Understanding the cost of carry in Nikkei 225 stock index futures markets: mispricing, price and volatility dynamics

Understanding the Cost of Carry in Nikkei 225 Stock Index Futures Markets: Mispricing, Price and Volatility Dynamics

by

Jieye Qin

Doctoral Thesis Submitted in Partial Fulfillment of the Requirements for the Award of Doctor of Philosophy of Loughborough University

September 2017

Abstract

This dissertation studies the cost of carry relationship and the international dynamics of mispricing, price and volatility in the three Nikkei futures markets - the Osaka Exchange (OSE), the Singapore Exchange (SGX) and the Chicago Mercantile Exchange (CME). Previous research does not fully consider the unique characteristics of the triple-listed Nikkei futures contracts, or the price and volatility dynamics in the three Nikkei futures exchanges at the same time. This dissertation makes a significant contribution to the existing literature. In particular, with a comprehensive new 19-year sample period, this dissertation helps deepen the understanding of the Nikkei spot-futures equilibrium and arbitrage behaviour, cross-border information transmission mechanism, and futures market integration.

The first topic of the dissertation is to study the cost of carry relationship, mispricing and index arbitrage in the three Nikkei markets. The standard cost of carry model is adjusted for each Nikkei futures contract by allowing for the triple-listing nature and key institutional differences. Based on this, the economic significance of the Nikkei mispricing is explored in the presence of transaction costs. The static behaviour of the mispricing suggests that it is difficult especially for institutional investors to make arbitrage profits in the OSE and SGX, and that index arbitrage in the CME is not strictly risk-free due to the exchange rate effect. Smooth transition models are used to study the dynamic behaviour of the mispricing in the three markets. The results show that mean reversion in mispricing and limits to arbitrage are driven more by transaction costs than by heterogeneous arbitrageurs in the Nikkei markets.

The second topic of the dissertation is to investigate the price discovery process in individual Nikkei markets and across the Nikkei futures markets. With smooth transition error correction models, this dissertation reports the leading role of the futures prices in the pre-crisis period and the leading role of the spot prices in the post-crisis period, in the first-moment information transmission process. Moreover, there is evidence of asymmetric adjustments in the Nikkei prices and volatilities. The cross-border dynamics suggest that the foreign Nikkei markets (the CME and SGX) act as the main price discovery vehicle, which implies the key functions of the equivalent, offshore markets in futures market globalisation.

The third topic of the dissertation is to study the volatility transmission process in individual Nikkei markets and across the Nikkei futures markets, from the perspectives of the volatility interactions in and across the Nikkei markets and of the dynamic Nikkei market linkages. This dissertation finds bidirectional volatility spillover effects between the Nikkei spot and futures markets, and the information leadership of the foreign Nikkei markets (the CME and SGX) in the second-moment information transmission process across the border. It further examines the dynamic conditional correlations between the Nikkei markets. The results point to a dramatic integration process with strongly persistent and stable Nikkei market co-movements over time.

Keywords:
Nikkei 225 futures; cost of carry relationship; mispricing; index arbitrage; price discovery; smooth transition; heterogeneity; volatility spillover; cross-border information transmission; dynamic conditional correlations; futures market integration; globalisation

JEL Classification:
C58; E44; F65; G01; G13; G14; G15; G23; G28

Acknowledgements

I am very grateful to my supervisors Professor Christopher J. Green and Dr Kavita Sirichand for their continuous guidance, support, encouragement and understanding during my PhD study. Their inspiring ideas, constructive suggestions and precious comments on earlier drafts of the dissertation are much appreciated. My special thanks go to Professor Green. In fact, without his help I would not have even commenced a doctoral study, let alone completed one.

My independent reviewers, Professor Mark Freeman and Professor Andrew Vivian, have supported my research during the PhD annual review process. They are the first (apart from supervisors) to carefully read my work and give insightful feedbacks. I am also very grateful to them.

I would like to thank Department of Economics, Loughborough University for the financial support for my PhD programme, and for the generous loan of a departmental laptop with which the research of a chapter of the dissertation was conducted.

The research in the dissertation has been presented in various seminars and conferences. I acknowledge the valuable comments from participants at these seminars and conferences, especially participants of the Portsmouth-Fordham International Conference on Banking and Finance (University of Portsmouth, 24th-25th September 2016), and of the 24th Forecasting Financial Markets (FFM) International Conference (University of Liverpool, 24th-26th May 2017). Meanwhile, I am very thankful that an extract from a chapter of the dissertation has been published in the FFM conference proceedings.

My deepest gratitude belongs to my parents and family, who have been with me in spirit while I am pursuing my doctoral degree overseas. I also would like to say thank-you to all my sisters and brothers in Trinity Methodist Church Centre, Loughborough for their friendship, support and company, especially my pastoral linker Mrs Kathleen Jackson who has kindly helped me with some of the proofreading in the dissertation.

Forever thanks and praise to my Lord Christ, whose love, grace and wisdom have been with me and will lead me to the future.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Background and motivations

Since the mid-1980s, globalisation has become a widely accepted idea in the international investment community. Arbitrage activities that span several continents seeking profits have been stimulated by the reduction in the costs of information processing and sharing, and by the growing mobility of financial capital through worldwide deregulation. In a macroeconomic sense, globalisation is reflected in the integration of several markets, especially those where similar products are traded such that these markets can be regarded as essentially equivalent. In a microeconomic sense, globalisation is reflected in one asset that can be traded on more than one venue, and between these venues are enormous flows of information generated by investment strategies such as arbitrage, hedging, speculation, diversification and risk management.

A seminal example of these phenomena is the Nikkei 225 stock index futures contracts. Based on one common stock market (Tokyo Stock Exchange, TSE), Nikkei 225 stock index futures contracts are traded on three different markets: Osaka Exchange (OSE), Singapore Exchange (SGX) and Chicago Mercantile Exchange (CME). Few futures contracts are like the Nikkei futures, which boast an international dimension with triple-listing in the three exchanges that have key institutional differences. Even today, in the course of futures market globalisation, futures contracts that start to trade in two or more exchanges do not typically enjoy a complete history as long as the Nikkei contracts do. The abundant and interesting characteristics of the Nikkei futures contracts provide a natural field to explore and examine the spot-futures relationship, market dynamics and the level of integration in and across the equivalent yet different markets.

This dissertation aims to study the cost of carry relationship and the international dynamics of mispricing, price and volatility in the three Nikkei futures markets. This is an important topic from three perspectives. First, the cost of carry model sets out equilibrium conditions between spot and futures markets. It defines theoretical (or fair) futures prices and thus departures from the theoretical prices, or futures mispricing. Understanding the cost of carry relationship and the behaviour of mispricing in interrelated markets is an essential task for investors worldwide who are keen to capitalise on temporary price deviations to make a profit. Second, price and volatility are important information transmission channels between financial markets. The cross-market information linkages and interactions have developed to such an unprecedented level that knowledge of the cross-border information transmission mechanism becomes vital for every participant involved in international financial markets, especially for asset managers who may wish to construct well-diversified portfolios and regulators who care about exchange competition, financial stability and integration in the global context. Third, the Nikkei futures contracts are one of the most actively traded derivatives in the world. Given the triple-listing nature and the institutional differences, the Nikkei spot-futures relationship and the cross-border price and volatility dynamics deserve a careful investigation. The reasons include:

a) Japanese firms adopt special dividend payout practices different from those in the US or the UK. This impacts the theoretical prices of the Nikkei futures contracts through the dividend streams on the underlying index, and hence Nikkei mispricing and index arbitrage.

b) Trading and settlement on the CME involve US dollars while trading and settlement on the underlying stock market, the OSE and the SGX involve Japanese yen. This introduces currency risk to the arbitrage between the CME and any other Nikkei market.

c) The three futures exchanges are located in different time zones. For example, the time used in the CME is 15 hours behind the time used in the OSE. The different trading hours may affect the Nikkei spot-futures relationship, futures price interactions and market co-movements.

d) The different levels of transaction costs in the Nikkei spot and futures markets affect the behaviour of Nikkei mispricing and index arbitrage, as index arbitrage will not be profitable until the size of mispricing is sufficiently large to cover the transaction costs incurred. The differences in market transaction costs also have implications for the information transmission mechanism across the border, as information tends to be disseminated more quickly in the market with lower transaction costs.

e) There are two hypotheses regarding the location of information leadership in international information dissemination: the home-bias hypothesis argues for the information leadership of the domestic market (OSE) for a set of home-market advantages; in contrast, the international centre hypothesis argues for the predominance of the foreign market (SGX or CME) for the better trading environment it can provide. It is an empirical issue whether the domestic or foreign exchange plays a leading role in specific markets such as the Nikkei.

Taking into consideration the special characteristics of the triple-listed Nikkei futures contracts and the major institutional differences, this dissertation investigates the following key issues:

1) The cost of carry equilibrium, the behaviour of mispricing and index arbitrage in the Nikkei markets.

2) The first-moment and second-moment information transmission mechanism in individual Nikkei markets and across the three Nikkei futures markets.

3) The dynamic Nikkei market linkages over time.

The first empirical chapter (Chapter 4) of the dissertation aims to investigate the static and dynamic behaviour of Nikkei futures mispricing in the three markets, using an adjusted cost of carry model for each contract, to explore the index arbitrage activities between Nikkei spot and futures markets. It addresses the specific question whether the mispricing, if any, represent profitable index arbitrage opportunities for investors in the three Nikkei futures markets. This is motivated by the fact that the cost of carry equilibrium and the mispricing behaviour of the three Nikkei futures contracts remain unclear to academics and practitioners, in that previous research does not fully consider the special characteristics of the Nikkei futures contracts when applying the cost of carry model. Yet ignoring them in the cost of carry model may lead to significant biases in pricing the Nikkei futures contracts. In addition, extant studies on the Nikkei futures mispricing were mostly published in the early 1990s when the three Nikkei futures markets were in their infancy. The futures mispricing behaviour in the currently mature Nikkei markets should be examined to enable a deeper understanding of the quickly changing market conditions and the impact of 2008 global financial crisis.

The second empirical chapter (Chapter 5) of the dissertation aims to study the international price discovery process in the Nikkei markets. It addresses the specific question of which market serves as the main price discovery vehicle in individual Nikkei markets and across the border. The price interactions constitute the first-moment information transmission channel in the Nikkei markets. With transactions taking place in the three exchanges, the Nikkei price dynamics could be quite different in the different exchanges due to the institutional differences. More importantly, it is not clear whether the home-bias hypothesis or the international centre hypothesis is more relevant for the Nikkei prices. There has been little published work on the price dynamics of all of the three Nikkei futures markets, except the paper by Booth et al. (1996) who use a linear error correction model without allowing for the effect of transaction costs. These considerations motivate Chapter 5.

