019	0.045	0.004	0.044	-0.013	0.006	**0.975**	-0.018	-0.018	-0.200	-0.061
	C10	Eff	0.112	-0.051	-0.209	0.060	0.099	0.099	0.035	-0.159	-0.898	0.287	-0.059
	C11	IS	0.002	-0.012	-0.053	0.019	0.030	-0.088	-0.100	0.063	-0.008	-0.204	**-0.966**

			C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
		2004	Prof	Ln&Ls	RBC	Sh-t liq	AQ-I	M(C)-II	Eff	Fnd-II	CG	AQ-II	IS
2003	**C1**	Prof	**0.974**	0.034	-0.030	-0.024	0.099	-0.086	0.153	0.036	0.035	0.037	0.065
	C2	Ln&Ls	-0.021	**0.983**	0.013	-0.038	0.074	-0.003	-0.148	-0.044	0.038	0.005	0.023
	C3	Sh-t liq	0.070	0.035	-0.022	0.746	-0.115	0.320	-0.207	0.515	-0.091	0.059	0.014
	C4	M(C)-II	0.025	0.031	-0.102	-0.329	0.027	0.899	0.259	0.004	-0.058	0.029	-0.006
	C5	AQ-I	-0.083	-0.085	0.032	0.023	**0.974**	0.018	-0.105	0.147	-0.012	-0.022	0.050
	C6	RBC	-0.054	0.007	**-0.963**	-0.084	-0.002	-0.128	-0.021	0.169	0.061	-0.028	0.114
	C7	AQ-II	-0.059	-0.001	0.005	-0.075	0.013	-0.072	0.046	0.065	-0.017	**0.988**	0.047
	C8	CG	0.036	-0.080	0.002	0.062	-0.002	0.164	-0.281	-0.146	0.925	0.060	-0.043
	C9	No Name	0.141	-0.107	0.060	-0.455	-0.109	0.059	-0.800	0.233	-0.205	0.002	-0.077
	C10	Grth	-0.098	0.061	0.209	-0.329	-0.081	-0.168	0.324	0.774	0.289	-0.105	0.022
	C11	IS	-0.037	-0.035	0.111	-0.024	-0.063	0.040	-0.078	-0.044	0.010	-0.040	**0.984**
		2005	Prof	M(C)-II	Ln&Ls	AQ-I	RBC	Sh-t liq	Eff	AQ-II	CG	IS	-
2004	**C1**	Prof	0.938	0.031	-0.043	-0.011	-0.015	0.018	0.004	-0.085	-0.232	0.019	
	C2	Ln&Ls	0.050	0.146	**0.987**	0.030	0.009	0.011	0.014	0.015	0.023	0.016	
	C3	RBC	-0.012	-0.030	-0.000	-0.004	**0.991**	-0.052	-0.071	-0.030	-0.075	0.038	
	C4	Sh-t liq	-0.026	0.063	0.006	-0.004	-0.055	**-0.981**	-0.004	0.020	-0.002	-0.001	
	C5	AQ-I	0.072	0.010	-0.037	0.943	0.016	-0.057	0.107	0.038	-0.056	-0.006	
	C6	M(C)-II	-0.111	0.744	-0.106	0.201	0.003	0.131	-0.276	-0.133	0.199	0.024	
	C7	Eff	0.088	0.057	-0.001	-0.060	-0.054	-0.066	-0.870	0.111	-0.133	-0.020	
	C8	Fnd-II	0.082	0.640	-0.100	-0.253	0.055	-0.064	0.387	0.046	-0.151	-0.054	
	C9	CG	0.287	-0.045	-0.031	-0.040	0.078	-0.053	-0.001	0.037	0.926	-0.014	
	C10	AQ-II	0.039	0.064	-0.026	0.009	0.030	0.053	0.037	**0.978**	-0.006	0.013	
	C11	IS	-0.006	0.015	-0.019	-0.015	-0.036	-0.009	0.013	-0.001	0.004	**0.997**	

1. Elements above .950 are in bold (Martikainen et al., 1994, p. 63).
2. Refer to Table 5.8 for the full names of the components.

CG also showed an unsatisfactory level of stability based on the .95 criterion. Nevertheless, its coefficients of coincidence were of a significant magnitude in the adjacent years over the period 2002-2005 (.940, .925 and .926). Between 2001 and 2002, however, it had a relatively lower coefficient (.858); over this period, CG transferred into a few components, amongst which were Fnd-II (-.319) and M(C)-II (.226), amongst others.

Regarding the Eff component, between 2001 and 2002, Eff had a coefficient of coincidence of -.761; this is a very low figure indicating that a change in the practical meaning of the component had occurred. As the first matrix in Table 7.11 shows, Eff transferred into M(C)-II (-.535) and AQ-I (.244), amongst others. Between 2004 and 2005, Eff showed a better level of stability with a coefficient of coincidence of -.870; however, a small amount of transference into other factors had occurred, with the highest being into Grth (-.133). In the matrix for 2002-2003, Eff transferred into other components where the highest amount of transference occurred into the undefined factor (-.898). In the matrix of the following period (2003-2004), Eff in 2004 appeared to evolve primarily from the undefined factor (-.800) besides many other components (see the Eff column in the matrix of 2003-2004 in Table 7.11).

A look at the row of the Grth factor in the matrix for 2001-2002 revealed that the factor had transferred into many factors, including Fnd-II and CG (elements .605 and .500, respectively). As Grth was not identified in 2002 (although it reappeared in 2003), the 2002-2003 matrix showed Grth in 2003 evolving mainly from Fnd-II (.751) and Sh-t liq (-.349), amongst other factors. Between 2003 and 2004, the factor totally transferred into Fnd-II (.774), Sh-t liq (-.329) and Eff (.324), amongst other factors. This implies that Fnd-II was the main factor engaged in the changes that happened to Grth over time.

Regarding Fnd-II, the components involved in its transference over the five years were M(C)-II [in 2001-2002 (.588) and 2004-2005 (.640)] and Sh-t liq [in 2002-2003 (.488) and 2003-2004 (.515)], as well as Grth as reported above.

Last but not least, concerning the undefined component, a look at the 2002-2003 transformation matrix revealed that this component had evolved mainly from Eff (-.898), besides other factors. Between 2003 and 2004, the undefined component transferred into several components where the largest amount of transference was into Eff (-.800) and Sh-t liq (-.455).

Residual matrices. After examining the changes that had occurred in the practical meaning of the components using transformation matrices, the abnormal transformations which occurred between the solutions in successive years were then studied. This required investigating the residual matrices given in Appendix 7.3[121]. Close-to-zero elements in the residual matrix indicated that the interpretative meaning of the different variables\ratios remained unchanged between the two solutions. Also, the sum of the squared elements (called the abnormal transformation) could be used to identify the ratios (or factors) with the highest abnormal or unexplained transformations. Following previous literature [Martikainen et al. (1995a, p. 41), amongst others), high abnormal transformations are those which are equal to or greater than .20. The four residual matrices are summarised in Appendix 7.3; Table 7.12, however, shows the abnormal and cumulative abnormal transformations for the years covered in the study.

Table 7.12: Cumulative abnormal transformations between components of saving banks (2001-2005)[*]

	2001-2002	2002-2003	2003-2004	2004-2005
X1	0.044	0.041	0.056	0.013
X2	0.021	0.107	0.107	0.043
X3	0.029	0.042	0.062	0.013
X4	0.040	0.131	0.123	0.115
X5	0.021	0.093	0.042	0.024
X6	0.093	0.107	**0.424**	**0.290**
X7	0.015	0.029	0.039	0.033
X8	0.013	0.031	0.029	0.040
X9	0.025	0.031	0.040	0.067
X10	0.024	0.030	0.040	0.068
X11	0.157	0.059	0.150	0.143
X12	0.027	0.067	0.119	0.134

[121] Components appearing in the residual matrix are those of the second period. For instance, for the transformation analysis performed between the solutions of 2001 and 2002, the resulting residual matrix shows the factors for year 2002; so, the observed abnormal changes can be tied to the factors of the second period (i.e. 2002 in the example given).

	2001-2002	**2002-2003**	**2003-2004**	**2004-2005**
X13	0.074	0.040	0.079	0.010
X14	0.027	0.105	0.120	0.041
X15	0.036	0.048	0.070	0.015
X16	0.084	0.062	**0.345**	0.199
X17	0.053	0.041	0.131	0.008
X18	0.024	0.060	0.071	0.013
X19	0.049	0.087	0.065	0.041
X20	0.039	0.076	0.070	0.041
X21	0.072	0.121	0.066	0.093
X22	0.078	0.136	0.188	0.022
X23	0.027	0.072	0.059	0.039
X24	0.021	0.060	0.069	0.016
X25	0.045	0.050	0.095	0.029
X26	0.024	0.034	0.077	0.073
X27	0.067	0.077	0.032	0.035
X28	0.139	0.079	0.136	0.091
X29	0.169	0.092	0.092	0.095
X30	0.141	0.055	0.104	0.185
X31	**0.210**	0.162	**0.227**	**0.210**
X32	**0.253**	0.175	0.114	0.190
X33	0.013	0.021	0.077	0.037
X34	0.188	**0.333**	**0.546**	0.035
X35	0.125	0.087	0.152	0.013
X36	0.134	0.134	0.196	0.078
X37	**0.967**	**1.080**	**0.834**	**0.380**
X38	0.040	**1.143**	**1.221**	0.039
X39	0.042	**1.326**	**1.181**	0.044
X40	0.174	**0.974**	**0.694**	0.080
X41	0.171	**0.419**	**0.470**	0.042
X42	0.076	**2.239**	**2.220**	0.076
X43	0.018	**0.410**	**0.533**	0.039
X44	0.092	**0.443**	**0.363**	0.068
X45	0.018	**1.489**	**1.339**	0.019
X46	0.027	0.091	0.088	0.050
X47	0.053	0.141	0.065	0.067
X48	0.068	0.085	0.110	0.057
X49	0.076	0.052	0.069	0.038
X50	0.030	0.050	0.034	0.049
X51	0.134	0.092	0.037	0.067
X52	0.075	0.177	0.120	0.057
X53	0.034	0.059	0.054	0.051
X54	0.126	0.123	0.078	0.105
X55	0.022	0.039	0.038	0.006
X56	0.022	0.042	0.037	0.006
Cumulative abnormal transformation	**4.866**	**13.451**	**13.995**	**3.934**

1. Figures over .20 are in bold (Martikainen et al., 1995a, p. 41).
2. Refer to Table 4.4 for the full names of ratios.

As can be seen from Table 7.12, between 2001 and 2002 only three ratios showed significant abnormal transformations (X31, X32 and X37). From the first residual matrix in Appendix 7.3, it can be seen that these abnormal transformations could be tied to Eff (1.486), Fnd-II (.868) and M(C)-II (.481). Between 2002 and 2003, however, ten ratios exhibited high abnormal transformations (X34 and X37-X45) which were attributed to Sh-t liq (4.698), M(C)-II (1.621), the undefined factor (1.589), and Grth (1.465), as the bottom of the residual matrix 2002-2003 in Appendix 7.3 shows. Similarly, when the years 2003 and 2004 were compared, the abnormal transformations of 13 ratios were over .20 (X6, X16, X31, X34 and X37-X45). The bottom of the matrix 2003-2004 in Appendix 7.3 shows the components to which the observed abnormal transformations could be attributed. These are Fnd-II (2.636), M(C)-II (2.574), Sh-t liq (2.513), Eff (1.856) and Prof (1.014). Finally, between 2004 and 2005, the abnormal transformations of ratios appeared to be of a smaller size where only three ratios had significant figures (X6, X31 and X37). The bottom of matrix 2004-2005 in Appendix 7.3 shows that the observed abnormal transformations could be tied to Prof (.739), Eff (.653) and M(C)-II (.501).

Overall assessment of abnormal transformations. The last row in Table 7.12 shows the cumulative abnormal transformations for the four pairs of successive years. Given the figures, the highest amount of unexplained transformations occurred between 2003 and 2004 (13.995), as did the period between 2002 and 2003 (13.451). However, between 2001 and 2002, the amount of unexplained changes was rather small (4.866) whereas the smallest level of unexplained changes in the ratios occurred between the solutions of years 2004 and 2005 (3.934).

Significance test for transformation matrices. Chapter 3 (Subsection 3.4.4.1) introduced a significance test for the transformation matrices. The test was intended to check how similar the factor solutions were over a period of time based on the transformation matrices obtained for the adjacent years. In the test, the z-score for the determinants of the product of the transformation matrices and their transposed matrices were calculated. The significance of the z-score was then assessed to test the null hypothesis of no significant differences in factor solutions over the years tested.

Before applying this test, however, and given that some components were not identified in all five years (Eff, Grth, Fnd-II and the undefined factor), these components had to be excluded from the test which left the nine components consistently identified over the period (Prof, Sh-t liq, Ln&Ls, M(C)-II, AQ-I, AQ-II, RBC, CG and IS). Hence, the eigenvectors of these nine components were placed in a similar order across the five years. Then, four transformation analyses were performed using the eigenvectors of the nine components in adjacent years. This resulted in four transformation matrices on which the significance test was based. In these matrices (not given), close-to-unity elements were found on the diagonals whereas the off-diagonal elements were close-to-zero. The test was then applied; all relevant results are summarised in Table 7.13.

Table 7.13: Results of transformation matrices' significance test for savings banks (2001-2005)

Period	$Det(B) = Det(M.M^T)$
2001-2002	1.001537
2002-2003	1.000743
2003-2004	1.001913
2004-2005	0.998584
$\overline{Det(B)}$	1.000694
$\hat{\sigma}$	0.001489
n	4
$z = \frac{\overline{Det(B)} - 1}{\hat{\sigma}}\sqrt{n}$	0.932418

As Table 7.13 shows, the z-score obtained was insignificant at any reasonable level. This means that the null hypothesis of no difference in the nine factors over the period 2001-2005 cannot be rejected. Accordingly, the nine components consistently identified for the savings banks over the period 2001-2005 appear to be stable.

Nevertheless, this test should be interpreted with caution. This is because, as stated earlier in Chapter 3 (Subsection 3.4.4.1), the test is based on the Central Limit Theorem and this requires a minimum of 30 observations to consider the results as reliable. With only four observations (the number of matrices on which the test was based in this part of the study), the results of the test could not be considered as conclusive. Thus, other techniques, such as those previously used in this study (e.g. visual comparisons, correlation coefficients, etc.), should be allowed to contribute to a final judgement concerning the extent to which the financial patterns of savings banks are stable over the short term.

7.5 Cross-sectional stability of financial patterns of savings and commercial banks (2001-2005)

In Chapter 5, the financial patterns of 56 ratios were identified for a sample of U.S. commercial banks; their time stability was also examined over the period 2001-2005. In the current chapter, similar work was carried out using a sample of U.S. savings banks and the same list of 56 ratios. In this section, the financial patterns for the commercial and savings banks were compared on a yearly basis over the period 2001-2005. The comparison was first made visually; then, some technical methods were used including correlation analysis, congruency coefficients, and transformation analysis.

7.5.1 Visual comparison

Table 7.14 summarises some relevant results concerning the patterns of commercial and savings banks. As the table shows, the sample sizes of the commercial banks ranged between 5,732 (2002) and 5,399 (2005) whereas much smaller samples were used for the savings banks; these ranged between 286 (2004) and 274 (2001). These figures are for the banks for which all 56 ratios were available in each of the years 2001-2005.

Table 7.14: Summary of results for commercial and savings banks (2001-2005)

	Commercial					Savings				
	2001	2002	2003	2004	2005	2001	2002	2003	2004	2005
Sample size	5,568	5,732	5,729	5,531	5,399	274	287	284	286	277
Number of factors (PA)	14	13	13	13	13	11	11	11	11	10
% of variance explained	79.44%	77.33%	77.49%	77.25%	77.04%	73.80%	74.14%	74.81%	75.95%	72.18%
insignificant loadings	X37-X40	X40-X52	X37	-	X52	-	X40	X40	X34	X32-X37

Principal component analysis (PCA) with a varimax rotation was used to derive the patterns of both types of banks; also, parallel analysis (PA) was used to decide on the number of factors to retain. As Table 7.14 demonstrates, 14 components were identified for the commercial banks in 2001 and 13 in the following years; however, for the savings banks, 11 components were extracted in 2001-2004 and only 10 in 2005.

Table 7.14 also shows that the solutions for the commercial banks accounted for a higher proportion of the variance compared to those for the savings banks. Also, the range in the proportion of the variance explained over the years was much smaller for the commercial banks (ranging between 77.49% and 77.04%) compared to the savings banks (ranging between 75.95 and 73.80). This could be taken as an indication that the level of short-term stability was higher for commercial banks than for savings banks.

Furthermore, Table 7.14 shows the ratios that failed to load significantly onto any component for both types of banks. However, it should be noted that different significance levels were used for the loadings for the commercial and savings banks. Due to the considerable difference in the sample size, loadings equal to or greater than .30 were considered as significant for the large commercial banks' samples; however, for the smaller sized samples used in the analysis of the savings banks, loadings equal to or greater than .35 were considered significant (see Table 3.2 in Hair et al., 1998, p. 112). Given this, there was not much point in comparing the ratios with insignificant loadings between the two types of bank. Nevertheless, it can be seen from Table 7.14 that ratios X37 and X40 loaded insignificantly in some years for both types of bank. Besides this, X52 did not have sizeable loadings onto any of the commercial banks' factors. Likewise, X32 and X34 had insignificant loadings on the savings banks' factors.

In regard to the labels assigned for the components of the commercial and savings banks, Table 7.15 summarises these labels over the period (refer to Table 5.8 for the full names of the components). As can be seen in Table 7.15, some components were present in the solutions of both types of bank over the five year period; these were

Prof, Sh-t liq, M(C)-II, Ln&Ls, AQ-I, AQ-II, RBC, CG and IS. Also, two components, Eff-I and Grth, were identified in all years for the commercial banks but only in some years for the savings banks. Moreover, some components were identified only for one category of bank; these included M(Y)-I, Eff-II and AQ-III for the commercial banks, and Fnd-II for the savings banks. Finally, two components could not be assigned to a label for the commercial banks whereas only one was left undefined for the savings banks.

Table 7.15: Labels assigned to components of commercial banks (2001-2005)*

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
2001	Prof	Sh-t liq	M(Y)-I	M(C)-II	RBC	Ln&Ls	CG	AQ-I	AQ-II	Eff-I	Grth	Eff-II	IS	AQ-III
2002	Prof	Sh-t liq	M(Y)-I	M(C)-II	Ln&Ls	AQ-I	RBC	CG	AQ-II	Eff-I	Grth	Eff-II	IS	-
2003	Prof	Sh-t liq	M(Y)-I	Ln&Ls	M(C)-II	RBC	AQ-I	CG	AQ-II	Eff-I	Grth	IS	No Name	-
2004	Prof	Sh-t liq	M(Y)-I	Ln&Ls	M(C)-II	RBC	AQ-I	CG	AQ-II	Eff-I	Grth	IS	No Name	-
2005	Prof	Sh-t liq	M(Y)-I	M(C)-II	Ln&Ls	RBC	AQ-I	CG	AQ-II	Eff-I	Eff-II	Grth	IS	-

* Refer to Table 5.8 for full names of the components.

Given these differences in the content of the solutions between commercial and savings banks, some of the visual comparison procedures previously employed were not carried out here. In this case, for example, where the solutions under comparison contained different components, checking the relative position of components to assess their importance in the different solutions was obviously a meaningless exercise. In addition, given this situation, carrying out a visual check on ratios forming each component became problematic. Therefore, other techniques were more effective in comparing the factor solutions for the commercial and savings banks. The following subsections report the findings of these techniques.