The third empirical chapter (Chapter 6) of the dissertation aims to study the international volatility transmission process in the Nikkei markets. It addresses the following two specific questions: whether there is volatility spillover in and across the Nikkei markets; and how the Nikkei market linkages evolve over time. Apart from price, volatility interactions serve as another information channel between the Nikkei markets. Despite that the importance of the cross-market information linkages through volatility is widely acknowledged, there has been little published work on the volatility dynamics of all of the three Nikkei markets, leaving the volatility transmission mechanism across the border opaque. Further, little attention has been given to the dynamic Nikkei market linkages and the effect of the time differences on the

Nikkei market linkages has not been treated explicitly in the literature. These considerations motivate Chapter 6.

1.2 Contributions to knowledge

The most important contribution of the dissertation is that it investigates the cost of carry equilibrium and disequilibrium, price discovery and volatility transmission in individual Nikkei markets and across the three Nikkei futures markets. Previous research does not fully consider the unique characteristics of the triple-listed Nikkei futures contracts, or the price and volatility dynamics in the three Nikkei futures exchanges at the same time. By studying the cost of carry relationship, mispricing, price and volatility dynamics in the Nikkei markets, this dissertation helps deepen the understanding of the Nikkei spot-futures equilibrium and arbitrage behaviour, international first-moment and second-moment information transmission mechanism, and futures market integration.

The dissertation uses a completely new 19-year daily dataset. Almost all studies on the Nikkei markets were published in the early 1990s-early 2000s, and thus their samples exclude a series of major historical events that may significantly impact the international dynamics of Nikkei futures mispricing, price and volatility. Figure 1.1 illustrates the timeline of these events and the sample range of the dissertation. The whole sample period spans from 1996 to 2014, and includes a pre-crisis period (sample A) and a post-crisis period (sample B) divided by the 2008 global financial crisis. As such, the dissertation is able to provide comprehensive new evidence for the three Nikkei futures markets, to compare and contrast the cross-border mispricing, price and volatility dynamics before and after the 2008 global financial crisis, and to analyse the effects of the major historical events on the Nikkei market relationships.

In terms of methodology, a major contribution of the dissertation lies in the modification of the standard cost of carry model, which cannot be applied directly to the Nikkei contracts given the triple-listing nature and the institutional differences. The dissertation finds that the effects of the dividend and currency risks are strongly significant on the pricing of the Nikkei futures contracts, while the effect of the time differences is insignificant. Based on this, the dissertation modifies the standard cost of carry model for each Nikkei contract. It also allows for the effect of transaction costs when examining the Nikkei futures mispricing. In this way, the dissertation extends the work of Brenner et al. (1989a) and Board and Sutcliffe (1996) in adjusting the standard cost of carry model for index futures contracts traded on more than one exchange, and improves understanding of the impact of dividend and currency risks on spot and futures prices and on mispricing.

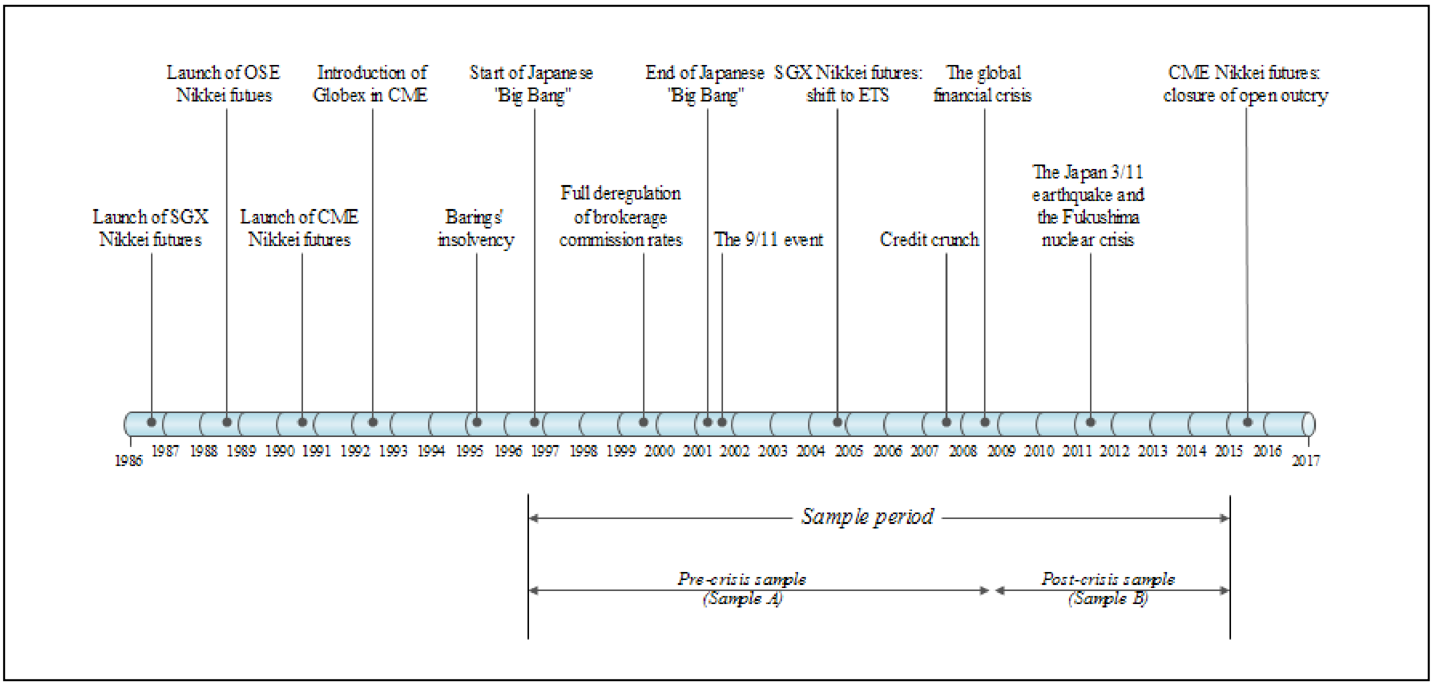


Figure 1.1 Major historical events in the Nikkei markets and the sample range of the dissertation

Notes: This figure displays major historical events in the Nikkei markets in chronological order. The Japanese "Big Bang" is a five-year financial reform aimed at deregulating and eliminating all partitions in Japanese financial markets (Flath, 2014). Globex is the electronic trading platform used in the CME. ETS is the electronic trading system used in the SGX. More details of these events are provided in Chapter 3. The whole sample period of the dissertation is 20/06/1996-31/12/2014 (OSE and SGX); 01/01/1997-31/12/2014 (CME). The pre-crisis period (sample A) is during 28/06/1996-09/10/2008 (OSE, SGX); 09/01/1997-12/09/2008 (CME). The post-crisis period (sample B) is during 04/11/2008-31/12/2014 (OSE, SGX); 02/12/2008-31/12/2014 (CME).

Smooth transition models have been studied in a few markets but never in the triple-listed Nikkei markets. This dissertation contributes to the smooth transition literature by showing that smooth transition nonlinearity is present in individual Nikkei markets and across the three Nikkei futures markets, and that the smooth transition models are appropriate for describing the nonlinear adjustment processes of the Nikkei futures mispricing and price. Furthermore, the dissertation analyses the effect of heterogeneity in investor structure and market transaction costs on the Nikkei spot and futures markets. The degree of heterogeneity as a futures market characteristic was not emphasised in the literature until the 2000s by Taylor et al. (2000), Tse (2001), McMillan and Speight (2006), for example. But none of these works consider the heterogeneity in an international setting. Using the smooth transition models, the dissertation is able to demonstrate that the degree of heterogeneity provides an important perspective at least for market regulation in separate countries and exchange competition across the border.

Studies on the Nikkei market dynamics tend to focus on the OSE and SGX, and circumvent the CME for its currency and time complexities. The only paper of Booth et al. (1996) on the price dynamics in the three Nikkei markets does not allow for the effect of transaction costs. The only volatility study on the three Nikkei markets is Bacha and Vila (1994) who look at the potential destabilising effects of the introduction of a new futures contract on the underlying stock volatility and the existing futures markets, but the volatility transmission mechanism across the three Nikkei exchanges have not been investigated. Focusing on the first-moment and second-moment information transmission across the three Nikkei markets, this dissertation finds the consistent result of the dominance of the foreign, offshore Nikkei markets (the CME and SGX) in the first-moment and second-moment information transmission processes across the border. This result is robust to the use of methodology and the time differences. In this respect, the dissertation makes an important contribution to knowledge by supporting the international centre hypothesis in the cross-border information dissemination procedure, and confirming the key role of equivalent, offshore markets in futures market globalisation.

There has been a substantial amount of research on the integration of stock markets, but futures market integration has not received much academic interest. To the best of my knowledge, no research has examined Nikkei market co-movements over time. The dissertation examines not only the dynamic Nikkei market linkages over the 19-year sample period, but also the effect of the different trading hours of the CME futures contracts on the Nikkei market linkages, an issue previously ignored in the literature. The dissertation fills in this research space and sheds light on the dramatic integration process of the Nikkei markets in the context of globalisation.

1.3 Organisation of the dissertation

The rest of the dissertation is organised as follows.

Chapter 2 critically reviews the extant literature on the spot-futures pricing relationship, based on two strands of research: the pricing efficiency of futures contracts, including the cost of carry relationship, mispricing, and index arbitrage; and the price and volatility dynamics between spot and futures markets, including the first-moment price discovery, second-moment volatility transmission processes within and across countries.

Chapter 3 introduces the Nikkei 225 index and index futures markets, and provides essential institutional and background information for the subsequent empirical chapters.

Chapter 4 studies the cost of carry equilibrium, futures mispricing and index arbitrage in the three Nikkei markets. It adjusts the standard cost of carry model for dividend lumpiness, currency risk, different trading hours and transaction costs. Based on this, it investigates the static behaviour of Nikkei mispricing using parametric and non-parametric methods. It then investigates the dynamic behaviour of Nikkei mispricing and heterogeneous arbitrage activities by an exponential smooth transition autoregressive (ESTAR) model.

Chapter 5 studies the international price discovery process through the price adjustments towards equilibrium in individual Nikkei markets and across the three Nikkei futures markets, using a linear error correction model (ECM) and a nonlinear exponential smooth transition error correction model (ESTECM). The robustness of the futures price interactions is checked by re-estimating the models with an alternative time sequence.

Chapter 6 studies the international volatility transmission process from two perspectives: the volatility interactions in and across the Nikkei markets, by a cross-correlation function (CCF) approach based on the ESTECM specification; and the Nikkei spot-futures and futures-futures dynamic conditional correlations (DCC), by a bivariate DCC model. The effect of the different trading hours of the CME futures contracts on the dynamic Nikkei market linkages is examined by re-estimating the DCC model with an alternative time sequence.

Chapter 7 provides main empirical findings, implications, limitations of the dissertation and directions for future research.

Chapter 2

The spot-futures pricing relationship: A literature review

2.1 Introduction

The chapter aims to critically review the extant literature on the spot-futures pricing relationship. On the whole, research has been conducted in the following two main areas: the pricing efficiency of futures contracts; and the price and volatility dynamics between spot and futures markets. To begin with, the pricing efficiency literature centres primarily on the cost of carry relationship, which gives the equilibrium condition between spot and futures prices. The cost of carry relationship argues that the theoretical (or fair) futures price should equal the deferred value of the underlying stock price over the remaining life of the futures contract in a perfect economy. In the presence of market imperfections, the cost of carry relationship becomes a no-arbitrage band whose lower and upper bounds are determined by factors such as transaction costs. Nevertheless, pricing deviations from the no-arbitrage relation, or futures mispricing, do exist and persist, evincing the possibility of profitable index arbitrage. Basically, index arbitrage activities will not be profitable until the size of mispricing is sufficiently large to cover the transaction costs incurred. Considering the option of liquidating futures contracts before expiration, another decision rule states that the absolute mispricing plus the value of early liquidation should exceed the transaction costs to create arbitrage opportunities. Econometric models have been developed to describe the index arbitrage behaviour and disentangle conditions required to profitably exploit the arbitrage opportunities.

Another area that attracts considerable academic interest is the price and volatility dynamics between spot and futures markets. Specifically, the first-moment price dynamics involves the interactions of conditional means, or the lead-lag relationship in price. Although all asset prices ultimately transmit information, the differences in market frictions can give rise to different speeds of information transmission, i.e. prices in one market are quicker in reflecting and disseminating information, such that its prices act as an important predictor for the subsequent prices in the other markets. Futures prices are generally thought to reflect and disseminate information more quickly than underlying spot prices, as is supported by theories concerning, *inter alia*, nonsynchronous trading, market frictions, nature of information, and trading mechanisms. Nevertheless, the lead-lag relationship between spot and futures prices in the real world can be more complex than the simplified theoretical prediction. Most empirical studies on the spot-futures price dynamics are conducted using an error correction mechanism (ECM). Some studies use the implicit efficient price implied by the cost of carry relationship to quantify the contribution of each market to price discovery to elucidate the relative efficiency of each market in response to information.

The second-moment volatility dynamics pertains to the interactions of conditional variances and covariances between spot and futures markets. Besides the information channel provided by price levels, price volatilities relay a considerable amount of information regarding risk perceptions and market efficiency, and therefore serve as another and arguably even more important channel for information transmission. The link between information flow and price volatility is reflected in several stylised facts of price volatilities. One of them is volatility spillover, or the lead-lag relationship in volatility, which captures the fact that price volatilities are not isolated but contagious from one market to the other. Multivariate GARCH-class models permeate the empirical research into the second-moment volatility transmission process. An alternative approach to examine causality-in-variance is the cross-correlation function test which values the information contained in sample residual cross-correlations. The importance of the cross-market information linkages through volatility is acknowledged in either methodology.

The globalisation of futures markets calls for investigation into the price and volatility dynamics across countries. A wealth of literature looks at the leads and lags in price and volatility among several stock markets, but far less attention has been paid to index futures markets. For futures contracts traded on the same (or nearly the same) underlying index but listed on more than one exchange, spread arbitrage maintains the equilibrium relationship between the futures markets in a similar way to index arbitrage. Due to institutional differences among the exchanges, these futures prices may react to information non-simultaneously; besides, volatility in one exchange may be predictable on the basis of volatility in the related exchange, and the futures volatilities can be closely related to each other. As such, the international price discovery and volatility transmission constitute the potential information linkages across the countries. There are two possible hypotheses as to the location of the information leadership in transnational information dissemination: the home-bias hypothesis and the international centre hypothesis (e.g. Fung et al., 2001; Covrig et al., 2004). The home-bias hypothesis argues for the information leadership of the domestic market for a set of home-market advantages. In contrast, the international centre hypothesis argues for the predominance of the foreign market for the better and more international trading environment it can provide. It is an empirical issue whether the domestic or foreign exchange plays a leading role in specific markets. The methodologies are extended in the multivariate context to measure the role and efficiency of each exchange in the cross-border price discovery and volatility transmission mechanisms.

The rest of this chapter is structured according to the above research areas. Section 2.2 looks at the cost of carry relationship, the pricing deviations from the cost of carry relationship, index arbitrage and its modelling techniques. Section 2.3 focuses on the price and volatility dynamics within and across countries, in the order of price discovery, volatility transmission, and cross-border dynamics in respective subsections. Section 2.4 concludes the chapter.

2.2 Index arbitrage

The crux of many theories in finance is rooted in the concept of arbitrage, which involves buying an asset and selling the same or equivalent asset simultaneously in pursuit of a costless, riskless, yet positive payoff (Sutcliffe, 2006). Naturally, any pricing deviations from equilibrium will not be sustained as arbitrage activities are able to drive prices back to their fair level (Brailsford and Cusack, 1997). At least three types of arbitrage activities can take place in index futures markets.

First, index arbitrage refers to the strategy whereby investors seek to make a profit from the price discrepancies between stock index and index futures markets (Chan and Chung, 1993). As the most important form of programme trading,[1] index arbitrage maintains the equilibrium between the two markets, in the sense that short-run deviations of the spot and futures prices can be removed promptly so that the two price series are aligned back to the equilibrium level in the long run. Second, spread arbitrage exploits the price differentials between index futures contracts listed on more than one exchange. Spread arbitrage maintains the equilibrium between the domestic and foreign exchanges where those futures contracts are traded. This links the domestic and foreign futures markets, and this link could be tighter than the spot-futures link due to the lower transaction costs incurred by spread arbitrage. Third, futures-options arbitrage focuses on index futures and index options markets, and capitalises on any departures from the no-arbitrage condition between the two markets derived from European put-call parity (Sutcliffe, 2006). In this literature review, index arbitrage is of my primary interest, although some discussion will also include spread arbitrage.

2.2.1 The cost of carry relationship

The no-arbitrage condition between spot and futures markets can be given by the cost of carry relationship of Cornell and French (1983a; 1983b). In a perfectly efficient economy absent market frictions such as taxes, transaction costs, and short sale restrictions, index futures prices should equal the deferred value of the underlying stock prices over the remaining life of the futures contract:

$$F_t^* = S_t e^{(r-d)(T-t)} \tag{2.1}$$

where F_t^* is the theoretical (or fair) futures price at time t, S_t is the spot price at time t, (r-d) is the net cost of carry for the underlying stocks in the index. That is, the single, constant, risk-free interest cost r minus the known, constant, continuous dividend yield d. T is the maturity date of the futures contract and (T-t) is time to maturity, or the number of calendar days remaining in a futures contract until expiration. The relationship is expressed in terms of

[1] Programme trading is known as the purchase or sale of an entire portfolio by a single, computer-generated order (Stoll and Whaley, 1990). Apart from index arbitrage, other forms of programme trading include portfolio insurance and index substitution (Chan and Chung, 1993).

continuous compounding.[2]

The no-arbitrage argument states that the above relationship must hold at every instant t; otherwise costless and riskless arbitrage opportunities with a guaranteed positive profit would occur. To be more specific, if the actual futures price, F_t, is lower than the deferred spot price (underpriced), i.e. $F_t<S_te^{(r-d)(T-t)}$, index arbitrageurs would short the underlying index, investing the proceeds at the risk-free interest rate and foregoing any dividend payouts, and long the futures, to ensure a net payoff of $S_te^{(r-d)(T-t)}-F_t$ at time T; if the actual futures price is higher than the deferred spot price (overpriced), i.e. $F_t>S_te^{(r-d)(T-t)}$, they would undertake the reverse strategy - borrow money at the risk-free interest rate to long the index, accumulating dividends, and short the futures, to generate a net profit of $F_t-S_te^{(r-d)(T-t)}$ at time T. Thus, the no-arbitrage condition maintains the fair price of the futures contract, so that $F_t^*=S_te^{(r-d)(T-t)}$ (Sutcliffe, 2006).

Equivalently, equation (2.1) can be written in logarithmic returns (Stoll and Whaley, 1990):

$$\Delta s_t = (r-d) + \Delta f_t^* \tag{2.2}$$

where $\Delta s_t=\ln(S_{t+1}/S_t)$, $\Delta f_t^*=\ln(F_{t+1}^*/F_t^*)$. Provided that the net cost of carry (r-d) is deterministic, equation (2.2) implies that the expected spot return equals the net cost of carry plus the expected futures return, and that the variance of the spot return equals that of the futures return. Besides, the contemporaneous rates of spot return and futures return are perfectly positively correlated, whereas the non-contemporaneous rates of return are uncorrelated (ibid). As such, there should be no temporal causality, or leads and lags between the non-contemporaneous spot and futures prices. In reality, however, it is common to observe causal relationships between the two price series, which were originally thought to be evidence violating the cost of carry model (e.g. Stoll and Whaley, 1987; Stoll and Whaley, 1990; MacKinlay and Ramaswamy, 1988).[3]

[2] The cost of carry relationship in discrete compounding can be formulated as $F_t^*=S_t(1+r-d)$.

[3] Nonetheless, a growing number of more recent papers prove that the causality detected is consistent with the cost of carry relationship because of cointegration. See section 2.3.1.2 for further discussions.

A plausible explanation for the violation is that the cost of carry relationship is a perfect market model. In the presence of market imperfections, it is possible for the deviations from the no-arbitrage condition to exist. First, the constant risk-free interest rate can hardly be justified in the real world. Since the cost of carry *per se* is a forward pricing model, the use of the assumption is to leave out the differences in futures and forward prices, which stem primarily from marking to market and the associated daily re-settlement procedure in the futures market. Cox et al. (1981) contend that futures prices are dependent on the correlation between spot prices and interest rates while forward prices are not. In the case of a positive correlation, for example, a rise (fall) of the interest rate followed by a rise (fall) of the spot prices triggers a rise (fall) of the futures prices and generates cash inflow (outflow) for a long futures position, which can be reinvested (financed) at a higher (lower) interest rate. The obvious benefit from both an increase and a decrease in the interest rate makes the futures contracts more attractive than the forward contracts, so that the futures prices are higher than the forward prices. The negative correlation between spot prices and interest rates attaches reinvestment and financing risks to the futures contracts, and thus makes the futures prices lower than the forward. If the risk-free interest rates are non-stochastic, futures and forward prices are identical (Hull, 2008). With marking to market and non-stochastic risk-free interest rates, the no-arbitrage condition still applies, and empirical findings show that the effect of marking to market with stochastic risk-free interest rates is small on the risk on the futures position (e.g. Chang et al., 1990; Yadav and Pope, 1994). Hence, although Cornell and French (1983a; 1983b) extend the cost of carry relationship in a perfect market to allow for stochastic interest rates, the generalised version of the cost of carry model is of little practical interest (Sutcliffe, 2006). The single risk-free interest rate is also unrealistic in that it is not very likely for the borrowing and lending rates to be equal. When the borrowing rate r_b exceeds the lending rate r_l, the cost of carry develops into a no-arbitrage band within which the fair futures price lies: $S_t e^{(r_l - d)(T-t)} \leq F_t^* \leq S_t e^{(r_b - d)(T-t)}$ (ibid).