7.5.2 Correlation coefficients

Correlation coefficients were calculated between the solutions of commercial and savings banks for each year in the period 2001-2005. Table 7.16 summarises the results where the coefficients for the consistent components are reported first, followed by components that were identified in some years only. In checking the figures in Table 7.16, there is no definite guide on how large the correlation coefficient should be to consider the component as similar in the two solutions. Therefore, what was judged was the relevant stability of a component compared to other components where the larger the correlation in absolute terms, the more analogous the component was between the commercial and savings banks.

As can be seen from Table 7.16, the highest correlation coefficients in an absolute sense were found for Sh-t liq over all five years of comparison (coefficients ranged between .947 and .976). The Prof component also had high correlation coefficients; however, in year 2005, a considerable drop in the correlation figure of Prof was observed (0.896) whereas the highest correlation for Prof was found for year 2004 (.962). RBC came third in the similarity level between the two types of banks; its smallest coefficient in an absolute sense was -.900. Components M(C)-II, CG and AQ-I showed an average level of similarity between the two samples over the period. Correlation coefficients for each of these components exceeded .900 in some years; in the other years, however, the coefficients generally ranged between .800 and .900. The only exception to this was found for CG in 2005 as its coefficient fell to .734. Also, as shown in Table 7.16, the correlation coefficients for IS ranged between -.771 (2001) and .891 (2004); this indicated the existence of some dissimilarity between commercial and savings banks regarding the IS component. Similarly, the correlations for AQ-II fell below .800 in two years (2003 and 2004) whereas their highest correlation was only .830 (in 2001) which reflected the poor consistency of AQ-II in the two samples of banks. Last but not least, the dissimilarity between the commercial and savings banks became more evident for the Ln&Ls component given its the poor correlation coefficients over the years, with the lowest coefficient being found for 2003 (.622).

Following this, similarity in the inconsistent components between the commercial and saving banks was checked starting with Eff. The Eff column in Table 7.16 shows the correlation coefficients between Eff of savings banks and Eff-I of commercial banks. Likewise, the Eff-II column shows the correlations between Eff of savings banks and Eff-II of commercial banks only for the years in which both components were identified in the two samples. Given the absolute size of the coefficients, Eff for the savings banks was more similar to Eff-I than Eff-II for the commercial banks. While no significant correlations were found between Eff and Eff-II, the coefficients for Eff and Eff-I ranged between -.683 (2002) and -.852 (2004); this indicated a rather inconsistent factor structure between the two samples. In regard to Grth, although its correlations between the types of bank were significant, rather low correlation (.768) was reported for 2003 whereas a much higher coefficient (.917) was found for 2001. Given this, it could be concluded that this component was rather dissimilar between the two types of bank. Finally, the last column of Table 7.16 shows the coefficient calculated between the undefined factors for the commercial and savings banks in 2003; this coefficient was small and insignificant which implied dissimilarity in the content of this factor in the two samples.

In order to isolate the interrelationships which existed among the different components for the two types of bank, further examinations of the correlation matrices (not shown) were conducted; further attention was paid to the correlations of M(Y)-I, Fnd-II and AQ-III in particular. These examinations revealed that M(Y)-I, which was found in the solutions of the commercial banks, had some highly significant correlations with Ln&Ls, Eff and AQ-I for the savings banks. Its highest correlations, which were with Ln&Ls, ranged between .657 (2001) and .788 (2003). Thus, it seemed that Ln&Ls for the savings banks might share some common characteristics with the M(Y)-I component for the commercial banks. Furthermore, Fnd-II, which was identified for the savings banks in 2002 and 2004, had highly significant correlations with the followings commercial banks' components: Grth, Sh-t liq and Ln&Ls. The highest correlations were found with Grth (.647 and .764 in 2002 and 2004, respectively). This indicated the existence of some similarity between Fnd-II for the savings banks and the Grth factor for the commercial banks. Last but not least, the AQ-III component found for the commercial banks in 2001 had a highly significant correlation in absolute terms (-.559) with AQ-I for the savings banks which indicated that the two components shared some characteristics. However, it should be noted that this observation was based on the results of one year only, which was the year in which AQ-III was identified for the commercial banks.

Also, exploring the correlation matrices (not shown) revealed that a few components for the commercial banks had fairly high and significant correlations with more than one component for the savings banks. The most prominent of these components was Ln&Ls for the commercial banks which had significant correlation coefficients with

Table 7.16: Correlation coefficients between components of savings and commercial banks (2001-2005)

	Prof	Sh-t liq	Ln&Ls	M(C)-II	AQ-I	AQ-II	RBC	CG	IS	Eff	Eff-II	Grth	No Name
2001	0.946	0.962	0.782	0.833	-0.864	0.832	-0.900	0.928	-0.771	0.802	(-0.251)	0.917	-
2002	0.954	0.950	0.728	0.924	-0.900	0.818	0.915	0.938	-0.830	-0.683	(0.223)	-	-
2003	0.929	0.947	0.622	0.911	-0.877	0.743	0.913	0.878	0.877	-	-	0.768	(0.073)
2004	0.962	0.976	0.734	0.937	-0.897	0.760	0.913	0.927	0.891	-0.852	-	-	-
2005	0.896	-0.965	0.691	0.883	-0.848	0.818	0.900	0.734	0.874	0.846	(-0.237)	-	-

1. Refer to Table 5.8 for the full names of the components.
2. All correlations are significant at 0.05 level (2-tailed) except those in brackets.
3. When no component appeared in either sample, a (-) sign is shown instead.

Table 7.17: Serial congruency coefficients between components of savings and commercial banks (2001-2005)

	Prof	Sh-t liq	Ln&Ls	M(C)-II	AQ-I	AQ-II	RBC	CG	IS	Eff	Eff-II	Grth	No Name
2001	0.949	0.962	0.803	0.843	-0.859	0.840	-0.900	0.914	-0.761	0.802	-0.242	0.919	-
2002	0.958	0.946	0.754	0.919	-0.898	0.826	0.914	0.934	-0.823	-0.681	0.229	-	-
2003	0.933	0.947	0.670	0.914	-0.872	0.755	0.913	0.870	0.877	-	-	0.770	0.073
2004	0.966	0.971	0.759	0.931	-0.890	0.771	0.913	0.922	0.888	-0.851	-	-	-
2005	0.903	-0.958	0.712	0.895	-0.842	0.814	0.900	0.714	0.875	0.842	-0.218	-	-
Mean	0.942	0.957	0.739	0.900	0.872	0.801	0.908	0.871	0.845	-	-	-	-

1. Refer to Table 5.8 for the full names of the components.
2. Mean values are calculated using the coefficients in absolute terms (Ketz et al., 1990, p. 71).
3. When no component appeared in either sample, a (-) sign is shown instead.

Sh-t liq, RBC and M(C)-II for the savings banks over several years. Also, Eff-II for the commercial banks had significant correlations generally with AQ-I for the savings banks. The undefined factor for the commercial banks had significant correlations with AQ-I for the saving banks in 2003, and with Eff and IS in 2004. Also, the undefined factor for savings banks in 2003 had significant correlations with Eff-I and a lower, but significant, correlation with Ln&Ls for the commercial banks.

In the following subsection, the similarity between the factor solutions for the commercial and savings banks was assessed using congruency coefficients. The size of the correlation and congruence coefficients might be very close; however, with the congruency coefficients, it was possible to assign labels describing the relationship between the components of the two solutions.

7.5.3 Congruency coefficients

Table 7.17 gives the congruency coefficients between the counterpart components for the commercial and savings banks for each year between 2001 and 2005. Components in the table are summarised in an order similar to that in Table 7.16, in which components appearing in both solutions over the whole of the five-year period are reported first, followed by the less consistent components. The mean values of the coefficients are also given for each of the nine consistent factors[122]. To judge the strength of the relationships, the coefficients were interpreted with the help of Table 3.1 which lists the labels describing how strong the match is, based on the absolute size of the coefficients.

Given the figures reported at the bottom of Table 7.17, Prof and Sh-t liq were the only two components with ‘good’ matches between the commercial and savings banks over the period. Also, CG, M(C)-II, AQ-I, RBC and IS each had an overall ‘borderline’ match whereas AQ-II and Ln&Ls, however, had generally ‘poor’ matches.

[122] Following Ketz et al. (1990, p. 71), congruency coefficients in absolute terms were used in calculating the means.

Now, regarding the coefficients in each year of the comparison, all matches of Sh-t liq were ‘good’, as were those for Prof, except for the year 2005 in which the match was ‘borderline’. Different to them were AQ-II and Ln&Ls as the matches of AQ-II ranged between ‘borderline’ and ‘poor’ over the years with the latter (Ln&Ls) having a ‘terrible’ match in one year and ‘borderline’ matches in four years. Matches for the rest of the consistent components were, nevertheless, predominantly ‘borderline’ with a few ‘good’ and ‘poor’ cases. The Eff column of Table 7.17 shows the congruency coefficients calculated between Eff for the savings banks and Eff-I for the commercial banks. The column which follows, Eff-II, shows the coefficients between Eff for the savings banks and Eff-II for the commercial banks. Given the ‘terrible’ matches shown in the Eff-II column, Eff for the savings banks was clearly dissimilar to Eff-II for the commercial banks. The factor (Eff) instead appeared to be more similar to Eff-I, yet the two factors had ‘poor’ matches in the first two years and only ‘borderline’ matches in the last two years. Furthermore, regarding the inconsistent components, matches of Grth in 2001 and 2003 could be described as ‘borderline’ and ‘poor’, respectively. This confirms the conclusion drawn earlier about this factor using correlation coefficients. Lastly, in Table 7.17, the undefined component, not surprisingly, had a ‘terrible’ match across the savings and commercial banks in year 2003.

Given that M(Y)-I, Fnd-II and AQ-III were only identified for one type of bank and sometimes only for one year, it was not possible to compare these components across the commercial and savings banks. However, in order to gain a deeper understanding of the contents of these components, their matches with other factors were assessed[123]. So, the congruency coefficients between M(Y)-I and each of the savings banks’ factors were calculated in all five years; the coefficients with Ln&Ls were found to be the highest. These coefficients could be described as ‘borderline’ in 2003 and ‘poor’ in the rest of the years. Thus even with the ‘poor’ and ‘borderline’ matches, it was apparent that Ln&Ls for the savings banks had a broader meaning than that for the commercial banks as it did not only seem to represent the Lending aspects of bank operations but also showed parts of a Margin dimension. The Lending and Margin dimensions, however, were independent from each other for the

[123] Relevant figures are not given and only results are discussed.

commercial banks given that Ln&Ls and M(Y)-I were both identified for this type of bank.

In regard to Fnd-II, relatively large coefficients, which were still considered as ‘terrible’ matches, were found between this factor for savings banks and each of the factors Sh-t liq and Ln&Ls for the commercial banks in years 2002 and 2004. The highest coefficients for Fnd-II, however, were found with Grth for the commercial banks. Nonetheless, these coefficients were still below a satisfactory level as they could be labelled as ‘terrible’ and ‘poor’ in 2002 and 2004, respectively. Even with these labels, the relationship between Fnd-II for the savings banks and Grth for the commercial banks was apparent. However, with Fnd-II being one of the inconsistent factors for the savings banks, it is important not to make any generalisation since the relationship was observed in only two of the five years covered by this study.

Finally, AQ-III, for the commercial banks identified in 2001, did not seem to have a satisfactory match with any of the factors for the savings banks. The largest congruency coefficient, however, was found with AQ-I, although even this was ‘terrible’.

Last but not least, the correlation matrices examined in Subsection 7.5.2 showed that some components had significant correlations with components other than their direct counterparts in the alternative banking sector. These components were Ln&Ls and Eff-II for the commercial banks and the undefined factor for both types of banks. To check the significance of these relationships, the congruency coefficients were calculated between each of these components and all of the other components. The resulting figures were all labelled as ‘terrible’, with the coefficient between the undefined factor for the savings banks and Eff-I for the commercial banks being the highest; yet the match here was still considered ‘terrible’.

The study so far has assessed the similarity between factor solutions of commercial and savings banks using visual comparison, correlation and congruency coefficients. The coefficients obtained from congruency and correlation analyses were reasonably close. However, the use of congruency coefficients enabled labels to be assigned to describe the level of the relationship between the components. Nevertheless, the comparison was further enriched by employing transformation analysis, which is considered in the following subsection.

7.5.4 Transformation analysis

Transformation analysis was carried out on the factor solutions for the savings and commercial banks for each year between 2001 and 2005. The software package SURVO 2.51 was used to perform the analysis.

Transformation matrices. First, it should be recalled that the similarity of solutions with different numbers of factors was assessed here; thus, in order to execute the analysis successfully using the software specified, the solution with the higher number of factors (i.e. for the commercial banks) needed to be inserted first in the transformation analysis command, followed by the solution with the smaller number of factors (i.e. for the savings banks). The transformation matrices across the period between 2001 and 2005 are given in Table 7.18.

In assessing the transformation matrices in Table 7.18, the size of the coefficients of coincidence for the components was checked first. As mentioned earlier, components with coefficients of coincidence equal to or above .95 (in absolute terms) could be considered as similar in the two types of banks. In contrast, components with coefficients of coincidence below .95 could be considered as having a different practical meaning between the commercial and savings banks. Also, it should be recalled that rows in the transformation matrices represent the commercial banks' factors, and columns represent the savings banks' factors. Thus, for every consistent factor [Prof, Sh-t liq, M(C)-II, AQ-I, AQ-II, CG, RBC and IS] with a coefficient of coincidence below .95, the factor's row and column in the transformation matrix were scanned for the sizeable elements. Large elements (in absolute terms) in the row uncovered which savings banks' factors were involved in the transference that had occurred for that particular factor. Similarly, sizeable elements in the factor's column revealed the commercial banks' factors behind the transference.

Results for the 'uncommon' or 'inconsistent' factors were interpreted as follows. The inconsistent factors found for both types of banks in some years (Grth and Eff) were interpreted in the same manner as the common factors explained above. For the inconsistent factors identified for the commercial banks only (AQ-III, Eff-II and M(Y)-I), the sizeable elements in their rows were checked; these lead to the savings banks' factors involved in the transformation. For the only factor identified for the savings banks (Fnd-II), the large elements in its column were examined to determine the commercial banks' factors involved in its transformation.

As can be seen from the transformation matrices in Table 7.18, the similarity level between the commercial and savings banks' factors was generally mediocre. Only a few components had their coefficients of coincidence in excess of .95 in some of the years. These were: Prof, Sh-t liq, RBC, CG, IS, M(C)-II (consistent factors) and Grth (an inconsistent factor).

The Prof factor appeared to be similar for the commercial and savings banks across the period between 2001 and 2004. In 2005, however, the size of its coefficient of coincidence was 'not satisfactory' although it was still reasonable (.934). By scanning the row and column of Prof in the year 2005 matrix, sizeable elements in absolute terms were found with Grth (.320 and -.309, respectively). This indicates an association of the Grth factor with the transference of Prof between the two types of banks.

Regarding the Sh-t liq factor, its coefficients of coincidence were of a satisfactory size in all years except for 2003, when it fell far below .95 (.764). In this year, a certain amount of transference occurred and this involved the undefined factor, M(C)-II, Grth and RBC for the savings banks; and Ln&Ls, the undefined factor and M(C)-II for the commercial banks.

The coefficients of coincidence for RBC were above the .95 criterion in the first two years of the period; in the rest of the period, however, they ranged between .90 and .95. Over the last three years, RBC exhibited a small amount of transference into factors such as M(Y)-I and Ln&Ls, amongst others.

Table 7.18: Cross-sectional transformation matrices for components of commercial and savings banks (2001-2005)

			C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
2001		**Savings**	Prof	Ln&Ls	M(C)-II	Sh-t liq	Eff	RBC	AQ-I	AQ-II	CG	IS	Grth
Commercial	**C1**	Prof	**0.979**	-0.099	0.065	-0.013	-0.041	-0.083	-0.050	-0.076	-0.068	0.013	-0.065
	C2	Sh-t liq	0.005	-0.012	0.036	**0.989**	0.007	-0.014	0.013	-0.032	-0.019	0.078	-0.021
	C3	M(Y)-I	0.137	0.620	0.046	-0.045	0.393	0.200	0.231	0.250	-0.001	0.176	0.111
	C4	M(C)-II	-0.083	0.016	0.902	-0.055	-0.282	-0.039	0.012	-0.142	0.077	0.069	-0.083
	C5	RBC	-0.056	0.142	-0.106	-0.028	0.011	**-0.956**	0.006	-0.003	0.047	0.057	0.003
	C6	Ln&Ls	0.035	0.650	0.137	0.060	-0.082	-0.089	-0.124	-0.026	-0.114	-0.255	-0.035
	C7	CG	0.084	0.060	-0.036	0.048	0.010	0.024	-0.018	0.064	**0.967**	-0.029	0.054
	C8	AQ-I	-0.022	0.046	0.018	-0.038	0.094	0.058	-0.859	-0.004	0.085	0.059	0.005
	C9	AQ-II	0.029	-0.238	0.139	0.015	-0.087	-0.090	-0.014	0.902	-0.035	-0.025	-0.058
	C10	Eff-I	-0.036	-0.204	0.290	0.029	0.817	-0.109	-0.150	-0.008	-0.066	-0.099	-0.036
	C11	Grth	0.039	-0.075	0.122	0.021	-0.037	-0.046	-0.000	0.016	-0.051	-0.018	**0.976**
	C12	Eff-II	-0.010	0.229	-0.048	0.066	-0.245	0.051	-0.299	0.281	-0.130	0.083	-0.002
	C13	IS	0.017	0.001	0.017	0.048	-0.009	0.017	0.050	0.053	0.020	-0.924	-0.009
	C14	AQ-III	-0.012	0.024	0.160	-0.020	0.111	-0.030	0.275	0.101	0.083	0.117	-0.120
2002		**Savings**	Prof	Ln&Ls	M(C)-II	Sh-t liq	AQ-I	RBC	Fnd-II	CG	AQ-II	Eff	IS
Commercial	**C1**	Prof	**0.983**	-0.050	-0.028	-0.039	0.026	-0.034	0.080	-0.109	-0.071	0.022	0.014
	C2	Sh-t liq	0.011	0.017	-0.007	**0.951**	0.051	0.003	0.244	0.003	0.004	0.093	0.076
	C3	M(Y)-I	0.051	0.793	-0.278	-0.056	0.144	0.179	-0.124	0.135	0.246	0.210	0.136
	C4	M(C)-II	0.001	0.144	0.904	-0.057	0.123	0.075	0.041	0.032	-0.067	0.046	0.105
	C5	Ln&Ls	0.027	0.553	0.176	0.019	-0.152	-0.171	0.335	-0.153	-0.083	-0.382	-0.201
	C6	AQ-I	0.039	0.045	0.023	0.048	-0.902	0.043	-0.153	0.058	0.038	-0.162	0.078
	C7	RBC	0.025	-0.066	0.016	-0.011	-0.035	**0.957**	0.130	-0.050	-0.070	-0.027	-0.066
	C8	CG	0.132	-0.043	0.073	0.064	0.019	0.009	-0.070	0.937	0.052	-0.158	-0.032
	C9	AQ-II	0.053	-0.162	0.125	-0.020	0.070	0.005	0.081	-0.101	0.922	-0.196	0.046
	C10	Eff-I	-0.051	-0.034	-0.204	-0.026	0.213	0.072	0.210	0.013	-0.099	-0.762	0.003
	C11	Grth	-0.073	-0.067	-0.105	-0.279	-0.065	-0.085	0.780	0.219	-0.045	0.273	0.079
	C12	Eff-II	-0.023	-0.021	-0.012	0.005	-0.253	0.037	0.306	-0.016	0.224	0.215	-0.230
	C13	IS	0.016	0.014	0.021	0.036	0.060	-0.009	-0.089	0.049	0.039	0.079	-0.923