Second, the known, constant, continuous dividend assumption is difficult to be valid. The size of the dividends, the ex-dividend date, and the actual dividend payment date constitute three major sources of dividend risk (Yadav and Pope, 1994). For performance indices such as the

Deutscher Aktienindex (DAX) 30, the dividend risk is negligible as the calculation of the index presumes that all dividends are reinvested (Buhler and Kempf, 1995; Theissen, 2012). But for other indices such as the Financial Times Stock Exchange (FTSE) 100, one has to estimate future dividends by adding a fixed percentage growth rate to historical dividends and use corresponding ex-dividend and payment dates (Yadav and Pope, 1994). Apart from dividend uncertainty, dividend flows tend to fluctuate seasonally due to the lumpiness in dividend payments (Cornell and French, 1983a). Dividend payouts in emerging markets such as Poland (Białkowski and Jakubowski, 2008) and China (Wang, 2011) are also irregular and clustered. Although the impact of uncertain dividends on futures prices is not important (Yadav and Pope, 1994), the cost of carry model is suggested to be modified to $F_t^*=S_te^{r(T-t)}-D_t$, where D_t is the sum of the future values at time T of all dividends on the underlying component stocks between t and T, to accommodate the lumpiness in dividend payouts (Brenner et al., 1989a). Dividends are found to contribute to the systematic pricing errors from the cost of carry relationship in some studies (e.g. Brailsford and Cusack, 1997; Fung and Draper, 1999).

Third, taxes can affect the no-arbitrage condition via differential tax rates and tax timing option. A simple tax structure consisting of capital gains rate, ordinary income rate and futures tax rate can be added to the cost of carry model, and the capital gains rate and the ordinary income rate are found to influence the theoretical futures price. The independence of the futures tax rate arises from the assumption of symmetry in the tax structure which well approximates cash settlement contracts such as index futures (Cornell and French, 1983a). The tax timing option owned by stockholders means that capital gains taxes are not levied until a transaction occurs, such that they have a motivation to defer capital gains and realise capital losses. However, investors in the futures market do not have this option due to marking to market (daily re-settlement). Unless the stockholders are tax exempt or cannot hold the spot asset indefinitely, the tax timing option should make the spot appealing and thus depress the futures prices (Cornell and French, 1983a; 1983b; Yadav and Pope, 1994). This gives rise to underpricing, and the discrepancy between the spot and futures prices should be larger for more volatile spot prices in which case the tax timing option is more valuable. Cornell and French (1983a) hold that the tax timing option is one of the reasons for the consistently lower actual futures prices of New York Stock Exchange (NYSE) composite index than those predicted by the cost of carry model, and that adding the tax timing option to the cost of carry model reduces the theoretical futures prices. Chen et al. (1995) argue that the tax timing option contributes to the net advantage, or "customisation value" of a stock position, which becomes more important in times of higher stock volatility.[4]

Fourth, transaction costs in spot and futures markets are at least composed of the following: bid-ask spreads, brokerage commissions, transaction taxes, borrowing costs, market-impact costs, and capital requirements.[5] It is widely accepted that the transaction costs of marginal traders together with other market imperfections bound the cost of carry relationship from above and below so that the no-arbitrage condition becomes the following no-arbitrage band:

$$F_t^L \leq F_t^* \leq F_t^U \tag{2.3}$$

where F_t^L denotes the lower limit and F_t^U denotes the upper limit. Index arbitrageurs compare the actual futures prices F_t with F_t^L and F_t^U to make decisions on programme trading to chase a costless and riskless profit (Kawaller et al., 1987; Wahab and Lashgari, 1993). Arbitrage activities only appear when F_t move outside the band given by F_t^L and F_t^U, in which case profitable arbitrage opportunities are available. For instance, if $F_t<F_t^L$, index arbitrageurs would short the underlying index and long the futures; conversely, if $F_t>F_t^U$, they would long the index and short the futures. The band becomes wider for larger transaction costs. However, it is difficult to estimate the width of the band *a priori*, as the transaction costs are likely to be risky, asymmetric, time-varying, and with threshold effects (MacKinlay and Ramaswamy, 1988; Sofianos, 1993; Board and Sutcliffe, 1996; Sutcliffe, 2006). More importantly, as investors are heterogeneous, their transaction costs are heterogeneous, and thus there is not a single level of

[4] See section 2.2.2 for a further review of the relationship between futures mispricing and spot volatility.

[5] Specifically, market makers sell at an ask price higher than the bid price at which they buy, and the gap between the two prices is the bid-ask spread, which is a monopoly right granted by the exchange in return for their providing liquidity (Tsay, 2005). Brokers charge commissions to compensate for order-processing costs incurred by their trading on behalf of customers (Fleming et al., 1996). Transaction taxes are imposed on stocks traded to discourage excess volatility through speculation and noise (Chou and Lee, 2002). Borrowing costs are faced by index arbitrageurs who finance their transactions by borrowing fixed interest capital and index stocks (Yadav and Pope, 1994). Market-impact costs in the form of price concessions are available for large orders as they move market quotes downwards or upwards (Fleming et al., 1996). Capital requirements usually take the form of margins earmarked for default and volatility reduction in the futures market (Sutcliffe, 2006).

transaction costs suitable for all in the markets (Tse, 2001). Gay and Jung (1999) construct four sets of lower and upper bounds using various combinations of transaction costs to describe three groups of arbitrageurs, and find that the transaction costs explain much, though not all, of the systematic pricing errors in the Korea Stock Price Index (KOSPI) 200 futures market.

Fifth, short selling is the ability of an investor to sell a borrowed security to a third party. Besides legal bans, impediments to short sales in spot market include prohibitive selling costs, delayed receipt of short sales proceeds, tracking errors, and nonsynchronous trading (Lin et al., 2013).[6,7] But such constraints are absent in futures market. The higher costs in holding a spot position push down the lower bound of the no-arbitrage band by permitting greater futures underpricings (Pope and Yadav, 1994; Gay and Jung, 1999). The short-selling constraints further shift the equilibrium position between spot and futures prices, increasing the spot price and thus the value of holding the spot position (McMillan and Phillip, 2012). In terms of informational efficiency, those constraints reduce the absolute and relative speed of adjustment of market prices to private information especially to bad news, and raise the bid-ask spread. This weakens the contemporaneous relationship between spot and futures markets, and hence contributes to the temporal leads and lags observed therein (Diamond and Verrecchia, 1987; Jiang et al., 2001). In contrast, lifting such restrictions narrows the no-arbitrage band by reducing the frequency and magnitude of underpricing, and increases the speed of adjustment of a market to the pricing deviations from the cost of carry relationship (Fung and Draper, 1999).

As a partial equilibrium model that premises the non-stochastic interest rate and an exogenous stock market, the cost of carry relationship can be nested as a special case of a closed-form general equilibrium model developed by Hemler and Longstaff (1991): in a continuous-time production economy, the logarithm of the dividend-adjusted futures-spot price ratio is represented as a linear regression on the stochastic risk-free interest rate and market volatility.

[6] Tracking errors stem from the fact that it is hardly possible to replicate the underlying index with perfect substitutes. This means that the value of the spot position held by arbitrageurs may not exactly track the futures prices (Figlewski, 1984; MacKinlay and Ramaswamy, 1988).
[7] See section 2.3.1.2 for details about nonsynchronous trading.

It seems that the general equilibrium model provides reasonable explanatory power in empirical studies. For example, Hemler and Longstaff (1991) document that the model generates lower level of pricing errors in times of high volatility in the NYSE composite index markets, and so is preferable to the cost of carry model. Moreover, Wang (2011) reports that the general equilibrium model outperforms the cost of carry model in the volatile FTSE China A50 and Hong Kong H-share markets. However, the support for the general equilibrium model is not clear, especially in markets with low volatility. Gay and Jung (1999) maintain that although the price series do not strictly follow the cost of carry model as evidenced by the systematic pricing errors prevalent in the literature, one cannot claim that they instead follow the general equilibrium model. For simplicity, the cost of carry relationship may be sufficient for index futures pricing (Brailsford and Cusack, 1997).

2.2.2 Futures mispricing, basis and index arbitrage

Research indicates that index arbitrage opportunities arise from futures mispricing (Richie et al., 2008). Following MacKinlay and Ramaswamy (1988), mispricing is defined as the difference between the actual and the theoretical futures prices, normalised by the index value:

$$Mis_t = \frac{F_t - F_t^*}{S_t} = \frac{[F_t - S_t e^{(r-d)(T-t)}]}{S_t} \tag{2.4}$$

Mispricing is split into underpricing (when $F_t < F_t^*$) and overpricing (when $F_t > F_t^*$). The sources of mispricing are the aforementioned market imperfections, and/or other factors including liquidity constraints (Richie et al., 2008), tracking errors (Figlewski, 1984; MacKinlay and Ramaswamy, 1988), different reactions of markets to information (Tse, 2001), and noise (Figlewski, 1984). Economically significant mispricing, regardless of the choice of the cash asset (Richie et al., 2008), is recorded to exist and persist in a vast range of markets, implying that index arbitrage opportunities do occur frequently. Given the potential risks such as interest rate risks, dividend risks, tracking error risks, margin variation risks and delayed execution, index arbitrage is seldom riskless in practice, although persistent mispricing implies that delayed execution is less likely to be a serious risk (Kawaller, 1987; Yadav and Pope, 1994; Wang, 2011). It is an empirical issue whether the mispricings can be profitably exploited.

A much explored topic in the literature is the time series properties of mispricing. The first-order autocorrelation of the mispricing series is usually positive and high, which suggests persistence in mispricing, and the average persistence ranges from a few minutes (Richie et al., 2008) to more than two trading days (Wang, 2011). However, the first-order autocorrelation of the first differences in mispricing tends to be negative, implying that mispricing is a mean-reverting process (MacKinlay and Ramaswamy, 1988; Neal, 1996; Kempf, 1998). Possible explanations of the mean reversion include: (a) arbitrage activities, which maintain the no-arbitrage bounds by preventing futures prices from diverting too far away from equilibrium (MacKinlay and Ramaswamy, 1988); (b) infrequent trading of the stock index, in the sense that even without arbitrage, the first differences in mispricing would appear to be negatively autocorrelated (Miller et al., 1994); and (c) the trading activities of heterogeneous arbitrageurs (Tse, 2001). On average, underpricing persists longer than overpricing, which can be attributed to the higher costs associated with short sales (Gay and Jung, 1999; Wang, 2011). Fung and Draper (1999), Fung and Jiang (1999) find that after the relaxation of the short-selling constraints, both underpricing and overpricing drop and the integration between the Hang Seng index (HSI) spot and futures prices improves. In addition, early unwinding and delayed unwinding introduce path dependence into the mispricing series.[8] Path dependence means that the stochastic behaviour of mispricing displays properties dependent on its historical properties, so that a positive (negative) mispricing will remain positive (negative), even with a further divergence between spot and futures prices, especially when coupled with capital constraints (MacKinlay and Ramaswamy, 1988; Shleifer and Vishny, 1997).