			C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
2003		**Saving**	Prof	Ln&Ls	Sh-t liq	M(C)-II	AQ-I	RBC	AQ-II	CG	No Name	Grth	IS
Commercial	**C1**	Prof	**0.977**	-0.076	0.054	0.012	0.002	-0.042	-0.087	-0.086	0.113	-0.037	-0.032
	C2	Sh-t liq	-0.014	-0.060	0.764	-0.365	0.094	-0.105	-0.096	0.054	-0.442	-0.205	-0.064
	C3	M(Y)-I	0.126	0.827	-0.144	-0.134	0.153	0.196	0.222	0.050	-0.261	-0.144	-0.053
	C4	Ln&Ls	-0.030	0.486	0.423	0.168	-0.142	-0.096	-0.026	-0.231	0.371	0.343	0.034
	C5	M(C)-II	-0.034	0.076	0.204	0.852	0.116	-0.075	-0.175	0.121	-0.158	-0.199	0.004
	C6	RBC	0.016	-0.115	0.103	0.068	0.023	0.946	-0.097	0.005	-0.027	0.020	-0.021
	C7	AQ-I	-0.003	0.084	-0.063	-0.057	-0.865	-0.014	0.019	0.079	-0.117	-0.134	-0.010
	C8	CG	0.108	0.030	0.049	0.028	-0.056	-0.019	0.069	0.931	0.046	0.175	0.029
	C9	AQ-II	0.025	-0.163	0.092	0.111	0.145	-0.033	0.882	-0.016	0.074	-0.152	-0.048
	C10	Eff-I	0.116	-0.091	-0.128	0.247	-0.193	-0.030	0.162	-0.197	-0.684	0.316	-0.060
	C11	Grth	0.002	-0.060	0.148	-0.056	0.054	0.046	0.122	0.021	-0.057	0.766	-0.053
	C12	IS	0.044	0.007	0.008	-0.030	0.036	0.011	0.040	-0.021	-0.113	0.024	**0.988**
	C13	No Name	0.000	-0.074	0.328	0.097	-0.347	0.185	0.260	-0.072	0.236	-0.136	0.074

2004		**Savings**	Prof	Ln&Ls	RBC	Sh-t liq	AQ-I	M(C)-II	Eff	Fnd-II	CG	AQ-II	IS
Commmercial	**C1**	Prof	**0.975**	-0.022	0.021	-0.038	0.071	-0.062	0.096	0.048	-0.070	-0.019	0.012
	C2	Sh-t liq	0.040	-0.021	0.031	**0.980**	0.063	0.019	-0.012	0.139	-0.016	0.036	-0.026
	C3	M(Y)-I	0.080	0.729	-0.195	-0.029	0.258	-0.116	-0.180	-0.157	0.086	0.234	0.046
	C4	Ln&Ls	-0.041	0.624	0.197	0.014	-0.168	0.062	0.025	0.384	-0.164	-0.139	-0.088
	C5	M(C)-II	0.028	0.093	-0.024	-0.018	0.115	**0.953**	0.094	-0.027	0.009	-0.035	0.040
	C6	RBC	-0.027	0.065	0.933	-0.024	0.040	-0.056	0.075	-0.151	0.007	0.130	0.010
	C7	AQ-I	0.128	0.072	-0.028	0.056	-0.914	0.111	-0.131	-0.209	0.017	0.177	-0.039
	C8	CG	0.049	0.030	0.037	0.025	-0.016	0.009	-0.002	0.060	**0.969**	0.061	0.015
	C9	AQ-II	-0.026	-0.101	-0.050	-0.015	0.111	0.066	0.024	0.006	-0.121	0.917	-0.094
	C10	Eff-I	0.008	-0.051	0.037	0.003	0.038	0.001	-0.877	0.087	-0.048	-0.031	0.085
	C11	Grth	0.030	-0.150	0.071	-0.176	-0.066	0.055	-0.078	0.823	0.046	0.143	-0.040
	C12	IS	0.026	-0.040	0.073	0.015	-0.011	0.055	-0.049	-0.005	-0.034	0.059	0.934
	C13	No Name	-0.129	0.148	-0.182	0.028	-0.166	-0.210	0.385	0.223	-0.021	0.079	0.308

			C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
2005		**Savings**	Prof	M(C)-II	Ln&Ls	AQ-I	RBC	Sh-t liq	Eff	AQ-II	CG	IS	-
Commercial	**C1**	Prof	0.934	-0.011	-0.098	0.010	0.023	-0.003	-0.017	-0.076	-0.309	-0.003	
	C2	Sh-t liq	-0.007	0.122	0.000	0.003	-0.006	**-0.976**	0.040	0.045	-0.025	0.022	
	C3	M(Y)-I	0.128	0.026	0.730	0.209	-0.169	0.099	0.301	0.258	0.004	0.088	
	C4	M(C)-II	-0.033	0.850	-0.028	0.196	-0.009	0.119	-0.209	-0.073	-0.002	-0.043	
	C5	Ln&Ls	-0.022	0.136	0.591	-0.052	0.225	-0.081	-0.079	-0.198	-0.059	-0.093	
	C6	RBC	-0.028	-0.099	0.073	0.041	0.913	0.010	-0.102	0.082	-0.115	0.000	
	C7	AQ-I	-0.006	-0.043	0.151	-0.842	-0.045	0.038	-0.081	0.102	0.024	0.002	
	C8	CG	0.320	0.034	0.051	-0.036	0.084	-0.058	-0.031	0.037	0.891	0.000	
	C9	Aq-II	0.008	-0.014	-0.115	0.151	0.019	0.004	-0.093	0.895	-0.021	-0.047	
	C10	Eff-I	-0.044	0.060	-0.105	-0.018	0.083	-0.010	0.836	-0.037	-0.073	-0.027	
	C11	Eff-II	0.032	0.223	0.110	-0.297	-0.135	-0.044	-0.136	0.199	-0.282	0.125	
	C12	Grth	0.052	0.420	-0.198	-0.303	0.218	0.097	0.338	0.139	0.084	-0.025	
	C13	IS	-0.016	0.028	-0.039	0.024	0.062	0.018	0.000	-0.026	0.028	**0.981**	

1. Elements above .950 are in bold (Martikainen et al., 1994, p. 63).
2. Refer to Table 5.8 for the full names of the components.

In regard to CG, this could be considered as similar in years 2001 and 2004. However, its coefficients fell below .95 in the rest of the years (.937, .931 and .891 in years 2002, 2003 and 2005, respectively). In these years, a small amount of transference certainly occurred but this was a small change given that the largest element found was only .309 with Prof for the commercial banks in 2005. The rest of the elements were of much smaller magnitude in absolute terms.

The IS component exhibited similar characteristics to the CG factor in that its coefficients of coincidence were in excess of .95 for two years (2003 and 2005) and between .90 and .95 for the rest of the years. Thus, IS could be considered as fairly similar for both the commercial and savings banks. However, in 2001 and 2002, this factor had significant elements with Ln&Ls and M (I and II) for the commercial banks. Likewise, in 2005, a large element was found with Eff-II for the commercial banks. Note that these sizeable elements were found only in the factor's columns in the transformation matrices. Thus, it could be said that the IS component for the savings banks appeared to hold some Ln&Ls, Margin and Eff aspects whereas IS for the commercial banks showed no clear connection with any other aspects of savings banks' performance.

In regard to M(C)-II when using correlation and congruency coefficients, this factor showed an average level of similarity between the two types of banks, and also it appeared to be the most similar over the period between 2002 and 2004. The transformation matrices reported in Table 7.18, however, show that the level of similarly for M(C)-II satisfied the .95 criterion only in 2004. In 2001 and 2002, its coefficients of coincidence were just above .9 whereas they were around .850 in 2003 and 2005. So, whilst there was a certain amount of similarity in this factor, the match was not perfect. The transference involved, generally, the Eff factors in 2001 and 2002, Sh-t liq in 2003, and Grth in 2005. Again, this was revealed by the sizeable elements in absolute size appearing in the rows, as well as in the columns of the M(C)-II factor.

The results for the AQ-I and AQ-II factors were then considered. As can be seen from Table 7.18, the coefficients of coincidence for AQ-I ranged between -.842 and -

.914 over the period, indicating a poor level of similarity for this factor. Accordingly, a certain amount of transference occurred with many other factors given the sizeable (in absolute terms) elements found (the highest element being -.299). These factors included M-(I and II), Ln&Ls, Eff and Eff (I and II). Likewise, AQ-II had fairly similar sized elements as AQ-I, although its coefficients of coincidence were slightly higher, ranging from .882 to .922. Thus, again, there was a similar but not perfect match between this factor for the commercial and savings banks. Furthermore, factors such as M-(I and II), Ln&Ls and Eff were also involved in the AQ-II transference.

The analysis of the consistent factors was completed by examining Ln&Ls, which was regarded in the earlier subsections (7.5.2 and 7.5.3) as the least similar component. Also, in the previous subsections, a significant association was found between Ln&Ls for the savings banks and the M(Y)-I component for the commercial banks, which indicated that the former factor had a broader meaning. Now, given the transformation matrices summarised in Table 7.18, the coefficients of coincidence of Ln&Ls were .650, .553, .486, .624 and .591 in the five years, respectively. However, higher elements were found in the intersection of Ln&Ls columns and M(Y)-I rows in the transformation matrices (.620, .793, .827, .729 and .730 in years 2001-2005, respectively). Thus, Ln&Ls for the savings banks appeared to have characteristics that were more in common with the M(Y)-I factor, than with its own counterpart for the commercial banks. This in turn indicated that the Ln&Ls factor for the savings banks appeared to measure both the Lending and the Margin dimensions of a bank's operations whereas each of these aspects seemed to be measured by a unique factor for commercial banks. Nevertheless, besides the large elements between Ln&Ls and M(C)-II, it can be seen in the transformation matrices that Ln&Ls had high elements in absolute terms with many other factors and that the highest element was found with the Sh-t liq factor for the savings banks in year 2003 (.423).

Similarity in the inconsistent components between commercial and savings banks was then examined by first studying the M(Y)-I factor. Besides the high elements of this factor with Ln&Ls for the savings banks, its row in the transformation matrices contained elements of an average size (around .200) with most of the savings banks' factors. Amongst these factors were the AQ and Eff factors. In 2003, however, the scale of these elements increased for virtually all other factors.

In regard to the similarity of the Eff factors, it should first be recalled that Eff was identified for the savings banks in all years except 2003, whereas two efficiency factors were identified for the commercial banks in 2001, 2002 and 2005 and only one factor was found in 2003 and 2004. So, in 2001, 2002 and 2005, Eff for the savings banks was matched with Eff-I for the commercial banks. In year 2004, Eff was matched between the two types of banks. Finally, in 2003, a look was taken at the savings banks' factors into which the commercial banks Eff factor had transferred.

As can be seen from Table 7.18, the coefficients of coincidence between Eff and Eff-I were .817, -.762 and .836 in the years 2001, 2002 and 2005. Also, in these years, some association could be found between Eff and Eff-II expressed by average sized elements (in absolute terms) (-.245, .215 and -.136 for the three years, respectively). Besides this, other factors had average sized elements; amongst these were M-(I and II) for the commercial banks and M(C)-II and Ln&Ls for the savings banks. In year 2004, the coefficient of coincidence for the Eff factor was -.877; the scale of the other elements was clearly small for this factor where the only significant element was found between Eff for the savings banks and the undefined factor for the commercial banks (.385). Finally, in 2003, the Eff factor for the commercial banks completely transferred into several savings banks' factors; the most important of these were the unlabelled factor, Grth and M(C)-II (elements -.684, .316 and .247, respectively). In regard to the Eff-II factor, it had moderate sized elements with several factors over the different years. The highest elements in absolute terms were found with factors such as AQ-I in 2001 and 2005, and Fnd-II in 2002 (these elements were -.299, -.297, and 306, respectively).

The Grth component was identified over the whole period for the commercial banks, and only in 2001 and 2003 for the savings banks; thus, it could be compared in these two years only. The coefficients of coincidence for this factor were .976 and .766 in the two years, respectively, which implies a sufficient level of similarity in year 2001 only. By examining the Grth's elements in the 2003 matrix, rather sizeable elements could be found in its column compared to the row elements. This indicates that the transference of the Grth factor between the two types of banks was more apparent for the savings banks than it was for the commercial banks. The factors involved in this transference include Ln&Ls, Eff-I and Sh-t liq, amongst others. In years 2002 and 2004, the Grth factor for the commercial banks had its highest elements with the Fnd-II factor for the savings banks (.780 and .823, respectively), which again reflects the association between the two factors. Finally, in year 2005, the largest element (.420) was found with M(C)-II for the savings banks.

Moving on to the Fnd-II factor for the savings banks, the factor's highest elements in 2002 and 2004 were with Grth for the commercial banks, as stated above. In addition, fairly high elements were found with other factors, such as Ln&Ls, as the Fnd-II columns in Table 7.18 show.

AQ-III was identified for the commercial banks in year 2001 only. In Subsection 7.5.2, the largest correlation coefficient was found between this factor and AQ-I for the savings banks. The match between the two factors, however, was described as 'terrible', as summarised in Subsection 7.5.3. Now, in the year 2001 matrix in Table 7.18, the AQ-III row did not contain any large elements; the highest element, however, was found for AQ-I (.275) which confirms the association between AQ-III for the commercial banks and AQ-I for the savings banks reported in the previous subsections.

Last but not least, in regard to the undefined component, it must be recalled that it was found in the commercial banks' solutions in years 2003 and 2004, and for the savings banks in year 2003 only; thus, the similarity of the factor could be assessed in year 2003 only. In this year, the factor had an insignificant correlation and a 'terrible' congruency match between the two types of banks. In year 2004, however, the undefined factor for the commercial banks had its highest coefficients with the Eff and IS factors for the savings banks. Concerning the undefined factor in transformation analysis, in year 2003 it had a coefficient of coincidence of .236, as shown in Table 7.18. This indicates the clear dissimilarity of the content of the factor for the two types of banks. The undefined factor's row in the matrix contained several moderate-sized elements where the highest elements (in absolute terms) were found for AQ-I and Sh-t liq for the savings banks (-.347 and .328, respectively). In the column of the undefined factor, the highest elements (in absolute terms) were found for Eff-I and Sh-t liq for the commercial banks (-.684 and -.442, respectively). In year 2004, the undefined factor for the commercial banks had moderately transferred into other savings banks' factors as its row in the matrix contained several moderate-sized elements where the highest elements were with the Eff and IS factors (.385 and .308, respectively).

Residual matrices. It was demonstrated above how the transformation matrices uncovered the 'normal' or 'explained' transformation in the components between the solutions. In the following paragraphs, the residual matrices which reveal the variables/factors behind the 'abnormal' or 'unexplained' changes between the solutions are examined. The residual matrices for each year between 2001 and 2005 are presented in Appendix 7.4. The last column and the bottom two rows of these matrices show the abnormal transformation for the different ratios and factors, respectively. To facilitate the process of interpreting the results, the abnormal transformations for the 56 ratios in the five years are summarised again in Table 7.19. The last row of the table gives the cumulative figures that were used for an overall assessment of the abnormal changes.

The figures in Table 7.19 were judged using the .20 criterion widely used in the previous literature (Martikainen et al., 1995a, p. 41). Accordingly, variables with an abnormal transformation in excess of .20 were considered to have encountered 'abnormal' or 'unexplained' changes in their meaning between the solutions. Given this, over the five-year period covered in this study, year 2003 had the largest number of ratios with abnormal changes between commercial and savings banks. In this year, 13 ratios had sizeable abnormal transformations: these were X2, X14, X25, X34, and X37-X45 (refer to Table 4.4 for the full names of ratios). In the other years, a much smaller number of ratios were identified. These were X25, X40 and X47 in 2001; X25, X37 and X40 in 2002; X31, X37 and X40 in 2004; and, finally, X25 and X40 in 2005. Amongst these ratios, it should be noted that X25 and X40 had significant abnormal transformations in all the five years covered by this study. Interestingly, it might be recalled from Section 7.3 that X40 was one of the ratios which failed to load significantly onto any factor in some of the years.

Table 7.19: Cumulative abnormal transformations between components of commercial and savings banks (2001-2005)

	2001	2002	2003	2004	2005
X1	0.031	0.069	0.050	0.038	0.017
X2	0.042	0.059	**0.220**	0.059	0.029
X3	0.032	0.058	0.046	0.034	0.020
X4	0.082	0.109	0.070	0.089	0.083
X5	0.026	0.077	0.059	0.015	0.044
X6	0.080	0.073	0.132	0.134	0.074
X7	0.026	0.022	0.029	0.011	0.046
X8	0.024	0.004	0.032	0.007	0.053
X9	0.046	0.016	0.045	0.008	0.085
X10	0.046	0.017	0.045	0.007	0.083
X11	0.080	0.161	0.145	0.082	0.124
X12	0.105	0.160	0.157	0.153	0.193
X13	0.030	0.048	0.029	0.045	0.024
X14	0.040	0.054	**0.206**	0.058	0.033
X15	0.032	0.049	0.049	0.032	0.019
X16	0.065	0.117	0.125	0.065	0.101
X17	0.022	0.036	0.042	0.126	0.045
X18	0.041	0.048	0.023	0.104	0.057
X19	0.107	0.158	0.174	0.183	0.149
X20	0.106	0.163	0.178	0.179	0.139
X21	0.176	0.174	0.239	0.192	0.172
X22	0.055	0.035	0.155	0.030	0.039
X23	0.072	0.108	0.101	0.052	0.067
X24	0.026	0.032	0.053	0.033	0.033
X25	**0.268**	**0.319**	**0.457**	**0.311**	**0.225**
X26	0.040	0.091	0.037	0.067	0.076
X27	0.100	0.087	0.110	0.107	0.119
X28	0.057	0.122	0.046	0.067	0.085
X29	0.075	0.084	0.047	0.046	0.141
X30	0.058	0.076	0.104	0.068	0.199
X31	0.177	0.097	0.079	**0.267**	0.097
X32	0.060	0.065	0.143	0.037	0.072
X33	0.051	0.044	0.061	0.047	0.059
X34	0.175	0.168	**0.231**	0.099	0.183
X35	0.093	0.118	0.147	0.060	0.078
X36	0.127	0.183	0.157	0.092	0.077
X37	0.182	**0.523**	**0.398**	**0.232**	0.049
X38	0.048	0.064	**0.937**	0.052	0.030
X39	0.067	0.135	**1.253**	0.109	0.040
X40	**0.227**	**0.268**	**1.127**	**0.220**	**0.272**
X41	0.133	0.121	**0.559**	0.091	0.035
X42	0.073	0.103	**2.174**	0.079	0.027
X43	0.036	0.008	**0.520**	0.017	0.019
X44	0.137	0.116	**0.258**	0.192	0.088

	2001	2002	2003	2004	2005
X45	0.031	0.047	**1.307**	0.054	0.024
X46	0.154	0.053	0.141	0.104	0.098
X47	**0.271**	0.129	0.078	0.175	0.116
X48	0.034	0.097	0.073	0.018	0.035
X49	0.064	0.128	0.148	0.058	0.024
X50	0.053	0.039	0.043	0.049	0.041
X51	0.087	0.063	0.044	0.035	0.046
X52	0.145	0.164	0.170	0.094	0.134
X53	0.045	0.032	0.073	0.025	0.088
X54	0.072	0.047	0.111	0.082	0.174
X55	0.067	0.067	0.061	0.046	0.048
X56	0.058	0.064	0.055	0.047	0.043
Cumulative abnormal transformation	**4.657**	**5.570**	**13.548**	**4.783**	**4.571**

1. Figures over .20 are in bold (Martikainen et al., 1995a, p. 41).
2. Refer to Table 4.4 for the full names of ratios.

After identifying the ratios with significant abnormal transformations, the components that could be tied to these unexplained changes were then named. This was carried out by selecting the components with the highest figures at the bottom of the residual matrices in Appendix 7.4. So, the components that were largely ascribed to the unexplained transformations were: M(C)-II (.728) and IS (.719) in 2001; Eff (.891) and Fnd-II (.794) in 2002; Sh-t liq (5.032), M(C)-II (1.793), and the undefined factor (1.150) in 2003; Ln&Ls (.689) and RBC (.600) in 2004; and, finally M(C)-II (.653) and Prof (.646) in 2005.