In theory, the magnitude of mispricing (or absolute mispricing) should be greater for longer times to maturity, which carries more uncertainties over interest rates, dividends, marking-to-market cash flows, and future volatility (Yadav and Pope, 1994). As a result, the no-arbitrage band may become wider. Nevertheless, longer dated contracts are more likely to

[8] Early unwinding is the option that arbitrageurs close out outstanding contracts by establishing an equal and opposite arbitrage position to that taken initially. Delayed unwinding is the possibility that arbitrageurs unwind the near contracts early and roll over their arbitrage positions into the far contracts. The goal of both strategies is to seek the potential arbitrage profits consisting of the gains from the initial arbitrage, arbitraging the reverse mispricings, and arbitraging the far contracts (Sutcliffe, 2006).

be unwound prior to maturity; in such cases the no-arbitrage band would be narrower (MacKinlay and Ramaswamy, 1988). The net effect on the band width cannot be determined theoretically. Yet the empirical findings from Standard &Poor's (S&P) 500, FTSE 100, KOSPI 200, HSI, FTSE China A50, H-share index futures markets unanimously support a positive relationship between absolute mispricing and time to maturity (MacKinlay and Ramaswamy, 1988; Yadav and Pope, 1994; Gay and Jung, 1999; Fung and Draper, 1999; Wang, 2011), implying that the lower and upper bounds are farther apart for further dated contracts. The signs of mispricing are studied by Yadav and Pope (1990) and Kempf (1998), who document that the FTSE 100 and DAX 30 futures contracts are more underpriced the longer the time to maturity.

Compared with index futures, stock positions have a net advantage or "customisation value", which investors tend to maximise (Chen et al., 1995). Intuitively, investors would retain the stock and short the futures to hedge the risk of a volatile stock market, in the hope that the marginal customisation value of holding the stock may increase. This argument also implies that futures tend to be underpriced, and the underpricing should be greater for longer time to maturity. The evidence in Chen et al. (1995), Gay and Jung (1999) appears that stock volatility decreases mispricing. However, since the mean mispricing in their research is negative, the finding actually indicates a positive relationship between the magnitude of mispricing and stock volatility. Besides, a more volatile stock market tends to depress the ability of stock prices to impound information, thereby resulting in more mispricing (Richie et al., 2008). The evidence that futures mispricing increases with stock volatility is found by Yadav and Pope (1994), Fung and Draper (1999), Richie et al. (2008), Cummings and Frino (2011), and Wang (2011), among others. A special case is Chan and Chung (1993), who find that mispricing (termed "arbitrage spread") leads to increased spot and futures volatility; yet higher spot or futures volatility is followed by a decrease in mispricing in the Major Market Index (MMI) markets, probably because the higher volatility encourages more arbitrage activities and speedier price adjustments that will ultimately reduce the magnitude of mispricing.

Frequent and persistent mispricing is likely to attract index arbitrage, which involves programme trading in spot and futures markets. In this way, futures mispricing is positively related to spot and futures trading volume. Furthermore, the relationship is associated with volatility given the positive link between volume and volatility. Nevertheless, a heavy volume may indicate a liquid and efficient market without any arbitrage opportunities, suggesting that a negative relationship between mispricing and volume is also possible (Brailsford and Cusack, 1997). The empirical evidence is mixed. Chan and Chung (1993) reveal that an increase in the futures mispricing is followed by an increase in the volume of the underlying index in the MMI markets. Richie et al. (2008) document low trading volume in the Standard & Poor's Depository Receipt (SPDR) market relative to that in the corresponding S&P 500 futures market during the periods of low volatility, and the insufficient stock volume is deemed as a limit to arbitrage; this indirectly signifies a positive relationship between futures mispricing and stock volume. Wang (2011) examines the effects of futures trading volume and spot volatility on mispricing in the FTSE China A50 and H-share markets. The results regarding the volume are all positive yet insignificant. Given that the spot volatility variable is significantly positive, his work suggests that arbitrage signals do encourage more trading volume and volatility in the China-related markets. Cummings and Frino (2011) study the impact of unexpected trading volume on mispricing in the Australian Share Price Index (SPI) 200 spot and futures markets, respectively, and find that the impact is negative and significant in the spot market, but positive and insignificant in the futures. Since unexpected trading volume signals unexpected information arrival, their finding implies that index arbitrage dominates trading activities based on firm-specific information in moving spot prices, and arbitrageurs in the spot market respond to small mispricings more often than those in the futures market.

After taking natural logarithms on both sides of equation (2.1), the model becomes the following:

$$f_t^* = s_t + (r-d)(T-t) \tag{2.5}$$

where $f_t^*=\ln F_t^*$ and $s_t=\ln S_t$. Basis is defined as the difference between F_t and S_t. If $f_t=f_t^*$, express the basis in natural logarithms:

$$\text{log-basis} = f_t - s_t = (r-d)(T-t) \tag{2.6}$$

where f_t=lnF_t. Equation (2.6) shows that the basis also plays an important role in index arbitrage. Its value equals the net cost of carry to maturity. As the maturity date draws near, the futures price converges to its underlying spot price, and the basis converges to zero, due to the diminishing risks attached to r and d (Antoniou and Garrett, 1993). At maturity, the futures price equals its underlying spot price, and the basis is zero. Similar to the mispricing, the basis is mean-reverting: investors would sell the futures and buy the index if the basis widens dramatically, and reverse their strategy if the basis narrows markedly. It is the arbitrage activities that drive prices back to equilibrium (Tse, 2001). The basis is also related to volatility and volume effects. Theobald and Yallup (1996) consider the relationship between basis (in a standardised form), volume and volatility in the FTSE 100 spot and futures markets. They find a feedback loop between basis and spot volatility, which means that past, contemporaneous, and future volatilities all have significant negative effects on the basis. On the side of volume, they find that lagged and current volume variables exert significant positive effects on the basis. Moreover, Yang et al. (2012) find that positive lagged basis has a significant positive effect on spot and futures volatilities, and the effect is larger on spot volatility than that on futures volatility in the China Securities Index (CSI) 300 markets. Given that a negative basis is closely related to underpricing, and a positive basis to overpricing, Wang (2011) uses a dummy variable to distinguish a positive basis from a negative basis, and discovers that the mispricing is greater in the case of a negative basis than a positive basis in the FTSE China A50 and H-share markets. The basis further serves as the error correction term indicating the cointegration between spot and futures prices in an error correction model.[9] Variance in the basis, or basis risk, measures the extent of integration between markets (Harris, 1989), and affects the hedging performance for index futures (Figlewski, 1984). Like the basis, the basis risk converges to zero as maturity approaches (Sutcliffe, 2006).

[9] See section 2.3.1.1 for further details about the error correction model.

2.2.3 Modelling index arbitrage

Based on the cost of carry relationship are two arbitrage decision rules: a basic rule and its extension considering the option of early unwinding. Assuming that the futures contract is held to maturity, the basic rule states that index arbitrage positions are established when the absolute mispricing is sufficiently larger than a constant transaction cost threshold, which is inclusive of bid-ask spreads, brokerage commissions, transaction taxes, borrowing costs, market-impact costs, and capital requirements. Arbitrage activities cease when the absolute mispricing becomes smaller than the transaction cost threshold. As such, the frequency of building up arbitrage positions is a step function of the absolute mispricing, and the mispricing threshold necessary to invite the arbitrage should be constant (Neal, 1996). Empirically, with the basic rule and a total transaction cost that equals 1% of the index value, Brenner et al. (1989a; 1989b) record persistent underpricings exceeding the transaction cost for the Nikkei 225 futures in Singapore in its early years of trading. As the market matured, the futures became persistently overpriced, and the mispricings declined substantially in magnitude such that they were largely less than a total transaction cost of 0.5% (Brenner et al., 1990). Using the same transaction cost structure and almost the same sampling period as those in Brenner et al. (1990), Lim (1992) confirms that profitable arbitrage opportunities in the Nikkei 225 spot and futures markets were very limited for brokers, and not exploitable for institutional investors. Taking early unwinding into consideration, the early liquidation option model of Brennan and Schwartz (1990) offers another decision rule. It predicts that index arbitrage positions are only established when the absolute mispricing plus the value of the early liquidation option exceeds the constant transaction cost. Yet the model does not predict a step function of the absolute mispricing, for the variation in the value of the early liquidation option makes the mispricing threshold changeable (Neal, 1996). It is held that the transaction cost of following an early unwinding strategy is higher than that of liquidating a contract at expiration, but lower than that of building up a new arbitrage position. Moreover, the option alleviates the capital constraints of arbitrageurs as their capital can be withdrawn early and put into other transactions (Brennan and Schwartz, 1990; Sofianos, 1993; Dwyer et al., 1996; Neal, 1996; Kempf, 1998; Sutcliffe, 2006). Accordingly, arbitrageurs may well consider closing out their positions before maturity. Neal (1996) finds empirical evidence supporting the early liquidation option model to a certain extent in the S&P 500 markets, and concludes that arbitrage trading is not a step function of the absolute mispricing.

Investigations into index arbitrage behaviour are mainly carried out by two econometric models: threshold autoregressive (TAR) models and smooth transition autoregressive (STAR) models. Directly following from the above, the TAR model of Tong (1990) and Tsay (1989) postulates the constant transaction cost threshold and homogeneous arbitrage behaviour, such that the arbitrageurs only enter a market when mispricing is sufficiently large to cover the transaction costs and risks (Martens et al., 1998). As an illustration, a TAR model can be formulated as below (ibid):[10]

$$z_t = k^{(r)} + \sum_{j=1}^{p} \pi_j^{(r)} z_{t-j} + u_t^{(r)} \qquad C_{r-1} < z_{t-d} \le C_r \tag{2.7}$$

where the basis adjusted for the cost of carry is the threshold variable z_t;[11] d is the threshold lag; the model lag j=1, 2, …, p, with p as a positive integer; C_r denotes the constant transaction cost thresholds, with r=1,…, m (m is the maximal number of the threshold regimes set arbitrarily) and $-\infty = C_0 < C_1 < \ldots < C_m = \infty$; u_t is iid with zero mean and finite variance; k is a constant. For stationarity outside the transaction costs bounds, the roots of the autoregressive (AR) coefficients $\pi_j^{(r)}$ should lie outside the unit circle (Brooks, 2014).