Overall assessment of abnormal transformations. Adding up the abnormal transformations of the ratios/factors enabled a comparison to be made regarding the level of unexplained changes across the different years. The last row in Table 7.19 provides the cumulative abnormal transformations for each year between 2001and 2005. As can be seen from the table, the highest unexplained transformations between commercial and savings banks occurred in the year 2003 (13.548); the least, however, was observed in 2005 (4.571). Close to the latter figure were the results for the other years, as can also be seen in the table.

Significance test for transformation matrices. The null hypothesis of no significant differences existing between the components for the commercial and savings banks was then tested. This significance test, however, only covered the nine ‘common’ components for the two types of banks over the five-year period (i.e. Prof, Sh-t liq, Ln&Ls, M(C)-II, AQ-I, AQ-II, RBC, CG and IS). The initial step leading to the calculation of the test statistics required setting the eigenvectors of the 'common' components into the same order for the commercial and savings banks and this, in turn, resulted in matrices containing nine components (columns) and 56 rows (ratios). Following this, transformation analysis was performed for the trimmed solutions for every year across the period. This produced five transformation matrices with supposedly close-to-one diagonal elements and close-to-zero off-diagonal elements[124].

In order to obtain the z-score for the test, the determinants of the transposed matrices were computed; then, the average and standard deviation of these determinants were calculated. Table 7.20 summarises all the relevant figures. As can be seen in the table, for a sample of five observations (one transformation matrix for each year between 2001 and 2005), the z-score value is .524. This is insignificant at any reasonable level of significance which implies that the null hypothesis of no significance differences for the nine factors for the commercial and savings banks given the period covered by the analysis cannot be rejected.

Table 7.20: Results of transformation matrices' significance test for commercial and savings banks (2001-2005)

Period	$Det(B) = Det(M.M^T)$
2001	1.000698
2002	0.997350
2003	1.001766
2004	0.999640
2005	1.003107
$\overline{Det(B)}$	1.000512
$\hat{\sigma}$	0.002185
n	5
$z = \frac{\overline{Det(B)} - 1}{\hat{\sigma}}\sqrt{n}$	0.524278

Nevertheless, as emphasised earlier, given the small number of observations (five) on which the test was based, the outcome of this test should be weighed with care. While

[124] Matrices are not shown.

the test uses the Central Limit Theorem, a minimum number of at least 30 observations are necessary for a potentially valid test.

7.6 Summary

In this chapter, first, the financial patterns for the U.S. saving banks were investigated and their time stability was assessed; second, these patterns were compared to the patterns for the U.S. commercial banks which were identified earlier in Chapter 5. The study used 56 ratios for a sample of savings banks ranging in size between 274 and 287 banks over the period 2001-2005. Principal Component Analysis (PCA) was used to derive the patterns for each year and the final number of factors were decided using Parallel Analysis (PA). All the solutions were rotated using the varimax method to facilitate the process of factor labelling.

The 56 ratios were successfully grouped into 11 components in 2001-2004 and 10 components in 2005. These solutions accounted for 72.18% to 75.94% of the variance in the datasets. All components were assigned to suitable labels except for one component in 2003. The following nine factors were found consistently over the period covered in the study: Prof, Sh-t liq, Ln&Ls, M(C)-II, AQ-I, AQ-II, RBS, CG and IS (refer to Table 5.8 for a full description of the factors). Other factors: Eff, Grth and Fnd-II were identified for some years only.

The identified groups/patterns of ratios were compared over time and with the commercial banks' patterns using visual comparisons, correlation analysis, congruency coefficients, and transformation analysis. The level of stability exhibited by the savings banks' patterns over time was, in general, higher than the similarity level demonstrated when the patterns for the savings and commercial banks were compared.

Given the overall results of all the factor comparison methods, the highest stability level over the period analysed by this study was exhibited by Ln&Ls, RBC and Sh-t liq. CG and M(C)-II, however, appeared to be the least stable groups of ratios for the savings banks. Other patterns, which were infrequently identified, did not show any satisfactory level of stability over the years in which they were compared. Yet, the Grth and Fnd-II groups, which were identified in some years, appeared to have some common characteristics with one another over the years. Likewise, the Eff and M(C)-II patterns also appeared to have some commonality with other factors. Given this, it could be concluded that financial ratios for savings banks could actually be classified into distinctive groups; however, unlike those for the commercial banks, the different dimensions represented by these patterns appear to be rather unstable over the short period.

Furthermore, the visual comparisons conducted between the financial patterns for the savings and commercial banks revealed clear differences. In general, the 56 ratios for the savings banks were grouped into a smaller number of patterns, and these groups in total accounted for a smaller proportion of the variance when compared to those for the commercial banks. However, given the five-year period the study covered, there were nine groups of ratios indentified for both types of banks. These were Prof, Sh-t liq, Ln&Ls, M(C)-II, AQ-I, AQ-II, RBC, CG and IS (refer to Table 5.8 for the full names). The M(Y)-I and AQ-III groups, however, applied only to the commercial banks, whereas the Fnd-II group applied only to the savings banks. Besides this, other inconsistent patterns were identified, such as Eff, Grth and some groups which remained unlabelled.

Additional comparison techniques revealed a rather poor similarity level between the financial patterns for the two types of banks. Thus, even when components for the savings and commercial banks held the same label, they did not necessarily represent the same dimension of banks' performance. The Prof and Sh-t liq groups of ratios appeared to be the most similar for the two types of banks. Ln&Ls, on the other hand, although identified for both types of banks, was the least similar. This component appeared to represent two aspects of performance for the savings banks: the Lending and Margin dimensions. However, these two dimensions were expressed by two unique components for the commercial banks: Ln&Ls and M(Y)-I. In addition, the inconsistent patterns appeared to underscore the observed dissimilarity between the solutions for the two types of banks given that each of these patterns represented more than one aspect of the banks' performance.

Furthermore, with the use of transformation matrices, two null hypotheses were formed and tested. The first tested the overall stability of the nine groups of ratios consistently found for the savings banks in the short term. Likewise, the second hypothesis tested the overall similarity level between the nine groups of ratios found for both types of banks. The null hypothesis of no significant differences in the patterns could not be rejected in the two cases. The test, however, had its drawbacks given the small number of observations it was based on. Thus, its results should only be seen within the perspective of other comparison methods. Clearly, the comparison techniques used showed that the consistent savings banks' patterns did not have the same level of stability over the short-term; some were actually considered unstable. In the same manner, the components that were common to the two types of banks exhibited different levels of similarity; some components were even deemed dissimilar.

Last but not least, the results of this study might have been influenced by some underlying issues, which should be highlighted. First, attention needs to be drawn to the rather small size of the sample used for the savings banks, which might have affected the findings of this study. Also, the results might be dependant on some idiosyncratic economic conditions relating to the U.S. banking industry which took place over the period of our analysis. Finally, the findings may possibly reflect the unique environment in which the U.S. savings banks operate.

In the end, this study so far has sought to identify the financial patterns for the U.S. commercial and savings banks, and to assess their stability in the short term. It has also sought to assess the effect of commercial bank size on the identified financial patterns. However, a noteworthy fact is that all the commercial banks used in the study have been in operation for over five years. Thus, the findings are only valid for incumbent U.S. commercial banks. A step towards generalising the results to all U.S. FDIC-insured commercial banks is taken by studying the financial patterns of the newly FDIC-insured (that is, newly-chartered or De Novo) banks. In the UBPR, newly chartered commercial banks are grouped together and, as previously explained in Chapter 4 (Subsection 4.3.3), remain in the same group for the subsequent five years. After this five-year period, the newly-chartered commercial banks are assigned to one of the 15 groups of commercial banks. The following chapter (eight) thus looks into the patterns of a set of financial ratios for the U.S. De Novo banks which received their charter in different years. The main purpose of this was to assess the existence of any distinctive patterns for newly-opened banks and to examine the extent of the similarity of these patterns over the different years and with the patterns of the incumbent commercial banks.

Chapter 8 The Classification Patterns of Financial Ratios for U.S. De Novo Commercial Banks

8.1 Introduction

In the three previous chapters, the questions about the existence of financial patterns for commercial and savings banks and their stability in the short term were answered empirically. Also, the similarity of the financial patterns for commercial banks, grouped according to their asset size, was checked. Using a very similar approach to that followed in the previous chapters, this chapter aims generally at exploring the financial patterns for U.S. De Novo banks. In the context of this study, newly-opened banks, new banks, newly-chartered banks, and De Novo banks, are all synonyms and refer to the same type of bank: that is, a U.S. commercial bank which is licensed by the Federal Deposit Insurance Corporation (FDIC) and which commenced operations in a particular year.

To answer the general research question in regard to De Novo banks, the ratio patterns for banks at the end of their first year of operation were derived and then compared across the five years the study covered. In addition, the financial patterns for new banks were investigated over the four years following the opening year and the results were viewed from the perspective of the findings in the previous chapters, mainly Chapters 5 and 6.

The chapter is structured as follows: following the introduction, the methodology and the original datasets on which the study was based are introduced in Section 8.2. In Section 8.3, the financial patterns for banks established in each year from 2001 to 2005 are identified and compared over the period. Following this, Section 8.4 looks into the patterns for small De Novo banks and compares them over the period. This section also derives the patterns of a smaller set of ratios chosen by utilising the results for Group 4 (G4) in Chapter 6. Section 8.5 investigates the financial patterns for banks chartered in 2001 in the four years following the opening year; the investigation is carried out utilising the findings of Chapter 5. Finally, the chapter concludes with Section 8.6 which summarises the results, highlights the limitations of this study and suggests future research in the area.

8.2 Methodology and data

Methodology. This study was mainly based on Principal Component Analysis (PCA) to derive the financial patterns, similar to the method used in previous chapters. The varimax rotation method was also applied to make the solutions easier to interpret. The current chapter only summarises the results of PCA whereas the detailed steps leading to the extraction of the components are summarised in Chapter 3 (Section 3.3). The analysis was run using the SPSS 15.00 statistical package.

Data. This study covered all the De Novo banks which commenced business in the years 2001-2005. As explained in Chapter 4 (Subsection 4.3.3), the Uniform Bank Performance Report (UBPR), which is the main source of our data, is available for all the De Novo banks based on the year of their chartering. For instance, banks commencing business in year 2001 were grouped together in a group called group 2001. These banks remained in group 2001 for five years following their opening (i.e. until year 2005). Then, in the following year, each bank was assigned to one of the 15 groups of commercial banks according to the bank's asset size, location and number of banking offices (FFIEC, 2006, p. II-1). Similar procedures were followed for the De Novo banks that were chartered in years 2002, 2003 and so on. The new banks were kept in their original group for five years and were then allocated to one of the 15 groups.

Thus, the samples used in this study consisted of De Novo banks in five groups: 2001-2005. As introduced in Chapter 4, Table 4.3 shows the number of the U.S. newly chartered banks in the groups as they were when the data collection for this study was carried out (December 2006 -January 2007). As Table 4.3 shows, 162 banks started business in 2005, which is the highest number of banks over the period covered.

Group 2002, however, is the smallest as only 85 banks received their charter in that year. More than 100 banks were chartered in each of the remaining years.

The UBPRs were downloaded for each of the banks in Table 4.3 using the FFIEC website as explained in Chapter 4. After downloading the reports, the variables/ratios of interest were extracted. With regard to the variables for this study, it is preferable to use the same list of 56 ratios that were investigated in the previous chapters. The list of the 56 ratios is given in Table 4.4 and their full names and descriptions are summarised in Appendix 4.1. As mentioned in Chapter 4 (Section 4.4), these 56 ratios were all selected from the UBPR data to represent generally the following dimensions of a bank's operations: earnings and profitability, margin analysis, loans and leases analysis, liquidity, capitalisation, and growth rates.

As can be seen from Table 4.4, the list includes six ratios: X28-X32 and X54, which represent different growth rates. Calculating the growth rate for an account requires the account's balance in the current period as well as the balance in the previous period (see Appendix 4.1). Since it was the first year of operation for De Novo banks, balances in the previous period were not available. This meant that the Growth ratios had to be omitted from the list. Excluding the six Growth ratios left a list of 50 other ratios supposedly available for banks in their first year. These 50 ratios formed the main list that was used in Sections 8.3 and 8.4. However, in Section 8.5, all the 56 ratios listed in Table 4.4 were available in principle and could all be used to find the patterns for the new banks in the four years following the banks' opening.

Last but not least, similar to the previous chapters, all the analyses in this chapter were carried out after applying the arcsinh transformation to the raw data. The arcsinh transformation succeeded in improving the normality of the distributions of the different ratios as reported in Chapter 5 (Section 5.3). A description of this method of data transformation is given in Chapter 4 (Section 4.5).

8.3 Financial patterns for De Novo banks (2001-2005)

In this section, the financial patterns for the banks chartered over the period between 2001 and 2005 are identified on a yearly basis. The section commences by introducing the sizes and the variables of the samples used.

As mentioned earlier, this study covered all the banks opened over a five-year period. From 2001 to 2005, the number of De Novo banks ranged between 85 (2002) and 162 (2005) as Table 4.3 shows. The list of variables obtained for these banks consisted of 50 ratios as explained in the previous section. It is now necessary to ask for how many of these banks the complete set of ratios is available and whether this is satisfactory enough to run a sound PCA.

The first row in Table 8.1 gives the number of new banks with all 50 ratios being available. Also in the table, the figures in brackets are the ratios of cases-per-variables. As can be seen from this table, only 10 banks in 2001 had the full set of observations. In the following years, the number of banks with a complete set of ratio was smaller (only three banks in 2002, five banks in 2003 and 2005, and nine banks in 2004). Clearly, a PCA cannot be carried out with small samples like this. Therefore, excluding a number of ratios from the analysis had to be considered in order to improve the cases-per-variable ratios. Selecting which ratios to exclude from the list of variables should be done with the least possible level of subjectivity and it is next necessary to consider how this can be achieved.

Table 8.1: Sample size and cases-per-variable ratio for De Novo banks (2001-2005)*

Number of deleted ratios	Number of ratios	Number of banks (listwise)					Deleted ratios
		2001	2002	2003	2004	2005	
6	50	10 (0.20)	3 (0.06)	5 (0.10)	9 (0.18)	5 (0.10)	X28-X32, X54
8	48	78 (1.63)	53 (1.10)	67 (1.40)	81 (1.69)	98 (2.04)	X28-X32, X54, X17, X18
15	41	78 (1.90)	53 (1.29)	67 (1.63)	81 (1.98)	98 (2.39)	X28-X32, X54, X17, X18, X16, X21, X25, X27, X40, X44, X50
18	38	100 (2.63)	75 (1.97)	91 (2.39)	101 (2.66)	136 (3.58)	X28-X32, X54, X17, X18, X16, X21, 25, X27, X40, X44, X50, X37, X51, X52

1. Refer to Table 4.4 for full names of ratios.
2. Numbers in brackets represent the cases-per-variable ratios.

Table 8.1 shows the figures that resulted after the number of ratios was gradually reduced. For instance, excluding 18 ratios from the variables' list appeared to give reasonable results compared to the figures resulting from omitting 8 or 15 ratios, as the table demonstrates. At this point, it is worth mentioning that deciding on which ratios to delete was not an arbitrary decision. Instead, this decision was made after carrying out a number of trials. The results of the different trials were then assessed and the set of ratios that produced the most reasonable sample size was kept while the other ratios were omitted. The outcomes of some of these trials are given in Table 8.1 and the reasons behind any deletion are explained below.

To begin with, ratios X17 and X18 were not available for a substantial number of the new banks over the period. When the two ratios were excluded, the sizes of the samples increased significantly as the relevant figures in Table 8.1 show. Referring back to Chapter 5 (Section 5.3), X17 and X18 were also not available for over 20% of the incumbent commercial banks. Chapter 5 also gives some explanations concerning the reasons behind the substantial number of missing values for X17 and X18. Briefly, the Net Loss, which comprises the denominator for the two ratios, is obtained by deducting the Gross Losses from the Gross Recoveries. However, when the Gross Recoveries exceed the Gross Losses, the UBPR does not report any value for the two ratios; instead, it gives an N/A sign (FFIEC, 2006, p. III-5). This certainly applies to X17 and X18 for the De Novo banks and that is why the two ratios were disregarded in seeking larger sample sizes and healthier cases-per-variable ratios. In Chapter 5, however, the two ratios were included in the analysis as excluding the banks with the missing observations did not seem to affect sample sizes significantly- all of which were in excess of 5,000 banks for every year across the period.

Having identified the ratios with substantial missing information, further visual checking of the data revealed a predominance of zero entries for certain ratios. Omitting these ratios would certainly enhance the outcomes of PCA. More importantly, it would increase the sample sizes and the cases-per-variable ratios. Ratios with dominating zero entries were identified then deleted in two steps. First, only a few entries for ratios X16, X21, X25, X27, X40, X44 and X50 were non-zero[125]. Disregarding these seven ratios as well as the ratios that were excluded earlier (the Growth ratios, X17 and X18), as Table 8.1 shows, left only 41 ratios on the variables' list. However, deleting these further ratios did not help in increasing the samples size as these ratios had few unavailable observations. This means that both sets of 48 and 41 ratios were available for the same number of De Novo banks. Nevertheless, it was clear that using 41 ratios offered better banks-to-variable ratios.

In order to improve both the sample size and the quality of the data (i.e. dealing with the issue of predominant zero entries), further investigations were carried out to identify the ratios that had, at the same time[126], a substantial number of zero entries and too many unavailable observations. The examinations revealed that three ratios, X37, X51 and X52, had these two characteristics in every year over the period; therefore they were subject to deletion. Excluding these three ratios reduced the variables' list to 38 ratios, and more importantly, it significantly enlarged the samples size and subsequently the cases-to-variables ratios.

The last row of Table 8.1 shows the number of banks with a complete set of 38 ratios. In years 2001, 2004 and 2005 the number exceeded 100 banks (100, 101 and 136 respectively). In years 2002 and 2003, however, the 38 ratios were available for 75 and 91 banks, respectively. Also, the last row in the table shows how keeping a smaller number of ratios for a larger sample size improved the cases-per-variable ratios. The highest ratio was found for year 2005 where around four banks were available for every variable, whereas in year 2002 only two banks were available for every variable used.

Nevertheless, the figures shown in the last row of Table 8.1 are considered poor when compared to the minimum cases-per-variable ratio required to run a compelling PCA (Hair et al. 1998, p. 98-99). However, the analysis can still be performed for samples of a small size or a low cases-per-variable ratio as long as the results are interpreted

[125] Almost all of these ratios had fewer than 20 non-zero entries in each of the five years.
[126] There is no clear-cut way to interpret the meaning of 'too many missing observations'. However, a 'substantial number of zero entries' is considered to be equal to 20% of the original sample size. This was set entirely by the researcher and led to the same ratios with zero entries for 20% the observations in each of the five years covered.

with caution (Hair et al. 1998, p. 99). In terms of this study, all the U.S. De Novo banks that opened between 2001 and 2005 were included in the analysis. However, the initial number of banks opened in each of these years can be still considered as small (Table 4.3) and the number of De Novo banks with complete observations was even smaller. Therefore, the only way to use samples similar or close in size to the initial number of new banks was to exclude ratios which had a preponderance of missing observations. By minimising the number of variables, the number of banks with complete observations increased for every year and consequently, the cases-per-variable ratios also rose. So, in the following subsection, the financial patterns for the 38 ratios are identified for the banks chartered in each year between 2001 and 2005.

8.3.1 Patterns in the five years

As explained in Chapter 3 (Subsection 3.3.1), the first step of running PCA involved assessing the factorability of the correlation matrices on which the analysis was based. This step is usually carried out subjectively by scanning the correlation matrix for high coefficients between the different variables. The existence of a substantial number of high correlation coefficients indicates that some factor patterns do exist in the dataset. Also, the factorability of the data can be judged by assessing the coefficients of the anti-image correlation matrix. The anti-image correlation matrix gives the negative signs of the partial correlations between two variables after accounting for all the other variables in the dataset. If these partial correlations are very small, the data can be deemed suitable for factor analysis. In addition, two statistical tests can be used in checking the factorability of the dataset. The first is Bartlett's Test of Sphericity (BTS) which tests the null hypothesis that the sample correlation matrix comes from a population in which the correlation matrix is an identity matrix. The second measure of sampling adequacy (MSA) is the Kaiser-Meyer-Olkin (KMO) statistic which computes the degree of common variance amongst all the variables.

The results of the various factorability tests show whether distinctive patterns actually exist in the dataset, and thus, whether PCA can help in uncovering these patterns. When the results of the tests show that the data matrix is not suited to PCA, dropping some variables could be an option to improve the factorability of the correlation matrix.

In this study, a number of factorability tests were carried out; the outcomes of these tests showed that the data for the De Novo banks were generally poor and that the factorability of the datasets was an open question for some of the years. For example, in years 2002- 2004, SPSS (the statistical software package used to run PCA) could not compute the anti-image correlation matrix, nor the KMO and BTS statistics. In years 2001 and 2005, however, the reported figures were good enough to proceed with PCA[127]. However, even with the reservations concerning the convenience of PCA for the De Novo banks' data, it was decided that the analysis for all the years would still be carried out without making any further amendments to the list of variables. The general aim of the study, nevertheless, was to *explore* the patterns of De Novo banks' ratios in the different years.

Having decided to continue with the analysis as planned, PCA was performed to derive the financial patterns of the De Novo banks. To answer the question of many components should be extracted, Parallel Analysis (PA) was used as the main technique, similar to that used in previous chapters (5, 6 and 7). Also, as in the previous chapters, the number of components suggested by other commonly used methods was also reported for comparison purposes. Amongst these methods, Table 8.2 shows the number of factors identified by the latent root (eigenvalue >1) method and Cattell's scree plot, as well as those identified by PA. The table also shows in brackets the percentage of variance accounted for by the proposed factor solutions for each of the methods. Also, Appendix 8.1 gives the scree plot figures for the De Novo banks' samples over the five years, the outputs of PA in detail as well as relevant rotated component matrices.

[127] KMO statistics were .777 and .759 in years 2001 and 2005, respectively. Based on these two figures, the factorability of the data in the two years could be described as 'middling' according to Sharma (1996, p. 116).

Table 8.2: Number of factors and percentage of variance explained for De Novo banks 2001-2005 (38 ratios)

	Eigenvalue >1	Cattell's Scree	PA
2001	8 (86.31%)	11 (93.99%)	5 (78.62%)
2002	7 (85.04%)	13 (96.55%)	5 (77.57%)
2003	8 (88.82%)	10 (92.86%)	5 (78.16%)
2004	8 (88.60%)	10 (92.63%)	6 (81.93%)
2005	8 (87.81%)	11 (93.57%)	5 (76.50%)

As can be seen from Table 8.2, Cattell's scree plot method recorded the highest number of components (between 10 and 13) compared to the other two methods. The scree plot method, however, involves a great deal of judgment and tends to propose a higher number of factors than other methods (Hair et al., 1998, p.104). This was evident in our study as can be seen from the table. Then, the latent root (eigenvalue) method suggested keeping eight factors for all the years except 2002, where only seven factors had an eigenvalue that exceeded unity. More importantly, PA suggested retaining only five components for all years except 2004, where six components appeared to be worth retaining.

The factor solutions suggested by PA explain a percentage of variance ranging between 76.50% in 2005 and 81.93% in 2004. This means that the 38 ratios for the De Novo banks could be represented by only five to six groups but these groups summarise more than 76% of the information of the whole dataset. Generally, solutions with a higher number of factors are expected to explain a higher percentage of the variance. This could explain why the 6-factor solution in year 2004 accounted for the highest percentage of variance compared to the solutions of 5 factors for the rest of the years. However, the 5-factor solutions did not account for the same amount of variance. The 5-factor solutions for 2001 and 2003 accounted for a very close percentage of variance (78.62% and 78.16%, respectively). For year 2002, however, the solution explained a smaller proportion of variance (77.57%) whereas in year 2005 only 76.50% of the variance was accounted for, as the last column of Table 8.2 indicates. Nevertheless, these results should be interpreted with caution given the overall low cases-per-variable ratios and the concerns raised earlier about the factorability of the data over the years tested.

After deciding on the number of components to keep, the components were extracted for every year. However, before trying to find meaningful labels for the factors, all the solutions were rotated using the varimax rotation method. This method in particular was used in all the previous chapters to facilitate the step of naming the factors. Chapter 3 (Subsection 3.3.3.1) gives a detailed description of the usefulness of the varimax rotation method.

The rotated component matrices for the De Novo banks in the years 2001-2005 are given in the last part of Appendix 8.1. A thorough examination of these matrices was carried out in order to assign the appropriate labels to the components. This involved identifying the ratios with significant loadings onto each of the components and looking for a common name that would describe the main characteristics of each group of ratios. When choosing the label for a factor, ratios with the highest loadings onto the factor are considered to be the most influential when compared to ratios with lower loadings. As explained in Chapter 3 (Subsection 3.3.3.2), the significance of the ratios' loadings depends on the sample size. Only high loadings in absolute terms are considered as significant for small samples whereas even smaller loadings are significant for larger samples. Based on Table 3.2 in Hair et al. (1998, p. 112) and the size of the samples used in this subsection (last row of Table 8.1), the significance levels of loadings for the De Novo banks over the study period were obtained and are presented in the first part of Table 8.3. Since the samples used were of different sizes, different significance levels for loadings were thus applied. As the table shows, for a loading to be considered significant, it should be, in absolute terms, equal to or greater than .65 in 2002, .60 in 2003, .55 in years 2001 and 2004 and .50 in 2005.

Given that the significance levels of loadings were determined, by looking at the five component matrices in Appendix 8.1 it can first be noted that a number of ratios did not load significantly onto any of the derived factors. These ratios are listed in the second part of Table 8.3. Also, it can be seen that some ratios in year 2005 only had significant loadings onto two different factors. These ratios are also presented in Table 8.3.

Table 8.3: General points to consider in interpreting the rotated component matrices for De Novo banks 2001-2005 (38 ratios)

Year	Significant loadings	Ratios	
		Insignificant loadings	Multiple significant loadings
2001	0.55	X4, X11, X34	-
2002	0.65	X4, X6, X11, X12, X34, X35, X41, X47, X56, X55	-
2003	0.60	X11, X23, X35, X36, X48, X49	-
2004	0.55	X4, X11, X34	-
2005	0.50	X4, X11, X34, X36	X23, X48, X6, X49

1. Significant loadings were decided using the guidelines in Hair et al. (1998, p.112, Table 3.2) and the study sample size (Table 8.1).
2. Refer to Table 4.4 for full names of the ratios.

As Table 8.3 shows, three to ten ratios had insignificant loadings across the years of the study. Amongst these ratios, X4, X11 and X34 reportedly failed to load significantly onto any factor in most of the years. By referring to Table 4.4, these ratios represent the Efficiency (Eff) dimension of a bank's performance. Clearly, this aspect of performance did not appear to be distinctive for the De Novo banks in their first year of operation. In year 2002, ratios X55 and X56 had insignificant loadings, causing there to be an absence of Risk-Based-Capital (RBC) from the factor solutions in this year. In year 2003, the Loans and Leases (Ln&Ls) ratios: X23, X48 and X49, failed to load significantly onto any factor which also resulted in the absence of the Ln&Ls factor from the financial patterns of the De Novo banks in that year.

With regards to the ratios with several significant loadings, in year 2005, the Ln&Ls ratios loaded significantly onto two factors, as did one of the Asset Quality (AQ) ratios: X6. Generally, ratios with cross loadings are not considered to be influential when the factors' labels are being chosen. Moreover, according to some references, these ratios should not be kept in the analysis (Hair et al., 1998, p. 113). However, deleting such ratios was not an option here as a general aim of this study was to compare the financial patterns for the same variables obtained for different datasets. Further deletion of ratios (i.e. ratios with cross loadings in year 2005) would then result in unbalanced datasets. Therefore, no deletion was made and the derived factors were assigned suitable labels, as Table 8.4 shows (refer to Table 5.8 for the full names of the components).

Table 8.4: Labels assigned to components of De Novo banks in 2001-2005 (38 ratios)*

	C1	C2	C3	C4	C5	C6
2001	Prof	Sh-t liq	M(Y)-I	M(C)-II	Ln&Ls	
2002	Prof	Sh-t liq	M(C)-II	M(Y)-I	AQ	-
2003	Prof	Sh-t liq	M(C)-II	M(Y)-I	AQ	-
2004	Prof	M(Y)-I	Sh-t liq	M(C)-II	AQ	Ln&Ls
2005	Prof	Sh-t liq	M(C)-II	M(Y)-I	AQ	-

* Refer to Table 5.8 for full names of the components.

As can be seen from Table 8.4, all the factors derived for the De Novo banks in years 2001-2005 were successfully labelled. The first four factors that were identified in every year are: Prof, Sh-t liq, M(Y)-I and M(C)-II. Furthermore, the AQ factor was identified in years 2002-2005 whereas the Ln&Ls factor was found in two years only: 2001 and 2004. Further details about the similarity of these factors are given in the following subsection.

8.3.2 Similarity of financial patterns of De Novo banks 2001-2005

In the previous chapters, following the identification of the financial patterns for banks, the similarity of these patterns was assessed, both over time and across the different types and sizes of banks. A stability check was also carried out using various methods that include visual comparison, correlation analysis, congruency coefficients, and transformation analysis. In terms of this chapter, given the rather small samples and the poor factorability results, the datasets were not generally the best suited to PCA. Thus, further caution was needed when the results were interpreted; and also it was not appropriate to use any technical method (i.e. correlation and congruency coefficients and transformation analysis) to investigate the similarity of the De Novo banks' financial patterns. Given this, conducting a visual comparison appeared sufficient to assess the degree of similarity of the patterns of the De Novo banks.

The visual comparison was made by studying Table 8.5; this shows the cumulative proportion of variance explained by the extracted components for the years 2001-

2005[128]. For each of the components (i.e. each row in Table 8.5), close figures could be considered as a sign of similarity in the De Novo bank's patterns over the different years. As can be seen from the table, there were slight differences in the figures especially for the first two components. For C2 in Table 8.5, the cumulative variance accounted for by the first and second components ranged between 39.33% (2001) and 47.27% (2002). Starting with C3 and as far as C5, the range of the cumulative percentage of explained variance became smaller. For example, looking at C4 reveals that the first four components accounted for a percentage of variance ranging between 67.74% (2004) and 70.62% (2003). It should be noted, however, that six components were extracted for year 2004 compared to only five components in each of the other years. This would definitely adjust the cumulative percentage of variance accounted for by the first five individual factors for year 2004 (see footnote 128).

Table 8.5: Cumulative proportion of total variance explained by components of De Novo banks 2001-2005 (38 Ratios)

	2001	2002	2003	2004	2005
C1	21.70	27.18	27.94	26.87	25.19
C2	39.33	47.27	45.30	43.25	42.40
C3	55.71	58.66	58.13	59.52	56.11
C4	68.80	70.00	70.62	67.74	68.79
C5	<u>78.62</u>	<u>77.57</u>	<u>78.16</u>	74.96	<u>76.50</u>
C6				<u>81.93</u>	

Furthermore, the relative position of the components in the final solutions can be viewed as an indication of similarity in these solutions. In the output of SPSS 15.00, the software used to run PCA, the components appear in descending order in terms of the proportion of variance accounted for by the individual components. So, the first component in the solution accounts for the highest amount of variance, and the second component accounts for the second highest amount of variance and so on. Based on this, a sign of similarity is implied when the same components appear in the same relative position in the different solutions[129]. It can be seen from Table 8.4 that Prof maintained its position as the first component in all five solutions; Prof was followed

[128] As mentioned earlier, factors in the final rotated solution account for a different amount of variance from the factors in the initial solution (i.e. the un-rotated solution). The figures in Table 8.5 are for the factors in the final rotated solution.

[129] As explained earlier, after applying a rotation to the factor solution, SPSS still presents the components in a descending order of the amount of variance they explain.

by Sh-t liq as the second component to be identified in all but year 2004 where M(Y)-I was extracted as second (refer to Table 5.8 for the full names of the components.) The two margin components, M(Y)-I and M(C)-II, rotated in the third and fourth position in all years apart from 2004 (where Sh-t liq was extracted as third). AQ was the fifth component in all the years in which it was identified (i.e. 2002-2005). Finally, Ln&Ls was the last to be extracted in the two years in which it was found: 2001 and 2004. Overall, given the relative positions of the components, the different solutions seemed to show a good degree of similarity.

It should be noted that the factors' labels were used above to check whether factors maintained their relative positions in the different solutions. However, factors with the same label are not necessarily made up of exactly the same ratios. Whereas some key ratios need to be loading significantly onto the factor to give it to a certain label, how far these ratios are related to the factor (i.e. the absolute size of their loadings) might not be exactly the same in the different solutions. Thus, it was crucial to consider the different ratios that loaded onto the factors before making a final judgement about similarities among the solutions. To do this, the rotated component matrices in Appendix 8.1 were closely examined with reference to Table 8.4 and Table 5.8 that lists the full names of the components. The aim of this step was to examine the key ratios loading onto each of the factors in order to ascertain whether there was any obvious violation of the compatibility requirement in the different solutions.

First examined were the two factors identified in some years only: Ln&Ls and AQ (refer to Table 5.8 for the full names of factors.) The two key ratios that loaded highly onto Ln&Ls were X48 and X49 (refer to Table 4.4 for the full names of ratios). Also, in year 2001, X23 loaded significantly onto Ln&Ls whereas this ratio had a rather small, yet significant loading onto Prof in 2004. In the three years where Ln&Ls was not identified as a unique factor, its ratios loaded as follows: in 2002, X48, X49 and X23 loaded highly on Sh-t liq; in 2003, these ratios failed to load significantly onto any factor; in 2005, the three ratios had two significant, yet small, loadings onto Prof and AQ. The AQ factor, identified in 2002-2005, generally consisted of X19, X20; also, X6 loaded onto the factor in some years. In year 2001, however, these three ratios loaded instead onto the M(Y)-I factor.

The visual comparisons continued by considering the factors that were consistently identified for the De Novo banks over the five years: M(Y)-I, M(C)-II, Sh-t liq, and Prof. Ratios X13, X1, X15 and X3 loaded highly onto M(Y)-I in all the years. Also, X36 loaded onto this factor in some years and, in 2001, as just mentioned, AQ ratios all loaded onto the M(Y)-I factor. Regarding the M(C)-II factor, the three key ratios that loaded highly onto this factor in most of the years were X2, X14 and X38. In addition, in 2001 and 2005, the RBC ratios had significant loadings onto the M(C)-II factor. As for the Sh-t liq factor, the six ratios which loaded highly onto this factor for all five years were X22, X39, X2, X43, X45 and X46. Also, X47 had moderate loadings onto this factor in some years while, in 2002, Ln&Ls ratios were all loading significantly onto Sh-t liq as mentioned earlier. Last but not least, although the Prof factor accounted for the highest proportion of variance in every year over the whole period, a close look at its ratios revealed how cluttered it was. Profitability in this factor was represented by X7, X8, X9, X10, X53, X26 and X33. Furthermore, many other ratios loaded moderately, yet significantly, onto this factor making it hard to interpret. These ratios originally represented different factors such as Eff (X5, X35 and X12), RBC (X24, X55 and X56) and Ln&Ls (X23 and X48) but nonetheless loaded onto the Prof factor in some of the years.

Overall, there seemed to be a degree of dissimilarity in the factor solutions for the De Novo banks in their first year of operation. The visual inspections that were carried out revealed some instability in the cumulative percentages of variance explained by the factors of the different solutions. However, the relative position of factors in the solutions was, to a certain degree, similar over the years. Nonetheless, the results of further visual examination of the component matrices showed that although factors with the same labels were formed by the same key ratios, there was no clear trend in which a number of other ratios loaded onto the different factors. This, in most cases, resulted in factors representing more than one aspect of the banks' performance. This would certainly imply a clear sign of dissimilarity and inconsistency in the financial patterns of the new banks in their first year of operation.

Given these poor results, the use of any other technical comparison method did not seem appropriate. So, the comparisons between the De Novo banks' patterns over the years were discontinued at this point bearing in mind the exploratory aspect of the current chapter. Having mentioned the exploratory aim of this chapter, the following sections briefly describe the different trials that were carried out on the datasets with a view to seeking a better understanding of the classification patterns of the De Novo banks.

8.4 Financial patterns for small De Novo banks (2001-2005)

The general aim of this section is to check whether distinctive and consistent financial patterns can be identified for small De Novo banks. This section consists of two parts; the first subsection explores the patterns of small De Novo banks whereas the second re-derives these patterns using a smaller number of selected ratios. The ratios used in the second subsection were chosen to represent the consistent financial patterns identified in Chapter 6 for Group 4 (G4) of the commercial banks.

Small De Novo banks. The newly opened banks analysed in this chapter were all commercial banks. The Uniform Bank Performance Report (UBPR) used only one criterion to classify these new banks and that is the year in which the banks commenced business. For the incumbent commercial banks, however, the UBPR classified them using three criteria: asset size, number of banking offices and geographical location of the bank. So, none of these three grouping criteria was used to represent the De Novo banks. Nevertheless, it was noticed that most of the new banks had an asset size of less than $50 million in the last quarter of the year in which they commenced business. New banks with this asset size can thus be described as small banks as they belong to the sixth and final asset size class used by UBPR to represent the incumbent commercial banks (FFIEC, 2006, p. II.2).

Table 8.6 gives the number of banks opened in every year between 2001 and 2005 together with the number of these banks with an asset size of less than $50 million in the last quarter of each year. A comparison between the two figures showed that a small number of banks had to be dropped in order to have samples that consisted only of small banks. The sample size now ranged between 81 (2002) and 133 (2005) small De Novo banks. Subsequently, the number of small banks with complete observations was checked as well as the cases-per-variable ratios.