In a three-regime case, for example, suppose d=1, the SETAR model can be expressed more explicitly as below:

$$z_t = k^{(1)} + \sum_{j=1}^{p} \pi_j^{(1)} z_{t-j} + u_t^{(1)} \qquad z_{t-1} \le C_1 \tag{2.7a}$$

$$z_t = k^{(2)} + \sum_{j=1}^{p} \pi_j^{(2)} z_{t-j} + u_t^{(2)} \qquad C_1 < z_{t-1} \le C_2 \tag{2.7b}$$

[10] Precisely speaking, this is a self-exciting TAR (SETAR) model as the dependent variable is the same as the threshold variable. The dependent variable is different from the threshold variable in a general TAR model.
[11] Some papers use the basis without the adjustment for the cost of carry as the threshold variable. See Kim et al. (2010) for a comparison of the two measures.

$$z_t = k^{(3)} + \sum_{j=1}^{p} \pi_j^{(3)} z_{t-j} + u_t^{(3)} \quad z_{t-1} > C_2 \qquad (2.7c)$$

Equation (2.7b) shows the no-arbitrage threshold range within which a small $z_{t\text{-}1}$ follows a non-stationary process without triggering any arbitrage activities, and the bounds of the range are determined by the constant transaction cost thresholds C_1 and C_2. Equation (2.7a) and (2.7c) provide the lower and upper regimes where $z_{t\text{-}1}$ is sufficiently large to offset C_1 and C_2, respectively, such that investors will enter the market to seek a riskless profit, reverting $z_{t\text{-}1}$ to the no-arbitrage regime. Such a discrete mean-reverting mechanism brings market prices back to equilibrium. In this way, the SETAR model exhibits nonlinear regime-switching behaviour of mispricing. Empirically, Martens et al. (1998) use a five-regime SETAR model with impulse response functions for the mispricing errors of the S&P 500 index futures contracts, and report that some of the mispricings may well be due to infrequent trading. With a three-regime SETAR, Brooks and Garrett (2002) find that the FTSE 100 basis exhibits more persistence in the lower regime than that in the upper regime, explained by the short sale restrictions in the spot market. Tsuji (2007) obtains similar results for the Nikkei 225 basis during 1995-1999, but he obtains more persistent Nikkei basis in the upper regime during 2000-2004, indicating a slower adjustment speed in the upper regime when the Nikkei stock market experienced successive downward pressure.

Because C_1 and C_2 apply to everyone in the market, the TAR model relies on the assumption that investors are homogeneous. However, investors are more likely to be heterogeneous, as they face different trading objectives, transaction costs, capital constraints, and perceived risks (Tse, 2001). It follows that there may be different transaction cost thresholds in the market, and in the aggregate these thresholds (or step functions) would be blurred so that the transition between the regimes would become gradual and smooth (ibid). For this reason, the STAR process of Granger and Teräsvirta (1993) and Teräsvirta (1994) may be more suitable for modelling mispricing for a market as a whole, as it assumes that the aggregation of the arbitrage conditions gives rise to a continuous, smooth transition function, either exponential or logistic. Since logistic smooth transition functions cannot depict the mean-reverting behaviour of mispricing, exponential transition functions are relatively common in the literature. An exponential STAR (ESTAR) model can be represented in the simplest form as follows (Tse, 2001):

$$y_t = y_{t-1} + (-y_{t-1}) \times T(y_{t-d}) + u_t \tag{2.8}$$

$$T(y_{t-d}) = 1 - \exp(-\gamma y_{t-d}^2) \tag{2.9}$$

where $\{y_t\}$ is a stationary, ergodic series, often acted by mispricing; d is a delay parameter, d>0; u_t is iid with zero mean and finite variance; $T(\cdot)$ is the exponential smooth transition function whose value varies from 0, the middle regime where no investor will trade, to 1, the outer regime where all investors will trade, in a continuous and gradual way. The rate of transition between 0 and 1 is controlled by γ (γ>0), the smoothness parameter. A higher value of γ represents a quicker response of a market to absolute mispricing, and hence more arbitrage activities. The ESTAR model can be viewed as a generalisation of a three-regime TAR model (Teräsvirta, 1994; Tse, 2001). The empirical findings of Anderson (1997) and Taylor (2007) are in support of the ESTAR model in terms of model fit. Taylor (2007) further generalises the standard STAR model to an augmented STAR model to allow γ to vary over time. A further comparison between the threshold and smooth transition models is provided later in section 2.3.1.2.

2.3 Price and volatility dynamics

2.3.1 The price discovery process

Price discovery is a process by which market participants impound all available information to reach equilibrium asset prices (Booth et al., 1999; Chen and Gau, 2009), representing the first-moment dynamics between spot and futures markets. In general, the literature on price discovery can be classified into two strands: one strand examines the direction and extent of causality-in-mean, or the lead-lag relationship between spot and futures prices; and the other strand measures the information content of spot and futures prices. Specifically, testing causality-in-mean is essentially the causality test in the spirit of Granger (1969) and Sims (1972): futures prices Granger-cause or lead spot prices if the past information about the futures prices helps to predict the current spot prices, relative to using only the past information about the spot, while the past information about the spot prices cannot help to predict the current futures prices using the past information about the futures (Sutcliffe, 2006). It follows that the futures prices act as an indicator of the subsequent spot prices, and the spot market lags behind the futures market in the process of price formation. Likewise, spot prices Granger-cause or lead futures prices when the reverse occurs. Given a series of efficient trading conditions in the futures market, economic theories predict that futures prices should lead spot prices, whereas the empirical studies of the leads and lags generate complex results. On the other hand, the information content of spot and futures prices is measured by common factor weights (CFW) or information shares (IS), and the empirical findings are also mixed. Despite differences in methodological details, the cointegrating relationship arising from the cost of carry relationship between spot and futures prices links both strands that together display a comprehensive picture of the first-moment efficiency of index futures markets.

2.3.1.1 Cointegration and error correction

Research on the price discovery process in spot and futures markets develops in line with the evolution of econometric modelling. In early studies (e.g. Kawaller et al., 1987; Stoll and Whaley, 1990; Chan, 1992), the conditional mean of price series was usually described by a vector autoregressive (VAR) model that specifies the linear dependence of current spot and futures returns on the past spot and futures returns. The main drawback of the VAR model, however, is associated with the notion of cointegration. A non-stationary series is integrated of order one, denoted I(1), if it becomes stationary only after first differencing. Two I(1) series are said to be cointegrated when it is possible to select a constant such that a linear combination of the two series is stationary, denoted I(0). That constant is called cointegrating parameter (Engle and Granger, 1987). The rationale behind the concept of cointegration is that the two series follow a long-run equilibrium relationship, notwithstanding that they may deviate from each other in the short run (Ghosh, 1993). Stock index and index futures prices are expected to be I(1) and cointegrated given the cost of carry relationship, and index arbitrage would correct short-run departures in the two price series such that they can move closely together in the long run. In this way, the VAR model in the returns is misspecified because it lacks consideration of the long-run cost of carry equilibrium relationship between the spot and futures prices.

Engle and Granger (1987) put forward a two-step approach to test for cointegration between two series. For cointegrated series, Granger Representation Theorem proves that they can be represented by an error correction model (ECM) and conversely (Granger, 1983; Engle and Granger, 1987). Nevertheless, if more than one cointegrating relationship is expected, the Engle-Granger two-step methodology becomes problematic as the parameter estimates would be inefficient (Engle and Yoo, 1987; Kim et al., 1999). Instead, Johansen trace and maximal eigenvalue tests should be used to test for the number of linearly independent cointegrating vectors (Johansen, 1991). In either scenario, provided that the common long-run trend(s) in spot and futures markets can be accepted, the use of the ECM is justified to examine the first-moment dynamics between the two markets. A typical linear ECM can be expressed as follows:

$$\Delta s_t = k_s + \sum_{j=1}^{p} \pi_{ss,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j} \Delta f_{t-j} + \alpha_s z_{t-1} + u_{s,t} \tag{2.10a}$$

$$\Delta f_t = k_f + \sum_{j=1}^{p} \pi_{fs,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j} \Delta f_{t-j} + \alpha_f z_{t-1} + u_{f,t} \tag{2.10b}$$

where Δs_t, Δf_t represent spot and futures returns, respectively; the model lag j=1, 2, …, p, with p as a positive integer; k is a constant; u_t is a white noise. The coefficients π_{sf}, π_{fs} are short-run cross-market adjustment parameters. Futures leading spot requires that at least one $\pi_{sf} \neq 0$, whereas the reverse causality requires that at least one $\pi_{fs} \neq 0$. If at least one $\pi_{sf} \neq 0$ and at least one $\pi_{fs} \neq 0$, the causality is bidirectional, and if $\pi_{sf} = \pi_{fs} = 0, \forall j$ then neither leads nor lags exist between the two price series. The coefficients π_{ss}, π_{ff} measure the short-run dynamics within the respective markets.

The basis z_{t-1} linking spot and futures markets is included in the framework as an error correction term, whose coefficient α measures the direction of causality in the long run and the speed of adjustment towards the long-run equilibrium. A significant error correction coefficient suggests that there exists an error correction effect, or basis effect, i.e. any previous departures from the long-run equilibrium would affect the price dynamics in one or both markets at present (Tao, 2008). Since two series should not be cointegrated in an efficient market according to the Efficient Market Hypothesis, the coefficient also has implications for testing the hypothesis, despite the fact that a significant error correction coefficient does not necessarily imply market inefficiency until trading rules based on the ECM generate sufficiently large profits after adjustment for transaction costs and risks involved (Ghosh, 1993; Wahab and Lashgari, 1993). Taking into account both long-run and short-run adjustments, the ECM is therefore more appropriate than the VAR model for describing the first-moment dynamics between spot and futures markets. Numerous empirical studies have reported statistically significant error correction coefficients, corroborating the presence of the error correction effect. Table 6.3 (p.156-157) of Sutcliffe (2006) provides a survey.

2.3.1.2 Leads and lags

When it comes to the relationship between cointegration and causality, traditional papers (e.g. Stoll and Whaley, 1987; Stoll and Whaley, 1990; MacKinlay and Ramaswamy, 1988) argue that the causal relationships between spot and futures prices are evidence against the cost of carry model. However, increasing works (e.g. Cuthbertson et al., 1992; Puttonen, 1993; Wahab and Lashgari, 1993; Green and Joujon, 2000) hold that cointegration requires the causal relationships to exist. In other words, the causality detected is consistent with the cost of carry relationship. By Granger Representation Theorem, short-run deviations of spot and futures prices must be corrected so as to reach equilibrium in the long run; thus investigations of the spot-futures price dynamics are anticipated to find some causal relationships, or leads and lags (Sutcliffe, 2006).

Before reviewing the leads and lags, it is necessary to be aware that the standard ECM implicitly assumes that the conditional means in spot and futures equations evolve over time following a linear pattern. To be more specific, it implies a constant cointegrating relationship and an adjustment speed independent of the size of mispricing (Theissen, 2012). It is increasingly realised that, however, market frictions, trader inertia, liquidity constraints and informational impediments could give rise to time-varying cointegration and dependent adjustment process, or in other words, nonlinear adjustment mechanisms (Anderson, 1997). For instance, investors may not react to mispricing until they believe that the mispricing is sufficiently large so that the benefits generated by index arbitrage can outweigh the fixed costs of adjustment plus interest rate and dividend risks (Anderson, 1997; Balke and Fomby, 1997; Martens et al., 1998; Brooks and Garrett, 2002). Behavioural finance literature contributes a different perspective that interactions between heterogeneous trader types account for the nonlinearity (McMillan and Speight, 2006; Röthig and Chiarella, 2007). More importantly, Tse (2001) and Brooks and Garrett (2002) show that a nonlinear specification may yield contrasting results with those of a linear specification about the functioning of spot and futures markets, suggesting that forcing the basis to stay in a single state space could lead to a misunderstanding of the nature of the basis and the speed of adjustment. Anderson (1997) maintains that nonlinear models outperform their linear counterparts in forecasting both in and out of sample. Hence, the linear framework should be extended to allow for the potential nonlinear dynamics in spot and futures markets.

Threshold-type nonlinearity has received growing interest since the proposal of a threshold ECM (TECM) by Dwyer et al. (1996) and Balke and Fomby (1997). Intuitively, the basis (or mispricing) can fluctuate freely within the no-arbitrage band which acts as a threshold range. Index arbitrage would not take place within the thresholds as factors such as transaction costs and risks would make arbitrage unprofitable, and thus the behaviour of the basis exhibits a non-stationary process similar to random walk. Once the no-arbitrage band is crossed, however, arbitrage profits are now sufficiently large as to exceed the transaction costs and risks. Therefore, index arbitrage would quickly bring the basis back inside the threshold range so that the long-run equilibrium is maintained. The feature is known as "threshold cointegration" (Balke and Fomby, 1997). A TECM can be established as below:

$$\Delta s_t = k_s^{(r)} + \sum_{j=1}^{p} \pi_{ss,j}^{(r)} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j}^{(r)} \Delta f_{t-j} + \alpha_s^{(r)} z_{t-1} + u_{s,t}^{(r)} \tag{2.11a}$$

$$\Delta f_t = k_f^{(r)} + \sum_{j=1}^{p} \pi_{fs,j}^{(r)} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j}^{(r)} \Delta f_{t-j} + \alpha_f^{(r)} z_{t-1} + u_{f,t}^{(r)} \qquad (2.11b)$$

where the basis z_{t-1} acts as a threshold variable, and r stands for different regimes. Similar to the TAR model in equation (2.7), in a three-regime case, for example, r=1 if $z_{t-1} \leq C_1$; r=2 if $C_1 < z_{t-1} \leq C_2$; r=3 if $z_{t-1} > C_2$; with real numbers C_1 and C_2 representing lower and upper thresholds, respectively.

The TECM successfully captures the discrete adjustment process and allows the error correction effect to vary across the regimes (Tao and Green, 2013). Another merit of the threshold model is that linear techniques such as the Engle-Granger two-step methodology and the Johansen trace test prove asymptotically applicable to the case of threshold cointegration, despite a loss of power or an increase in size distortion (Balke and Fomby, 1997). Empirically, the TECM is able to provide an independent, endogenous estimate of the no-arbitrage band (Tao and Green, 2013) and the TECM fits significantly better than the linear ECM (Dwyer et al., 1996). Yet a practical problem is that the classical approach based on the recursive arranged autoregressions of Tsay (1989) proves difficult to identify the number of regimes of the TECM (Martens et al., 1998). While Bayesian estimation can be used to generate simultaneous estimates of all parameters and exploit prior knowledge of transaction costs, it assumes three regimes (two thresholds) *a priori*, and postulates cointegration between price series without formal testing. As a consequence, a significant drift can be found in the outer regimes, implying a drift-away rather than mean reversion (Forbes et al., 1999; Kim et al., 2010). It seems that the SupLM statistic of Hansen and Seo (2002) is more advantageous because it can determine the number and location of the thresholds and enable estimation of the cointegrating relationship without including the drift term (Kim et al., 2010).

However, the discontinuous mean-reverting mechanism, which is the foundation of the TECM, is not realistic, relying as it does on the assumption of homogeneous investors. A natural outcome generated from the model is an abrupt on/off switch between the regimes, which reflects that every investor has the same belief about the fair price of futures contracts, and every investor is subject to the same objectives, costs, and risks. Hence, once the thresholds are crossed all investors engage in index arbitrage at the same time to remove disequilibrium (Tse, 2001). Tse (2001) and Taylor (2007) maintain that this is not possible because investors tend to have diverse understandings of the fair price and face different transaction costs. Even if they share similar knowledge and transaction costs, they are deterred from responding to mispricing simultaneously due to differential objectives, constraints and risks. As a result, they are more likely to enjoy different thresholds and these thresholds will be blurred after aggregating over heterogeneous investors (Tse, 2001). This means that in the aggregate the transition between the regimes can be slow, gradual, and smooth to accommodate the heterogeneity of investors. With that logic as its basic spirit, a smooth transition error correction model (STECM) may therefore be more powerful in depicting the nonlinear price dynamics in spot and futures markets.

There are two versions of the STECM: exponential STECM (ESTECM) and logistic STECM (LSTECM). The ESTECM is usually preferred for the more desirable property of its exponential transition function that arbitrage is positively and gradually linked to absolute mispricing (Tse, 2001; McMillan and Speight, 2006; Taylor, 2007). An ESTECM based on Anderson (1997) and Tse (2001) can be established as below:

$$\Delta s_t = k_s + \sum_{j=1}^{p} \pi_{ss,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j} \Delta f_{t-j} + (k_s^* + \sum_{j=1}^{p} \pi_{ss,j}^* \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j}^* \Delta f_{t-j} + \alpha_s z_{t-1}) \times T_s(z_{t-d}) + u_{s,t}$$

$$T_s(z_{t-d}) = 1 - \exp[-\gamma_s (z_{t-d} - c^*)^2 \times g_s(z_{t-d})]$$

$$g_s(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_s (z_{t-d} - c^*)]\} \quad (2.12a)$$

$$\Delta f_t = k_f + \sum_{j=1}^{p} \pi_{fs,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j} \Delta f_{t-j} + (k_f^* + \sum_{j=1}^{p} \pi_{fs,j}^* \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j}^* \Delta f_{t-j} + \alpha_f z_{t-1}) \times T_f(z_{t-d}) + u_{f,t}$$

$$T_f(z_{t-d}) = 1 - \exp[-\gamma_f (z_{t-d} - c^*)^2 \times g_f(z_{t-d})]$$

$$g_f(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_f (z_{t-d} - c^*)]\} \quad (2.12b)$$

where $T(\cdot)$ is the exponential smooth transition function whose value varies between 0, the middle regime where no investor will trade, and 1, the outer regime where all investors will trade; $g(\cdot)$ is the asymmetry function that describes the asymmetric behaviour of investors. Three parameters in the above framework relate to the informational efficiency of spot and futures markets. Specifically, the error correction coefficient α measures the long-run speed of adjustment within a single regime. It is expected to be positive, significant for the spot, and negative, insignificant for the futures, provided that the futures market reflects information more quickly than the spot. The smoothness parameter γ controls the steepness of $T(\cdot)$, and measures the speed at which the transition function switches between 0 and 1. The higher is γ, the steeper the transition function, and the quicker adjustments between the regimes. The asymmetry parameter θ gauges the asymmetric market responses to positive and negative pricing deviations, and is expected to be negative if more investors correct a negative pricing deviation than a positive pricing deviation of the same magnitude. In addition, Tse (2001) shows that the model captures the non-simultaneous establishment of spot and futures positions, labelled as the "legging" process in Sofianos (1993), which is omitted in other alternative specifications. Despite that the smooth transition models are relatively new in studying the spot-futures price dynamics, the empirical evidence from index futures markets to date has been obtained by Taylor et al. (2000), Tse (2001), McMillan and Speight (2006) and Fung and Yu (2007).

There are several reasons for predicting the price leadership of futures markets: nonsynchronous trading, market frictions, nature of information, and trading mechanisms. First, nonsynchronous trading of the stocks comprising the index results in stale information in spot prices and hence they lag futures prices by a short time period, usually an intraday period at most. The problem of stale prices may be caused by infrequent trading of the component stocks, whose prices are determined by their most recent transaction prices. If they are not traded when the index is recorded, past information may remain in the observed index values. Since it is assumed that futures prices immediately reflect new information, futures prices appear to lead spot prices (Stoll and Whaley, 1990). The nonsynchronicity may also be caused by the higher transaction costs in the stock market, which prevent investors from trading more than a limited amount of stocks in the index and thus the component stocks cannot reflect information continuously and sufficiently. But the lower transaction costs in futures market allow investors to trade the whole index in one transaction, so that the futures market can disseminate information more promptly than the spot (Green and Joujon, 2000). Moreover, the nonsynchronous effect could be exacerbated by the time delays in the computation and reporting of the stock index, while price changes in the futures market are assumed to be recorded instantly (Stoll and Whaley, 1990). Other than futures leading spot, the nonsynchronous trading of the component stocks tends to induce positive first-order cross-correlation between those stock returns, positive first-order autocorrelation in the index return, and negative autocorrelations in the return series of a particular stock, even though the correlations in itself may not have economic significance (Tsay, 2005). It can further introduce a moving-average (MA) error structure in stock returns (Antoniou and Garrett, 1993), although Chan (1992) holds that the MA process is due to bid-ask spreads.

To reduce or eliminate the effect of nonsynchronous trading, three solutions have been suggested. One solution is to replace transaction data with quote data, which are executable prices better at representing market conditions (Shyy et al., 1996). Since the FTSE 100 index is constructed using the weighted average of the mid-quotes of the component stocks, its effect of nonsynchronous trading should be less serious (Antoniou and Garrett, 1993; Abhyankar, 1995). However, studies of the FTSE 100 markets cannot avoid the problem, in that different closing times on the spot and futures exchanges and different observed quotes from closing quotes still constitute sources of nonsynchronicity (Theobald and Yallup, 1996). Shyy et al. (1996) adopt mid-quote data to examine the Cotation Assistée en Continu (CAC) 40 markets and find reverse causality of spot leading futures, but the finding may result from other factors, e.g. the use of second nearest futures contracts (Alphonse, 2000), rather than the use of quote data. Theissen (2012) estimate the DAX 30 markets by a modified version of the TECM with mid-quote data, and obtain results in contrast with those of Shyy et al. (1996). A more effective solution is to simulate the nonsynchronous effect and filter it out from the return series. For example, Stoll and Whaley (1990) develop an autoregressive moving average (ARMA) process to purge the effect of infrequent trading. Later, Chan (1992) argues that the ARMA process may not be adequate for the changing effects of infrequent trading throughout the day; he dismisses the MA components as they are insignificant and applies the AR specifications, similar to Miller et al. (1994) and Kim et al. (1999). Yet to allow for the MA component in return innovations, Antoniou and Garrett (1993) employ a Kalman Filter which is *per se* compatible with the ARMA process. Nevertheless, Theobald and Yallup (1996) point out that the ARMA process could yield downward bias in parameter estimators, and they handle the nonsynchronous effect by including standardised changes in the observed index value. Moreover, as Exchange-Traded Funds (ETFs) are popular in replicating a stock index with less transaction costs but are free from infrequent trading, recent studies (e.g. Schlusche, 2009; Theissen, 2012) mitigate the problem by substituting an ETF for the associated stock index.