Table 8.6: Small De Novo banks sample size (2001-2005)

Group	De Novo banks	De Novo banks with an asset size less than $50 M in Q4
2001	109	104
2002	85	81
2003	105	102
2004	118	111
2005	162	133

8.4.1 Patterns for small De Novo banks (38 ratios)

This subsection uses the same list of variables that was used in the previous section; this includes 38 ratios. The full list of 56 ratios is given in Table 4.4 and the ratios excluded from the list are shown in the last row of Table 8.1. Table 8.7 gives the number of small De Novo banks with all 38 ratios available in 2001-2005 and the corresponding cases-per-variable ratios. As can be seen from the table, the 38 ratios were available for a number of small new banks ranging between 71 (2002) and 115 (2005). The cases-per-variable ratios were slightly smaller than those reported in Table 8.1. There are three small new banks for every ratio used in 2005 compared to around two banks for every ratio in 2002. Again, despite reservations concerning both the fairly small sample size and the low number of cases-per-variable ratios, PCA was performed on the data for every year. All the relevant results obtained from running PCA are given in Appendix 8.2 while the following paragraphs elaborate this further.

Table 8.7: Small De Novo banks with 38 ratios available (2001-2005)

Group	Number of banks	Cases-per-variable ratio
2001	95	2.50
2002	71	1.87
2003	88	2.32
2004	94	2.47
2005	115	3.03

Table 8.8 shows the number of factors suggested by each of the three commonly used methods: the latent root (eigenvalue >1), Cattell's scree plot and PA. Also, the proportion of variance explained by each of the suggested solutions is shown in brackets. As stated in Chapter 3 (Subsection 3.3.2), only the results of PA were considered to decide on the number of components in the final solutions. As the table shows, PA suggested keeping four components in 2002, five components in 2001, 2003 and 2005, and six components in 2004. These solutions explain between 71.92% (2002) and 82.28% (2004) of the variance. These results were very similar to the results for all the De Novo banks reported earlier in Table 8.2 with the exception that a 4-factor solution was suggested for small De Novo banks in 2002 compared to a 5-factor solution for the De Novo banks of all sizes in the same year.

Table 8.8: Number of components and proportion of variance explained for small De Novo banks 2001-2005 (38 ratios)

	Eigenvalue >1	Cattell's Scree	PA
2001	7 (85.04%)	11 (93.70%)	5 (79.29%)
2002	8 (87.23%)	13 (96.52%)	4 (71.92%)
2003	8 (88.17%)	9 (90.58%)	5 (76.69%)
2004	8 (88.82%)	10 (92.90%)	6 (82.28%)
2005	8 (87.96%)	11(93.70%)	5 (76.49%)

After deciding on the number of components to keep in every year, the components were extracted and the initial solutions were rotated using the varimax rotation method. Following this, a close look was taken at the rotated component matrices in Appendix 8.2 in order to give suitable labels to the components. Table 8.9 summarises some relevant results regarding the labelling.

Table 8.9: General points to consider in interpreting the rotated component matrices for small De Novo banks in 2001-2005 (38 ratios)

Year	Significant loadings	Ratios	
		Insignificant loadings	Multiple significant loadings
2001	.60	X4, X6, X11, X24, X34, X55, X56	**-**
2002	.65	X4, X6, X11, X34, X35, X36, X38, X41, X47, X55, X56	-
2003	.60	X4, X6, X11, X23, X35, X36, X48, X49	-
2004	.60	X4, X11, X34	-
2005	.55	X4, X11, X19, X20, X24, X34, X35, X41, X38, X55, X56	-

1. Significant loadings were decided using the guidelines in Hair et al. (1998, p.112, Table 3.2) and the study sample size (Table 8.7)
2. Refer to Table 4.4 for full names of the ratios.

First, Table 8.9 gives the minimum size required for loadings to be considered significant and hence important in the labelling process (Hail et al., 1998, p.112). For larger samples, small loadings are considered significant and vice versa; so, the significance level for loadings in this part of the study was .65 for 2002, .60 for 2001, 2003 and 2004, and .55 for 2005. Given these significance level, a number of ratios failed to load significantly onto any of the factors whereas no ratio had multiple loadings in any of the years. With reference to Table 4.4 for ratios' names, ratios with insignificant loadings generally represented efficiency (X4, X11, X34 and X35) and capital (X24, X55 and X56). Other ratios which failed to load significantly in some of the years included X6, X38 and X41, among others as Table 8.9 shows.

The labels assigned to the factors of the small De Novo banks over the period 2001-2005 are reported in Table 8.10 (refer to Table 5.8 for the full names of factors.) As can be seen from the table, the four factors that were consistently identified for the years of this study were Prof, Sh-t liq, M(Y)-I and M(C)-II. The two less consistent factors were Ln&Ls and AQ. Clearly, the names given to the factors were more or less similar to those in Table 8.4. However, it was apparent that the presence of the Ln&Ls factor was stronger for the small De Novo banks than it was for the De Novo banks in general. By looking at Table 8.10, it could be seen that Ln&Ls was identified as a distinctive factor in three years: 2001, 2004 and 2005. In two of these years, 2001 and 2005, the two AQ ratios (X19 and X20) had rather sizeable loadings onto the Ln&Ls factor; however, the highest loadings were for the Ln&Ls ratios. Also, in 2002, Ln&Ls ratios loaded significantly and highly onto the second factor. However, that factor was labelled as Sh-t liq because the majority of the ratios loaded onto this factor represented the Sh-t liq aspect of the banks' performance. The observation regarding the stronger presence of Ln&Ls for the small De Novo banks is interesting as it supports the findings of Chapter 6.

Table 8.10: Labels assigned to components of small De Novo banks in 2001-2005 (38 ratios)

	C1	C2	C3	C4	C5	C6
2001	Prof	Sh-t liq	M(Y)-I	M(C)-II	Ln&Ls (AQ)	-
2002	Prof	Sh-t liq (Ln&Ls)	M(C)-II	M(Y)-I (AQ)	-	-
2003	Prof	Sh-t liq	M(Y)-I	M(C)-II	AQ	-
2004	Prof	M(Y)-I	Sh-t liq	M(C)-II	AQ	Ln&Ls
2005	Prof	Sh-t liq	M(Y)-I	Ln&Ls (AQ)	M(C)-II	-

In Chapter 6, the financial patterns of different asset-size classes of commercial banks were identified. It was found that Ln&Ls ratios loaded onto a distinctive factor only for smaller commercial banks. Also, the Ln&Ls factor appeared to have a higher relative importance in the solutions compared to the position of AQ-II (AQ in the current chapter) for all five years, i.e. Ln&Ls was extracted before the AQ-II in all five years of the study. This appeared to hold for small De Novo commercial banks even though much smaller samples were used in this chapter when compared to the samples used in Chapter 6.

8.4.2 Patterns for small De Novo banks (20 ratios)

Further trials were carried out in order to reach a better understanding of the financial patterns for the small De Novo banks. In this subsection, the patterns were derived using a smaller set of 20 ratios. The aim was to explore how these 20 ratios, which were carefully selected to represent a few distinctive financial patterns, would be classified for samples of small De Novo banks.

Ratios selection. As mentioned in the introduction of Section 8.4, De Novo banks with less than $50 million asset size match the last asset-size group (G4) for the incumbent commercial banks. The financial patterns and the short-term stability of all asset-size groups of commercial banks were studied in details in Chapter 6. Given the relevant results of Chapter 6, a number of ratios were selected to represent the consistent patterns identified for G4. Table 8.11 shows the eleven financial patterns consistently identified for the commercial banks in G4[130].

In regard to the variables to be selected, recall here that earlier in this chapter, the growth ratios were dropped from the initial list of variables given their unavailability for banks in their first year of operation. Other ratios were omitted to maximise the number of De Novo banks with complete observations and to improve the quality of data (i.e. ratios with too many missing values and those with prevailing zero entries). This left a list of 38 ratios. Any ratio to be selected for this subsection had to be

[130] In addition to these 11 patterns, two less consistent components were found for G4 in some of the years only (Fnd-II in 2003 and Eff in 2005). Also, in years 2001, 2003 and 2004, one component could not be assigned any label.

picked from the 38-ratio list if viable samples, both in size and quality, were to be used. Therefore, no ratios were selected to represent Grth and IS. As for the remaining nine components, ratios with the highest loadings onto these components over the period were selected. Certainly, this required taking a look back at the rotated component matrices for G4 over the period[131]. This led to the selection of 20 ratios representing the nine components as shown in Table 8.11 (See Table 4.4 for full names of ratios and Appendix 4.1 for descriptions of their components).

Table 8.11: Consistent financial patters for small commercial banks (G4) and their representative ratios*

Financial patterns	Selected ratios
1. Prof	X7, X10, X53
2. Sh-t liq	X39, X43, X46
3. M(Y)-I	X3, X15, X36
4. M(C)-II	X2, X38
5. Ln&Ls	X48, X23, X49
6. AQ-I	X6
7. AQ-II	19, X20
8. RBC	X24, X56
9. CG	X26
10. Grth	-
11. IS	-
Number of ratios	20

* Refer to Table 4.4 for full names of the ratios.

Samples size. Table 8.12 shows the number of small De Novo banks for which all 20 ratios were available and the resulting cases-per-variable ratios. As can be seen from the table, these samples were slightly larger than those of the small De Novo banks with all 38 ratios available. The size of the samples here ranged between 75 (2002) and 127 (2005) small banks. The smaller number of ratios and slightly larger number of available banks resulted in healthier cases-per-variable ratios than those previously used in this chapter. Around four banks were available for every ratio used in 2002, five banks for every ratio used in 2001, 2003 and 2004, and six banks per ratio in 2005.

However, even with these healthier figures, again, the datasets for the small De Novo banks did not appear to be suitable enough to apply PCA. The factorability statistics could only be calculated for 2005, similar to the previous subsection. For 2005, the

[131] These matrices are reported in Appendices 6.2 and 6.4 of Chapter 6.

BTS statistic was significant, and the KMO test result could be described as 'middling'. Both results were good enough to justify applying PCA for the year 2005. Nevertheless, given the exploratory nature of this chapter emphasised in earlier paragraphs, PCA was performed over all the datasets between 2001 and 2005.

Table 8.12: Small De Novo banks with 20 ratios available (2001-2005)

Group	Number of banks	Cases-per-variable ratio
2001	99	4.95
2002	75	3.75
2003	97	4.85
2004	99	4.95
2005	127	6.35

Appendix 8.3 gives all the outputs of PCA performed over the five datasets. Tables 8.13 and 8.14 summarise some of the relevant results. In Table 8.13, PA suggested grouping the 20 ratios into three factors in 2001, four factors in 2002 and 2003, and five factors in 2004 and 2005. So, the number of factors suggested by PA was far below nine which was the number of dimensions supposedly represented by the 20 ratios. Similarly, the nine dimensions were not implied by the latent root (eigenvalue >1) method which suggested instead retaining only 5/6 factors over the five years. Cattell's scree plot, however, proposed retaining eight factors in 2001, eleven in 2002 and ten in the following years. Nevertheless, following what was emphasised in Chapter 3 and practiced in Chapters 5, 6 and 7, the number of factors to extract was solely decided by PA The 3 to 5-factor solutions suggested by PA explained a percentage of variance ranging between 71.24% (2001) and 81.91% (2005).

Table 8.13: Number of components and percentage of variance explained for small De Novo banks 2001-2005 (20 ratios)

	Eigenvalue >1	Cattell's Scree	PA
2001	5 (85.61%)	8 (96.54%)	3 (71.24%)
2002	5 (83.78%)	11(98.80%)	4 (78.55%)
2003	6 (88.63%)	10 (98.25%)	4 (76.12%)
2004	6 (87.22%)	10 (97.83%)	5 (81.56%)
2005	6 (88.47%)	10 (97.59%)	5 (81.91%)

Table 8.14: General points to consider in interpreting the rotated component matrices for small De Novo banks 2001-2005 (20 ratios)*

		Ratios	
Year	**Significant loadings**	**Insignificant loadings**	**Multiple significant loadings**
2001	.60	X7, X26, X53	-
2002	.65	X6, X36, X56	-
2003	.60	X36	-
2004	.60	X56	-
2005	.50	X38	-

1. Significant loadings were decided using the guidelines in Hair et al. (1998, p.112, Table 3.2) and the study sample size (Table 8.12).
2. Refer to Table 4.4 for full names of the ratios.

After rotating the initial solutions using the varimax rotation method, the rotated component matrices summarised in Appendix 8.3 were studied in order to assign suitable labels to the components. Given the size of the samples used in this subsection, the significance levels for loadings were .50 in 2005, .60 in 2001, 2003 and 2004, and .65 in 2002, as Table 8.14 shows. Given this, a few ratios had insignificant loadings whereas none of the ratios had multiple significant loadings. With reference to Table 8.11, the ratios with insignificant loadings belonged to different factors.

Table 8.15 shows the labels given the factors onto which the 20 ratios for the small De Novo banks loaded. These 20 ratios that were initially chosen to represent nine factors were left to load onto 3-5 factors in the different years. Therefore, it was not surprising to see that nearly every derived factor represented more than one dimension of performance. Nevertheless, only one label had to be chosen for each of these extracted factors; the chosen labels generally described the dominant dimension represented by the factors. The prevailing dimension of a particular factor was decided by the ratios that had the highest loadings onto the factor. Consequently, the less influential aspects were given in brackets in Table 8.15.

Table 8.15: Labels assigned to components of small De Novo banks in 2001-2005 (20 ratios)*

	C1	**C2**	**C3**	**C4**	**C5**
2001	Ln&Ls (Sh-t liq +RBC)	AQ-II (AQ-I+M(Y)-I)	M(C)-II	-	-
2002	Ln&Ls (Sh-t liq)	Prof (CG + RBC)	M(Y)-I (M(C)-II)	AQ-II	-
2003	Ln&Ls (Sh-t liq)	Prof (CG + AQ-I)	M(Y)-I (M(C)-II)	AQ-II	
2004	M(Y)-I (AQ-I)	Prof (CG)	AQ-II (Ln&Ls)	Sh-t liq	M(C)-II
2005	Prof (CG)	Ln&Ls (AQ-I)	M(Y)-I (RBC+ M(C)-II)	Sh-t liq	AQ-II

* Refer to Table 5.8 for full names of the components.

As can be seen from Table 8.15, the different dimensions of performance were, to a large extent, jumbled in all the years covered. However, Ln&Ls, AQ-II, M(Y)-I and M(C)-II were the dominating aspects for the small De Novo banks. Other aspects like RBC, CG and AQ-I were clearly less significant for the small new banks.

In the following section, the study follows another path looking for further understandings of the classification patterns for the De Novo banks. This time, however, the patterns in the early years following the opening of banks are under scrutiny.

8.5 Financial patterns for De Novo banks founded in 2001 in years 2002-2005

The analyses carried out in Sections 8.3 and 8.4 investigated the financial classifications of ratios for the De Novo banks in their first year of operation. In this section, however, banks which were founded in 2001 (i.e. 2001 De Novo banks) were tracked in the four years following the year in which they were established: 2002-2005. A separate PCA was carried out for each of these years using two sets of variables comprising 54 and 27 ratios. The general aim of this section is to check whether there is any change in the way in which these ratios are grouped during the years that follow the opening year; and whether the patterns identified in these years show any similarity to the patterns for the incumbent commercial banks investigated earlier (Chapter 5).

The reason why this part of the study used only De Novo banks that were established in 2001 is purely practical and related to the availability of data. As mentioned earlier (Chapter 4, Subsection 4.3.3), the UBPR groups together all the banks that open in a particular year and keeps them in the same group for a total period of five years. At the end of these five years, each of the banks is assigned to one of the 15 groups of commercial banks based on specific criteria also defined by the UBPR (FFIEC, 2006, pp. II-1–II-2). A standard UBPR obtained for a specific date (for example 31/12/2005) contains data for the previous five years including the stated date when the report is retrieved (i.e. 31/12/2001-2005). For this thesis, the specified date used when the data were collected was 31/12/2005, which meant that every UBPR downloaded for a bank contained the banks' data for a period of five years starting from 31/12/2001. As for the De Novo banks, this meant that for the De Novo banks founded in 2005, the UBPRs retrieved for the date 31/12/2005 contained data for the year of opening only (2005). For the 2004 De Novo banks where data were obtained on 31/12/2005, the UBPRs contained the banks' data for two years (2004 and 2005) and so on. So, for the 2001 De Novo banks, data were available for a five-year period between 2001 and 2005. Furthermore, there were 109 banks chartered in 2001; certainly, some of these banks were expected to have incomplete observations and thus, to be excluded from the sample. Nevertheless, the initial size of the sample was sufficient to carry on the planned study.

Unlike the previous section that used De Novo banks with an asset size of less than \$50 million, this section places no restrictions on the size of the assets. Table 8.6 shows that the majority of De Novo banks had a relatively small asset size in their first year of operation. However, the asset size of these banks gradually rose above \$50 million in the years following their establishment. For the De Novo banks chartered in 2001, Table 8.16 shows the number of banks with an asset size of less than \$50 million in the fourth quarter of each year. As can be seen from the table, the figures were very small and therefore it was decided to include banks of all sizes in this part of the study.

Table 8.16: 2001 De Novo banks of less than \$50 million asset size in Q4 for 2002-2005

Year	2001 De Novo banks	<\$50 m
2001	109	104
2002	109	77
2003	109	43
2004	109	27
2005	109	13

Concerning the variables on which this part of the study was based, two sets of variables were used: one had 54 ratios and the other had 27. Having decided to use De Novo banks of all classes of asset-size, the following two subsections start by giving the number of De Novo banks with full observations as well as the cases-per-variable ratios.

8.5.1 54 ratios

Table 8.17 shows the number of De Novo banks with all 56 ratios available in years 2002-2005 (see Table 4.4 for the full list of ratios). As the table shows, the number of banks with a complete set of valid observations was relatively small. For instance, the figure in year 2002 shows that there were fewer cases than variables for this year; the figures in years 2003-2005 were also still considered small. Unquestionably, running PCA using samples of these small sizes is not recommended (Hair et al., 1998, pp. 98-99). Therefore, a closer look at the data matrices was taken to check whether dropping some ratios would help in increasing the sizes of the samples.

After checking the data matrices in years 2002-2005, ratios X17 and X18 appeared to have missing observation percentages ranging from 31% (2004) to 62% (2002). In addition, ratios such as X21, X25, X27, X40 and X50, amongst others, had a substantial number of zero entries. However, in order to draw a basic comparison between the patterns for the De Novo banks and the incumbent commercial banks, it was crucial to use the same set of ratios. Therefore, it was decided to exclude only ratios X17 and X18 and to maintain all the other ratios on the list. As can be seen from Table 8.17, the size of the samples ranged between 84 (2002) and 100 De Novo banks (2005). Deleting the two ratios clearly increased the size of the samples. However, given that 54 ratios were used, the resulting cases-per-variable ratios were still very poor. The last column in Table 8.17 shows that barely two banks were available for every ratio in use. Nevertheless, regardless of the concerns raised by these figures, the analysis was carried out.

Table 8.17: 2001 De Novo banks with full observations in 2002-2005

2001 De Novo banks	56 Ratios	54 Ratios (X17-X18 excluded)	Cases-per-variable ratio
2002	30	84	1.56
2003	59	97	1.80
2004	67	98	1.81
2005	66	100	1.85

PCA was performed for the 2001 De Novo banks for years 2002-2005. All the relevant results are summarised in Appendix 8.4. Similar to the previous sections, little emphasis was given to the factorability tests. This is because of the concerns raised earlier regarding the rather small size of the samples and the corresponding low cases-per-variable ratios. For two years, 2002 and 2003, the statistical factorability tests (the anti-image correlation matrix, BTS and KMO) could not be performed and thus were not reported in the SPSS outputs. In years 2004 and 2005, however, the BTS statistics were significant whereas the KMO statistics were considered 'miserable' and 'mediocre' in the two years, respectively[132].

With regard to the number of components extracted for every year, Table 8.18 shows that PA suggested classifying the ratios for the 2001 De Novo banks into six groups for 2002 and 2005, seven for 2004 and eight for 2003. A higher number of components, however, was suggested by the latent root (eigenvalue >1) method and Cattell's scree plot. The former method suggested keeping 13-14 components and the latter pointed to 10 to 14 components over the years of the study, as is also shown in Table 8.18. PA solutions accounted for a percentage of variance ranging between 61.88% (2005) and 70.02% (2003). Clearly, these percentages were the smallest to be reported regarding the De Novo banks. However, here it is important to note that a larger number of ratios (54) was used in this subsection compared to the number of variables used in the previous ones (38 and 20 ratios). Table 8.18 also shows that the solutions suggested by the latent root (eigenvalue >1) and the scree plot methods captured larger percentages of the variance.

Table 8.18: 2001 De Novo banks: initial results in 2002-2005 (54 ratios)

2001 De Novo banks	Eigenvalue >1	Cattell's Scree	PA
2002	13 (84.68%)	10 (77.85%)	6 (64.74%)
2003	13 (83.01%)	12 (81.13%)	8 (70.02%)
2004	14 (84.77%)	14 (84.77%)	7 (65.77%)
2005	14 (84.66%)	12 (80.57%)	6 (61.88%)

The solutions suggested by PA were all rotated using the varimax rotation method. Then, the rotated component matrices were extensively examined in ordered to find appropriate labels with which to describe the factors. These matrices are given in the last part of Appendix 8.4. Moreover, Table 8.19 gives the significance levels for the ratio loadings in the different years. Based on this, the table lists the ratios that failed

[132] The KMO statistics were .590 and .621 in years 2004 and 2005, respectively.

to load significantly onto any component (see Table 4.4 for the full names of the ratios).

As Table 8.19 shows, a substantial number of ratios had insignificant loadings across the four years. Generally, these ratios described the following aspects of banks' performance: Eff, Grth and IS (see Table 5.8 for the full names of the components). In addition, a number of AQ and Ln&Ls ratios had insignificant loadings in some of the years. It also can be seen from the table that none of the 54 ratios had more than one significant loading in any of the four years. However, whether the components are meaningful or not is another matter. This is discussed in the following paragraph.

Table 8.19: General points to consider in interpreting the rotated matrices for 2001 De Novo banks in 2002-2005 (54 ratios)

Year	Significant loadings	Ratios	
		Insignificant loadings	Multiple sig. loadings
2002	.65	X30, X35, 42, X37, X34, X31, X3, X13, X44, X49, X15, X1, X4, X36, X50, X52, X40, X32, X16, X21, X28, X25, X51, X12, X11	-
2003	.60	X39, X41, X44, X5, X25, X21, X35, X27, X16, X37, X19, X48, X30, X40, X4, X31, X50, X6, X51, X34, X11, X52	-
2004	.60	X47, X32, X51, X25, X44, X11, X50, X37, X34, X40, X48, X23, X52, X31	-
2005	.55	X29, X47, X48, X44, X31, X54, X37, X25, X32, X4, X11, X35, X50, X52, X34, X51, X40	-

1. Significant loadings were decided using the guidelines in Hair et al. (1998, p.112, Table 3.2) and the study sample size (Table 8.17).
2. Refer to Table 4.4 for full names of the ratios.

Table 8.20 gives the labels that were assigned to the components into which the 54 ratios of the 2001 De Novo banks were grouped. Most components were successfully assigned to appropriate labels. The components that could not be labelled were C8 for 2003, and C5 and C7 for 2004. The components that were consistently identified for all four years were Prof, RBC and M(C)-II. Components which appeared in three years of the study were Sh-t liq, M(Y)-I and and AQ. Finally, the components that were identified in one year only over the period were Ln&Ls, Eff and Grth.

Table 8.20: Labels for patterns of 2001 De Novo banks in 2002-2005 (54 ratios)*

	C1	C2	C3	C4	C5	C6	C7	C8
2002	Prof	Sh-t liq	Ln&Ls	RBC	AQ	M(C)-II	-	-
2003	Prof	Sh-t liq	M(Y)-I	AQ	M(C)-II	RBC	Eff	No Name
2004	M(C)-II (Sh-t liq)	Prof	M(Y)-I	RBC	No Name	Grth	No Name	-
2005	Prof	Sh-t liq	M(Y)-I	AQ	M(C)-II	RBC	-	-

* Refer to Table 5.8 for full names of the components.

As can be seen in Table 8.20, the solutions in the different years consisted of a different number of components; also, the components that were identified over the years were different. In other words, the identified patterns did not seem consistent over the short period. At this point it was interesting to question whether, at any point in the short term, these patterns started to converge towards the patterns identified for the incumbent commercial banks.

In Chapter 5, 56 ratios for a large sample of incumbent commercial banks were grouped into 13 factors for every year between 2002 and 2005. At least 12 of these factors were successfully labelled across the years (see Table 5.12 for the labels for all years). Some of these factors were found for the 2001 De Novo banks in their early years. However, the solutions for the De Novo banks consisted of a far smaller number of factors compared to those for the incumbent commercial banks. Furthermore, no sign of similarity appeared between the patterns for the De Novo and incumbent banks, at least for the short period covered in the study. Also, the patterns for the De Novo banks did not appear to become convergent to those for the incumbent banks at any point in time over the short period.

So, using a set of 54 ratios for the De Novo banks did not appear to achieve similar results to those obtained for the incumbent banks. However, it is important to note the size of the samples used for the new banks (see Table 8.17) and, besides this, the use of the large number of 54 ratios resulted in generally low cases-per-variable ratios; this would certainly have an effect on the results obtained for the De Novo banks. However, whilst the number of the banks used in this part of the study could not be increased, the only way to enhance the case-per-variable ratios was to use a smaller set of ratios. The results of this procedure are described in the following subsection.

8.5.2 27 ratios

In this subsection, the financial patterns for the 2001 De Novo banks for years 2002-2005 were identified using a small set of ratios. Since no restriction was placed on the asset size of the De Novo banks in the samples, this part of the study was also be based on the results obtained for the U.S. commercial banks for all asset-size groups examined in Chapter 5. The set of ratios used here represented the consistent financial patterns identified for the incumbent commercial banks and the purpose was to check whether similar dimensions could be identified for the De Novo banks in their early years. Another goal was to see whether any signs of convergence could be found in the early years of the De Novo banks when their patterns were compared with the patterns of the 'mature' commercial banks.

Table 8.21 lists the 12 factors consistently identified for the U.S. commercial banks (See Table 5.8 for the full names of the factors). Besides these factors, Eff-II was identified for the commercial banks in years 2002 and 2005 only, and therefore it was not included in the table. A careful examination was made of the ratio loadings onto the factors of the commercial banks (Table 5.11). Consequently, two or three ratios were selected to represent each of these factors[133]. The AQ-I factor, however, was represented only by ratio X6 since the other key ratios associated with the factor, X18 and X19, had a substantial number of missing observations and therefore had to be excluded in order to obtain a reasonable sample size.

Compared to Table 8.11 in subsection 8.4.2, the Grth and IS factors are now included in Table 8.21 because of the availability of their ratios for the new banks in their first four years. Also, Table 8.21 includes the Eff-I factor which was inconsistent for the small commercial banks (banks in G4) on which subsection 8.4.2 was based.

[133] Selecting either two or three ratios to represent a factor was based on how many key ratios loaded significantly onto the factors.

Table 8.21: Consistent financial patterns for all commercial banks and their representative ratios*

Financial patterns	Selected ratios
1. Prof	X7, X10, X53
2. Sh-t liq	X43, X46, X39
3. M(Y)-I	X3, X15, X36
4. M(C)-II	X2, X38
5. Ln&Ls	X23, X49
6. AQ-I	X6
7. AQ-II	X19, X20
8. RBC	X24, X56
9. CG	X29, X54
10. Grth	X32, X28
11. Eff-I	X4, X5, X11
12. IS	X50, X51
Number of ratios	27

* Refer to Table 4.4 for full names of the ratios.

So, the total number of ratios selected was 27. Using this small set of ratios slightly increased the sizes of the samples which now ranged between 93 (2002) and 104 (2005) banks, as Table 8.22 shows. More importantly, the cases-per-variable ratios increased significantly. As can be seen from Table 8.22, for every ratio used around four banks were available in each of the four years. While this was not yet the most preferable ratio of five cases-per-variable (Hair et al., 1998, pp. 98-99), it was decided to use all 27 ratios without further reducing the number. This is because dropping some ratios would result in an incomplete number of dimensions being represented by the set of variables.

Table 8.22: 2001 De Novo banks with 27 ratios available in 2002-2005

Year	Number of banks	Cases-per-variable ratio
2002	93	3.44
2003	100	3.70
2004	103	3.81
2005	104	3.85

When the samples were ready to perform PCA, the factorability tests were not in favour of running the analysis. Contrary to what had been experienced and recorded earlier in this chapter, SPSS, the statistical software package, reported the factorability results for all the years but these results were not impressive. The amount of common variance shared by the variables was rather small in all four years. This was implied by the KMO statistics which were considered to be 'miserable' according to the guidelines of Sharma (1996, p.116)[134]. The analyses nevertheless were performed for all four years bearing in mind the points that were raised above if any generalisations were to be made.

Table 8.23 shows that PA suggested classifying the 27 ratios into six groups in 2002, and seven groups in the following three years. So, PA found that 6-7 factors were sufficient to represent the 27 ratios. The PA solutions over the years explained different percentages of variance ranging between 70.54% in 2002 and 75.13% in 2004. The latent root (eigenvalue >1) method suggested keeping nine factors for every year; this explained more than 82% of the variance. Cattell's scree plot suggested retaining 12 factors in 2002, 11 in 2003 and 10 in 2004 and 2005. The solutions suggested by Cattell's plot explained between 85.99% (2005) and 92.66% (2002) of the variance. However, the solutions that were finally extracted are those suggested by PA. Appendix 8.5 gives all the detailed outputs of PA and PCA over the samples for the four years.

Table 8.23: Initial results for 2001 De Novo banks in 2002-2005 (27 ratios)

2001 De Novo banks	Eigenvalue >1	Cattell's Scree	PA
2002	9 (83.73%)	12 (92.66%)	6 (70.54%)
2003	9 (82.25%)	11 (88.85%)	7 (72.90%)
2004	9 (83.21%)	10 (86.53%)	7 (75.13%)
2005	9 (82.37%)	10 (85.99%)	7 (73.91%)

Given the size of the samples used (see Table 8.22) and the significance levels of the loadings (Hair et al., 1998, p. 112, Table 3.2), Table 8.24 shows that significant loadings should be equal to or greater than .60 in 2002 and .55 in years 2003-2005. Based on this, Table 8.24 also lists the ratios that failed to load significantly onto any of the factors in the four years. By referring to Table 8.21, these ratios represent Eff-II (X4, X5 and X11) and Grth (X32 and X28), amongst other factors. The table also shows that none of the ratios had loaded significantly onto more than one factor over the period.

[134] The KMO statistics were .588, .524, .571 and .531 in years 2002-2005, respectively.

Table 8.24: General points to consider in interpreting the rotated matrices for 2001 De Novo banks in 2002-2005 (27 ratios)

Year	Significant loadings	Ratios	
		Insignificant loadings	Multiple significant loadings
2002	0.60	X4, X11, X28, X32, X56	-
2003	0.55	X11, X32, X46	-
2004	0.55	X11, X23, X50	-
2005	0.55	X5, X6, X32, X39, X46	-

1. Significant loadings were decided using the guidelines in Hair et al. (1998, p.112, Table 3.2) and the study sample size (Table 8.22).
2. Refer to Table 4.4 for full names of the ratios.

Table 8.25 shows the labels that were assigned to the factors after closely examining the rotated component matrices as summarised in Appendix 8.5[135] (refer to Table 5.8 for full names of all factors). Studying the component matrices revealed that, for many factors, ratios initially representing different dimensions were loading significantly onto one factor. Such factors were labelled according to the ratios with the highest loadings. Other dimensions represented by the factors are shown in brackets in Table 8.25.

Table 8.25: Labels assigned to components of 2001 De Novo banks in 2002-2005 (27 ratios)*

	C1	C2	C3	C4	C5	C6	C7
2002	Prof (CG+RBC)	M(Y)-I	M(C)-II (Sh-t liq)	Ln&Ls	AQ-II (AQ-I)	IS	
2003	Prof (CG)	M(C)-II (Sh-t liq)	M(Y)-I	AQ-II	RBC (AQ-I)	IS	Eff-I
2004	M(C)-II (Sh-t liq + Ln&Ls)	Prof (CG)	M(Y)-I	AQ-II (AQ-I)	RBC (IS)	Grth	Eff-I
2005	Prof (RBC)	M(C)-II (Sh-t liq)	M(Y)-I	CG	AQ-II	IS	Eff-I

* Refer to Table 5.8 for full names of the components.

As can be seen from Table 8.25, only four factors were consistently identified in the first four years for the De Novo banks founded in 2001. These factors were Prof, M(Y)-I, M(C)-II and AQ-II. Less consistent factors included Eff-I (2003-2005), IS (2002, 2004 and 2005) and RBC (2003 and 2004). Factors that were identified for one year only over the period were Ln&Ls (2002), Grth (2004) and CG (2005).

So, amongst the 12 dimensions represented by the set of ratios, only four dimensions appeared consistently over the years, and another six dimensions were inconsistent. The only two aspects that could not be identified as distinctive factors were Sh-t liq and AQ-I. By referring to the rotated component matrices, it can be seen that Sh-t liq

[135] The varimax rotation method was applied to all the solutions.

ratios (X43, X46 and X39) loaded together with the M(C)-II ratios (X2 and X38) in all the years. However, the M(C)-II ratios had higher loadings in most of the years while some of the Sh-t liq ratios failed to have significant loadings in two years. Given this, the M(C)-II aspect of performance prevailed over the Sh-t liq aspect and, for this reason, the M(C)-II label was given to the factor. With regard to AQ-I, this was represented by one ratio only (X6). This ratio loaded onto AQ-II in two years (2002-2004) and onto RBC in one year (2003) while it failed to have any significant loadings in 2005.

To sum up, 27 ratios which initially represented 12 consistent dimensions for the incumbent commercial banks were grouped into only 6-7 groups for the De Novo banks in their early years of operation. Amongst these 6-7 patterns, only four were identified in every year over the four-year period whereas the other patterns were largely inconsistent. Thus, no evidence was found that financial patterns for the De Novo banks and the incumbent banks were similar or convergent during the first four years of the life of the new banks.

Overall, it should be emphasised that any results reached in this section as a whole need to be considered carefully. First, this section only covered banks that were chartered in 2001 and continued to operate in the following four years. Therefore, more groups of banks that were chartered in other years should be studied before generalising our findings. Second, given that the samples used were bordering on around 100 cases, the issue of whether these datasets were suitable enough to apply PCA should also be borne in mind. Other drawbacks of the study are covered in the concluding section which follows.

8.6 Summary

This chapter explored whether the financial ratios for De Novo banks could be grouped into distinctive patterns in the first year of the banks' operations. In addition, a part of the study tracked the patterns for the newly-chartered banks in the years that followed the opening year. This study used different samples which were all extracted from the population of newly-chartered banks. The variation in these samples included using different sets of ratios and also using banks of a particular asset size. In most cases, only a few banks had to be excluded from the initial samples because of incomplete observations. Whenever it was possible, the consistency of the results was indirectly assessed by running the analysis simultaneously on a yearly basis using banks chartered in every year between 2001 and 2005 and by comparing the results visually. Also, whenever relevant, the results were compared to the findings of the previous chapters that studied incumbent U.S. commercial banks.

All the data used in this chapter were transformed using the archsinh method of transformation to enhance the approximation of the distributions to normality. The number of components retained and interpreted in all the trials were decided by Parallel Analysis (PA). Principal Component Analysis (PCA) with a varimax rotation was performed to extract the patterns of the ratios. The samples used ranged in size according to the number of ratios used and to the asset size of the banks but the initial samples were generally in a range of between 85 (2002) and 162 (2005) De Novo banks. The group of banks that was tracked in the short period after the opening year included the De Novo banks that were chartered in 2001 (109 banks).

The study first identified the patterns of 38 ratios for the new banks in their first year. 5-6 patterns were found; four of these patterns were identified in every year over the period between 2001 and 2005. These were Prof, Sh-t liq, M(Y)-I and M(C)-II (see Table 5.8 for the full names of the patterns). The inconsistent patterns included Ln&Ls and AQ. These factor solutions explained at least 76% of the variance in the datasets.

When the same 38 ratios were analysed for the new banks with an asset size of less than $50 million at the end of their first year, fairly similar results were obtained. However, the Ln&Ls factor was identified more frequently for the small De Novo banks and this factor seemed to be of more importance than the AQ factor for these banks. Similarly, in Chapter 6, the Ln&Ls factor was stronger (i.e. appeared more frequently) for groups of small incumbent commercial banks. So, it could be said that the Ln&Ls ratios appeared to make a distinctive pattern, especially for groups of small commercial banks whether these banks were incumbent or newly-established.

In addition, a smaller set of 20 ratios was selected and analysed for the small De Novo banks in their first year. These ratios were selected to represent nine out of eleven financial patterns found consistently for small incumbent commercial banks in an earlier chapter (Chapter 6). For the small De Novo banks, these 20 ratios were clustered into only three, four and five groups over the period between 2001 and 2005. The solutions explained a minimum of 71% of the variance. Some of these dimensions clustered together in an unpredictable way over the five years. However, the most distinctive and consistent dimensions for the small De Novo banks over the years were Ln&Ls, AQ-II, M(Y)-I and M(C)-II.

Moreover, the study identified the financial patterns for a group of the De Novo banks for four successive years after the year of establishment. The aim was to assess whether there is any trend in which the patterns developed in the early years of the banks' lives. This was carried out using a sample of De Novo banks which started business in 2001. For these banks, a large set of 54 ratios was first classified into a different number of groups over the different years. The solutions accounted for a minimum of 61% of the variance, which was by far the smallest proportion of explained variance for the De Novo banks. Interestingly, the study identified some patterns of ratios which could not be identified for banks in their first year of operation. The RBC factor, for example, appeared consistently over the four years. Furthermore, Eff and Grth factors were identified, albeit inconsistently, over the period. Nevertheless, over the short period, the financial patterns for the De Novo banks did not seem to converge towards the patterns identified for the incumbent banks.

The last part of the study was replicated but using a different sampling procedure. This time it used 27 carefully selected ratios to represent the 12 consistent factors identified for the incumbent commercial banks over the period between 2002 and 2005. Amongst these 12 patterns, only 6-7 were identified for the De Novo banks; these explained a minimum of 70% of the variance. Nevertheless, no obvious trend was identified concerning the way in which the ratios were clustering in the short term. For example, the patterns for banks in their fourth year were rather more similar to the patterns for the banks in their first or second year than to the patterns of the incumbent banks.

Nevertheless, it was emphasised that all the results should be interpreted with caution and that no generalisation should be made without further studies. This is because of the reservations that were stressed regarding the rather small sizes of the samples, the low cases-per-variables ratios and the suitability of the overall data for PCA. For the same reasons, this chapter did not use any statistical techniques (i.e. correlation and congruency coefficients and transformation analysis) to compare the different solutions. Thus, the similarity of the different solutions was assessed only visually.

A step towards generalising the findings of the current chapter could be taken firstly by using larger samples and secondly, expanding the period of the study to consider the longer term. Here, it could be argued that some parts of the study could have been carried out differently, for example, using only one sample that included all the De Novo banks chartered in the period between 2001 and 2005 to derive the financial patterns. A sample like this would certainly be of a good size which, in turn, would give a satisfactory cases-per-variable ratio. However, in Chapters 5 and 6, a certain degree of short-term instability was noted in the financial patterns for the commercial banks over the period 2001-2005. Such differences were found using samples of the whole population of the U.S. commercial banks and also for samples of banks that belonged to different classes of asset-size. Uncovering the reasons behind the observed short-term instability was beyond the scope of this study. Certainly, disregarding the finding of the previous chapters and pooling all the newly-opened banks into one sample was not the right procedure to follow in the current study.

In addition, it would be necessary to check whether a small number of ratios, representing a certain number of consistent dimensions for the incumbent banks, would load significantly onto the same number of factors for the De Novo banks. While the results of such a procedure would have been interesting, it should be noted that the number of dimensions derived for each sample was solely decided by Parallel

Analysis. Forcing ratios to load onto a pre-determined number of factors is arguably not a wrong procedure. However, such procedure does not suit the exploratory nature of this study given the lack of evidence reported so far on the financial patterns for the De Novo banks.

Last but not least, studying the financial patterns of the De Novo banks for a short period of five years is certainly insufficient to produce rigorous evidence of their stability or maturity over time. The short period is particularly insufficient given that a study by DeYoung and Hasan (1998) found that it will not be until nine years have passed before De Novo banks start to perform as their counterpart mature banks.

Chapter 9 Conclusion

9.1 Introduction

This chapter summarises the findings that emerged from the empirical analysis carried out in Chapters 5, 6, 7 and 8 of this thesis; it also relates these findings to the research questions that were posed at the beginning of this study. The significance of this study lies in the fact that, for the first time in the literature of ratio classification, we have classified financial ratios for commercial and savings banks and measured their time stability; it also tested the cross-sectional stability of the patterns between commercial and savings banks. Furthermore, the study checked whether ratios for banks in different asset-size classes could be classified in the same manner and whether the time stability of patterns for the different asset-size groups was the same. Finally, the study offered the first attempt to explore the classification patterns of financial ratios for De Novo (that is, newly-opened) commercial banks.

The strengths of this study can be summarised by the following points. First, most of the analyses carried out in this study used very large samples. Second, the arcsinh transformation was utilised for the first time in the ratio classification literature to improve the distributional properties of the data. Third, different factorability tests were performed and their results were reported here, unlike the previous literature which generally paid no attention to such tests. Fourth, unlike the previous literature that mainly used the ‘eigenvalue greater than one’ criterion to decide on the number of patterns, this study mainly used the method of Parallel Analysis (PA). However, it also reported the results of the eigenvalue criterion and Cattell’s scree plot. Fifth, the use of different factor comparison techniques distinguishes this study; also, the study is the first in the ratio classification literature to assign labels describe the goodness of match of the patterns either over years or across the different samples [this was provided in Richman and Lamb (1985, Appendix)]. Last but not least, the study is the first outside of Scandinavia to apply transformation analysis and, most importantly, it developed a significance test to assess its overall results.

The rest of the chapter is organised as follows: after the introduction, Section 9.2 summarises the study's main findings in regard to the four primary and secondary questions on which the study was based. Section 9.3 discusses the implications of this study. Section 9.4 addresses the limitations of the study and offers some suggestions for further research. Section 9.5 ends the chapter with concluding remarks.

9.2 Summary of findings

This study has generally aimed to deepen the understanding regarding the dimensions which exist in a large set of bank financial ratios, together with the time and cross-sectional properties of these dimensions. Using data from the Uniform Bank Performance Report (UBPR), the patterns of ratios were identified using Principal Component Analysis (PCA) which was performed over the different samples of U.S. banks. As explained earlier in the study, PCA is a data reduction technique in which ratios that are highly correlated are considered to represent one dimension and thus are grouped together into what can be called patterns, groups, dimensions, etc. Each of the identified groups is then given a label that describes the dimension which these ratios represent. These identified groups are independent of each other; in other words they describe completely different and unique dimensions of performance. So, after transforming the data using the arcsinh transformation method, the factorability of the data was tested by visually checking the correlation matrices and also by using two statistical tests: Bartlett's Test of Sphericity (BTS), in addition to the Kaiser-Meyer-Olkin (KMO) measure of sample adequacy (MSA). This step was followed by running PA and using its outputs to decide on the number of patterns to derive. To facilitate the interpretation step of the patterns, the solutions were all rotated using the varimax orthogonal rotational method which results in patterns which are easy to interpret but which are still independent of each other (i.e. uncorrelated). Following the identification of the patterns for the different samples on a yearly basis, these patterns were compared over time and across the different samples using visual comparison, correlation, congruency and transformation analyses. Last but not least, a significance test was used for an overall assessment of the outputs of transformation analysis. Using all these factor comparison methods helped in reaching concrete conclusions on the extent to which the patterns of bank ratios were similar / dissimilar over time and across banks of different types and asset size classes.

The following subsections restate the research questions posed at the beginning of the study (Chapter 1, Section 1.2) and summarise the findings of the study in regard to these questions.

9.2.1 Findings for research question 1

Research question 1: What are the classification patterns of financial ratios for commercial banks?

- *To what extent are these patterns stable over a short period?*

These questions were investigated in Chapter 5 using samples of over 5,399 U.S. commercial banks for the years between 2001 and 2005, and a list of 56 financial ratios selected from the UBPR; this list generally covered the following aspects of bank performance: earnings and profitability, margin analysis, loan and lease analysis, liquidity, capitalisation, and growth rates. The study found that the financial ratios for commercial banks could generally be represented by 12 dimensions. The following dimensions were found in every year over the period: Profitability, Short-Term Liquidity, Margin (Yields), Margin (Costs), Loans and Leases, Risk-Based Capital, Capital Growth, Asset Quality I and II, Efficiency I, Investment Securities, and Growth. These patterns exhibited a satisfactory degree of stability over the period except for the Growth group which was found to be the least stable. In addition to these groups, another Efficiency group (labelled Efficiency II) was identified for some of the years; also, a third Asset Quality group (Asset Quality III) was found only for the year 2001.

9.2.2 Findings for research question 2

Research question 2: To what extent are the classification patterns of financial ratios for commercial banks belonging to different asset-size classes similar?

- *Do these patterns exhibit the same level of stability over a short period?*

These questions were investigated in Chapter 6 in which the samples of commercial banks used in Chapter 5 were arranged into four groups, based on asset size. These four groups contained banks with asset sizes in excess of $300 million, between $100 and $300 million, between $50 and $100 million, and less than $50 million, respectively. This part of the study also used all 56 ratios which were classified in Chapter 5 for the commercial bank sample as a whole. The analysis was performed for each of the four groups in every year over the period between 2001 and 2005. The stability of the identified patterns was then compared over time and between the different groups. The number of ratio patterns found for the different groups ranged between 11 and 13 over the years. The patterns that were consistent (that is, identified for all four groups in all the years) represented: Profitability, Short-Term Liquidity, Margin (Yields and Costs), Asset Quality (I and II), Risk-Based Capital, Capital Growth, and Investment Securities. Amongst these, the first two patterns showed the highest similarity level both over time and across the different groups whereas the least stable pattern was the Margin (Yields). The patterns that were identified for some of the groups in some years were: Loans and Leases, Growth, Efficiency (I and II), and Funding and Funding II). Also, the study identified two patterns (Short-Term Investment and Asset Quality III) for one group only in one year (group 2 and group 3 in year 2003, respectively). Nevertheless, one of the more significant findings that emerged from this study was that the Funding pattern of ratios was generally identified for the group of banks with the largest asset size. The same pattern of ratios, however, could not be identified for banks in the smaller asset-size groups; instead, a dimension that represented Loans and Leases was found for these groups. Moreover, ratios that described the Efficiency of banks tended in general to cluster with the Margin (Yields) ratios for the group of banks with a small asset size (less than $50 million). In other words, Efficiency did not represent a distinctive dimension for small banks. Last but not least, there were no apparent differences in the time stability of the patterns identified for banks in the different asset size classes;

to put it differently, the level of time stability for the patterns seemed to be independent of the asset size class of banks. Nevertheless, it was evident that the ratio patterns for banks in different asset-size groups were more stable over time than across groups.

9.2.3 Findings for research question 3

Research question 3: What are the classification patterns of financial ratios for savings banks?

- *To what extent are these patterns stable over a short period?*
- *To what extent are these patterns similar to the patterns of commercial banks?*

The patterns of ratios for savings banks were investigated in Chapter 7. The samples consisted of over 274 savings banks, for which 56 ratios were analysed on a yearly basis over the period 2001-2005. The time stability of these patterns was then assessed; also, the similarity between these patterns and those for the commercial banks was compared. The 56 ratios for the savings banks were classified into 10 to 11 groups over the years; amongst these, nine groups were identified in every year: Profitability, Short-Term Liquidity, Loans and Leases, Margin (Costs), Asset Quality (I and II), Risk-Based Capital, Capital Growth, and Investment Securities. Other inconsistent groups included Efficiency, Growth and Funding II. Amongst the consistent groups of ratios (that is, groups found in every year), Loans and Leases, and Risk-Based Capital were the most stable over time whereas Margin (Costs) and Capital Growth were the least stable. Moreover, some similarity was found between the Growth and Funding II groups of ratios; also the Margin (Costs) and Efficiency groups exhibited some commonality with other dimensions of different years. So, in general, the time stability of ratio patterns was generally lower for savings banks compared to commercial banks. Nevertheless, the two types of banks had nine patterns that held the same label: Profitability, Short-Term Liquidity, Loans and Leases, Margin (Costs), Asset Quality (I and II), Risk-Based Capital, Capital Growth, and Investment Securities. Nevertheless, the ratio groups describing Growth, Efficiency and some undefined patterns were less frequent for the two types of banks (i.e. could not be identified in every year over the period). Also, the Margin (Yields) and Asset Quality III patterns were found only for the commercial banks whereas the

Funding II group was only found for the savings banks. When the content of groups was compared, the Profitability and Short-Term Liquidity patterns showed the most similarity between the savings and commercial banks. Nevertheless, Loans and Leases for savings banks seemed to reflect two dimensions: lending and margin. These two dimensions, however, were completely independent from each other for the commercial banks (i.e. they were identified as two independent patterns). To sum up, the same set of ratios was, to some extent, classified in a different manner for savings and commercial banks and even when the same groups were identified for the two types of banks, the content of these groups was not exactly the same.

9.2.4 Findings for research question 4

Research question 4: What are the classification patterns of financial ratios for the De Novo commercial banks in the first year of their operation?

- *Are these patterns similar to those for the incumbent commercial banks?*
- *If the answer to the previous question is no, in which year after starting their operations are the ratio classification patterns for the De Novo commercial banks analogous to their counterparts, the incumbent commercial banks?*

The ratio patterns for the commercial De Novo banks were explored in Chapter 8. The sample sizes used in this chapter were small as only 85 to 162 banks made up the population of the U.S. newly-chartered banks between 2001 and 2005. In order to make the most of the available De Novo banks and minimise the number of banks with missing observations, the study analysed different sets of 38, 20, 54 and 27 ratios chosen from the list of 56 ratios used in the previous chapters. First, the 38 ratios were grouped into 5 to 6 patterns for the banks in their first year of operation. Amongst these patterns, only four were found in all five years covered by the study; these were Profitability, Short-Term Liquidity, Margin (Yields) and Margin (Costs). The patterns that were infrequently identified described the Loans and Leases, and Asset Quality dimensions. However, the Loans and Leases pattern was found more often when only small De Novo banks (i.e. those with an asset size of less than \$50 million) were analysed. This implied that for smaller banks, whether newly-chartered or incumbent, the Loans and Leases ratios generally formed a distinct dimension. Moreover, in order to answer the question of the similarity between the dimensions of small incumbent and newly-opened commercial banks, 20 ratios were selected to represent 9 out of the 11 consistent patterns found for the small commercial banks in Chapter 6. This step, however, returned some results which could not be justified or, in other words, they appeared to be random; thus, it can be concluded that the patterns of ratios for small new commercial banks in their first year of operation did not seem to resemble those for the incumbent banks. By tracking the patterns of ratios for the De Novo banks in years 2 to 5 after chartering, the study first used a list of 54 ratios. Interestingly, some patterns which were not identified for the banks in the first year could be identified in the following years; these included Risk-Based Capital, Efficiency, and Growth. However, the study could not conclude that there was a trend of convergence for the patterns of De Novo banks towards those for the incumbent commercial banks, at least in the first five years after chartering. When the 54 ratios were reduced to a list of 20 that were carefully selected to represent 12 from amongst the 13 patterns found for the commercial banks, these ratios were grouped into 6 to 7 groups over years 2 to 5 after the chartering year. However, no evidence of convergence was found between the patterns of De Novo and their counterparts for the incumbent commercial banks.

9.3 Implications of the study

The main aim of the research carried out in this study was to aid in the selection amongst the massive number of bank ratios. The selection could be made after classifying bank ratios into groups; hence, by selecting one ratio from each group it would be possible to obtain a small set of ratios that describes all the dimensions that exist in the larger set. Moreover, the study investigated whether the type, size, and age of banks should be considered when choosing amongst ratios.

Practitioners and researchers who use bank financial ratios can benefit from the results of this study as follows. First, the study showed that it was possible to group 56 ratios for commercial banks into a smaller number of dimensions: Profitability, Short-Term Liquidity, Margin (Yields), Margin (Costs), Loans and Leases, Risk-Based Capital, Capital Growth, Asset Quality I and II, Efficiency I, and Investment Securities. Thus, a small set of ratios could be obtained by including ratios that had the highest loading onto these patterns over the five years covered in the study. The

Efficiency II and Growth dimensions were less consistent for commercial banks; thus, excluding ratios associating with these two patterns should not cause a major concern when samples of commercial banks are analysed. Nevertheless, as the study showed, the patterns for small and large commercial banks were not quite the same. Thus, the study implied that when commercial banks of a particular asset size class are under investigation, slightly different sets of ratios should be selected. Furthermore, the patterns of ratios for savings and commercial banks were rather dissimilar; thus, it would be incorrect to assume that a set of ratios that represents the patterns for commercial banks would also represent the patterns for savings banks. In other words, ratios that could be described as important for commercial banks would not necessarily be the same for savings banks. Last but not least, the study implied that for the newly-chartered (De Novo) commercial banks in their first year of performance, ratios that represented the following dimensions could be selected: Profitability, Short-Term Liquidity, Margin (Yields) and Margin (Costs). If small De Novo banks are under investigation, some ratios that described the Loans and Leases pattern could also be selected. Nevertheless, ratios for the De Novo banks were clustering in an inconsistent manner over the first five years after chartering; even in the fifth year, ratio patterns for the De Novo banks were still divergent from those for the incumbent commercial banks. Thus, this study casts some doubt on the approach followed by the UBPR in which the De Novo banks after five years are allocated to one of the fifteen peer groups of the incumbent commercial banks. Clearly, De Novo banks require further years until their patterns become similar to those of the incumbent commercial banks.

9.4 Limitations and suggestions for future study

This section lists a number of caveats that need to be noted regarding the present study; it also provides some insights for future research.

The current study was limited by the following four issues. First, the use of the U.S. UBPR as the data source for this study made the results unique to the U.S. banking industry. Therefore, caution should be exercised in generalising the results for banks in other countries. Second, the study covered a period of only five years (2001-2005);

thus, generalising the results to other periods should not be carried out without further investigations.

Third, it should be also recalled that the UBPR arranges banks into peer groups; in regard to commercial banks, the peer group criteria include asset size, location and the number of banking offices. While the current study only investigated whether differences exist in the way in which ratios for commercial banks in different asset size classes are grouped, the effects of banks' locations (in urban or rural areas) and the number of branches were not accounted for in this study. The UBPR peer groups for savings banks, however, only consider the banks' asset size. In order to have a reasonable sample size to perform PCA, savings banks of different asset size classes were compiled into one sample. Thus, investigating how the ratios for savings banks in different asset size classes would be grouped was not a practical question to address in this study given the small number of savings banks on which our analysis was based.

A fourth limitation of this study concerns the results of the analysis carried out on the De Novo commercial banks. Given the small sample sizes that were available for this type of bank, caution must be applied as the PCA results for small samples could be considered as sample specific; thus, these might not be transferable to other samples.

Nevertheless, the following recommendations for future work are suggested in order generally to address the limitations identified above.

To begin with, in order to address the first and second limitations of this study and given that the current study represents the first attempt to investigate the patterns of banks' financial ratios, further work needs to be done to establish whether the results for the U.S. banks reported in this study can hold using data for banks operating in different countries and over different time periods. Furthermore, as the study covered a period of 5 years, another question that could be investigated would be to check the long term stability of banks' ratio patterns. Given the current condition of the banking industry, some instability in the patterns could be expected; nevertheless, it would be interesting to investigate whether the patterns of bank ratios are grouped differently in recent years given the new regulations and tight supervision that has been recently placed on banks.

Furthermore, in regard to the third limitation of the study, further analysis is required to check whether a bank's location affects the way in which ratios are grouped and also, whether the number of banking offices has any effect. Also, if satisfactory sample sizes of savings banks are available for different classes of asset-size, it would be interesting to investigate whether the size effect on the classification patterns of ratios is similar for commercial and savings banks. For example, it could be checked to see whether the patterns for large savings banks are more similar to those for large commercial banks than for small savings banks.

In regard to the fourth limitation, while using small samples of De Novo banks was inevitable, a possible procedure that could be followed in future research to increase the sample size would be to gather the banks which were opened in different calendar years into one sample; then, the patterns of ratios for these banks in their first, second, and so on years of opening could be studied. This would certainly increase the reliability of the results. A further suggestion could be to track the patterns of De Novo banks after five years of their establishment. Here, the question to investigate would be: at what age could the ratios of newly opened banks be grouped in the same way as the incumbent commercial banks? This could be a possible way of increasing understanding in regard to this type of bank. Also, the U.S. Federal Deposit Insurance Corporation (FDIC) could then utilise the output of the suggested research question by keeping De Novo banks in separate groups until they exhibited similar patterns to the incumbent banks (i.e. not just for five years).

Last but not least, the current study used a set of ratios that were extracted directly from the UBPR. However, the UBPR provides, besides figures in ratio form, some figures in dollar values which give the users of the report the option to compute their own ratios. By taking this option, the current study could be extended by calculating a set of ratios often cited as important in the literature of U.S. banks. The first step in this approach would be to survey the recent studies which used U.S. banks' financial ratios and to compute the most cited ratios using the UBPR data. The question to be addressed then would be to what extent the patterns of the most cited ratios in the banking literature are similar to the dimensions that were identified in the current study. In this sense, the findings of the current study are linked to the literature and to decision-making processes.

Finally, a possible research question would be to test empirically whether ratios representing the six CAMELS criteria (that is: Capital, Asset Quality, Management, Earnings, Liquidity, and Market Sensitivity) are empirically measuring these six dimensions. The suggested research question is of a confirmatory nature for which the use of Confirmatory Factor Analysis (CFA) would be most appropriate.

9.5 Concluding remarks

Given the current state of the global financial system, the banking industry in particular has started to receive, and will continue to attract, the attention of researchers, regulators and other parties. In the empirical analysis carried out regarding the banking industry, as in many other research areas, financial ratios remain the preferred units of analysis. Thus, understanding the properties of these ratios is crucial to enhance their efficiency and usefulness in empirical analysis. The insights offered in the current study concerning the classification patterns of bank financial ratios are thus expected to be of excellent value for future research in the area, particularly when these results are utilised in conjunction with advanced statistical analysis for event prediction purposes such as failure, mergers and acquisitions, amongst others.

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