The second reason that futures are likely to lead spot is that futures markets have fewer frictions such as transaction costs (including bid-ask spreads) and short-selling constraints (Abhyankar, 1995). Unlike infrequent trading, the effect of bid-ask spreads is to induce negative first-order autocorrelation (cross-correlations in multivariate case) in return series, i.e. bid-ask bounce (Stephan and Whaley, 1990; Miller et al., 1994; Tsay, 2005). In response, an MA filtering is usually used after Stoll and Whaley (1990) within the system of ARMA. As mentioned, it is sometimes left out in the literature because of insignificance. An alternative way is to select the index with relatively higher price and larger market capitalisation stocks for its bid-ask spreads are considerably lower (Stoll and Whaley, 1983; Bhardwaj and Brooks, 1992; Kim et al., 1999). It is observed that the average bid-ask spreads in futures are smaller than those in spot, and this is also true for other types of costs (Kuserk and Locke, 1993; Fleming et al., 1996; Shyy et al., 1996; Kim et al., 1999; Berkman et al., 2005). Based on transaction costs hypothesis that the market with the lowest overall transaction costs will be the quickest to reveal new information (Fleming et al., 1996), it is expected that futures reflect information more quickly than the underlying spot. Transaction costs can be further interrelated with systematic information: market-wide informed investors have an incentive to trade futures to circumvent a larger capital outlay otherwise. Accordingly, market-wide information flows from futures to spot, and the lead could last longer than a trading day (Chan, 1992; Abhyankar, 1995; Green and Joujon, 2000; Sutcliffe, 2006; Cummings and Frino, 2011).

The short-selling constraints in stock market, *inter alia*, bar investors from making use of negative information or discourage them by imposing prohibitive costs, yet investors in futures market are aloof from such constraints. Thus, they affect the temporal causality between the two markets. During “bad news” periods in which arbitrageurs would wait to short-sell stock, the speed of mean reversion of stock prices slows down and in some cases becomes insignificant (Diamond and Verrecchia, 1987; Puttonen, 1993; Jiang et al., 2001; McMillan and Phillip, 2012). This implies that the arbitrage link between spot and futures markets weakens and therefore futures should lead the spot to a larger extent under bad news than under good news. Besides, short-selling restrictions result in significant futures underpricings (Pope and Yadav, 1994; Gay and Jung, 1999). Since arbitrageurs are restricted from removing the underpricings by longing futures and shorting stock, futures will stay underpriced, and so the informational efficiency of the futures market could be dampened (McMillan and Philip, 2012). The empirical evidence of Puttonen (1993), Fung and Jiang (1999), and Tse and Chan (2010) supports the restrictions on short selling as a major cause of the leadership in index futures. Chan (1992) confirms the finding, but notices that index futures prices do not enjoy a longer lead over spot prices during bad news periods.

The causal relationship is also dependent on the trading mechanism of each market (Green and Joujon, 2000). Floor trading is a system of open outcry, with traders standing in a pit and negotiating prices face to face, whereas screen trading has a fully computerised structure that matches orders automatically (Grünbichler, 1994). Differences exist between the two mechanisms. Floor trading tends to be more liquid as the transactions supplied by locals are sufficient; screen trading, however, brings along more advantages such as rapid execution, reduced expenses on people and building, flexibility of trading places, and effective prevention of out trades (Khan and Ireland, 1993; Board et al., 2002). Apparently, screen trading is better at reflecting and transmitting information. As such, causality could go from a screen-based market, such as index futures, to a floor-traded market, such as stock index (Grünbichler et al., 1994). As London International Financial Futures and Options Exchange (LIFFE) moved from floor trading to an electronic trading platform named LIFFE CONNECT, Tao and Green (2013) find improved informational efficiency after the reform, which is consistent with the conjecture that screen trading facilitates the price discovery process (Grünbichler et al., 1994). For regulatory purposes, albeit no consensus on choosing the "best" trading mechanism, there is a view that screen trading appears desirable when market volume and volatility are low or normal; but that floor trading turns out superior during periods of high volume and volatile prices (Sutcliffe, 2006; Chung et al., 2010).

Using the linear ECM or vector ECM (VECM) in multivariate case, a wealth of literature reveals that index futures prices lead the underlying spot prices, with no or weak reverse causality from spot to futures. See, for example, the evidence of Ghosh (1993) in the S&P 500 markets; Antoniou and Garrett (1993), Brooks et al. (2001) in the FTSE 100 markets; Shyy et al. (1996) in the CAC 40 markets; Tse (1995) in the Nikkei 225 markets. After testing for threshold-type nonlinearity, Dwyer et al. (1996), Martens et al. (1998), Forbes et al. (1999), Kim et al. (2010) report similar results about the leadership of the S&P 500 futures market by threshold VECM (TVECM). Theissen (2012) modifies the TVECM by explicitly taking into account time-varying transaction costs, and obtains results supporting the predominant role of the DAX 30 futures market. Allowing for the heterogeneity of investors, Tse (2001) describes the nonlinear dynamics between the Dow Jones Industrial Average (DJIA) spot and futures prices with an ESTECM, and documents that the DJIA futures reflects information faster and mispricings occur in the futures. Also, investors establish futures position first and respond more quickly to futures underpricings. McMillan and Speight (2006) compare a set of linear and nonlinear models in estimating the FTSE 100 spot-futures pricing relationship, and support the use of an ESTECM. In addition, they substantiate the interpretation in behavioural finance that noise traders tend to engage in momentum trading in bullish markets; but fundamental traders respond quickly to small mispricings in an attempt to maintain market equilibrium. Fung and Yu (2007) extend the previous work to a four-regime ESTECM by incorporating dummy variables representing conditions of order imbalance in the HSI stock market. They find that the lead of the HSI futures over the order imbalance strengthened during the 1997 Hong Kong stock market crash.

In contrast to the theoretical prediction, some empirical studies find that spot markets reflect information faster and thus assume the price discovery function relative to futures. See, for example, the evidence of Ghosh (1993) in the Commodity Research Bureau (CRB) markets; Wahab and Lashgari (1993) in the FTSE 100 markets; Green and Joujon (2000) in the CAC 40 markets. This phenomenon can be explained by the transaction costs related to unsystematic information. For information that affects only a few companies, investors are more likely to trade individual stocks rather than index futures, as the firm-specific information is trivial in determining derivative prices so that the involved costs of exploiting such information are relatively cheaper in the spot market. Thus it is possible for the spot to react faster to firm-specific information and lead the futures (Chan, 1992; Sutcliffe, 2006). Moreover, a spot market with a more efficient trading system is likely to lead the corresponding futures due to the differential transaction costs involved. Tao and Green (2013) apply a three-regime TVECM for the FTSE 100 spot and futures prices, and report causality from spot to futures in the lower and upper regimes. Their finding matches the observation period when the quote-based FTSE 100 index is able to impound information more quickly than the corresponding transaction-based futures. Yang et al. (2012) report that information flows from the CSI 300 spot to futures at the infancy stage of the futures market, probably resulting from the high entry barriers or transaction costs set by regulators to protect the futures market. The above reasons reinforce the contention that the lead-lag relationship depends on relative transaction costs (Fleming et al., 1996; Kim et al., 1999). On the other hand, because of legal or contractual restrictions, some institutional investors such as pension funds and foundations are not allowed to trade derivatives and thus the spot market acts as the only vehicle of price discovery. Given the special privileges associated with stocks such as the tax timing options, voting rights, and shareholder discounts, if they are important for certain reasons, investors would prefer stocks over futures to which no such privileges are attached (Puttonen, 1993).

A few studies find a feedback relationship between spot and futures markets, meaning that futures prices Granger-cause spot prices and *vice versa*. See, for example, the evidence of the second sample period of Green and Joujon (2000), and the second regime of the TVECM of Tse and Chan (2010). The bidirectional causal relationship may result from the fact that information is impounded into spot and futures markets simultaneously (Kang et al., 2013), and that market microstructures in the two markets ensure lagged price adjustments even after the direct price impact of the information has been fully understood by investors (Tao and Green, 2012). Occasionally it is documented that there is no significant causality between spot and futures, e.g. under the lower regime of the bivariate TAR model of Chung et al. (2011). The mixed empirical results suggest the complexity of the price dynamics in reality which could be far away from the simplified theoretical prediction of futures dominating spot. Notwithstanding the research focus on leads and lags, it is noteworthy that stock index and index futures markets largely react to information in a simultaneous manner, and the contemporaneous relationship between the two markets is in fact stronger than any leads and lags. The contemporaneous relationship should not be overshadowed in the literature (Sutcliffe, 2006).[12]

2.3.1.3 Information content

Another aspect of studying the first-moment dynamics in spot and futures markets is measuring the contribution of each market to price discovery. Spot and futures prices are expected to be cointegrated, and thus they share a common stochastic factor which is the implicit efficient price (Baillie et al., 2002). Methodologically, proposed by Schwarz and Szakmary (1994) and formally justified by Gonzalo and Granger (1995), the common factor weight (CFW) measure, also known as the "permanent-transitory decomposition", directly uses the coefficients of the error correction term in the linear VECM to obtain the extent to which each market contributes to the implicit efficient price. A simple way to calculate the CFW in spot and futures markets, respectively, is given by (Theissen, 2012):

$$CFW_s = \frac{\alpha_f}{\alpha_f - \alpha_s}, \quad CFW_f = \frac{-\alpha_s}{\alpha_f - \alpha_s}$$

[12] With a VAR model, Kawaller et al. (1987) argue that the S&P 500 spot and futures prices move largely in unison. Lim (1992) notice a strong positive correlation between contemporaneous Nikkei 225 spot and futures returns in Singapore, despite that the work is based on a very small sample consisting of only 20 observations. The simultaneity between spot and futures markets is formally studied by Koch (1993), who recommends a simultaneous equations model (SEM) where contemporaneous terms are included as explanatory variables. Yet Chan and Chung (1995) demonstrate that if information shocks are unobservable, the SEM would generate unreliable inferences about the causal relationships between the two markets.

where α_s, α_f are the error correction coefficients in equations (2.10a) and (2.10b). The CFW model decomposes the common factor into a combination of spot and futures prices (Baillie et al., 2002). The value of common factor weights varies between zero, when no price discovery occurs in a market, and unity, when price discovery occurs exclusively in that market (Schlusche, 2009). The higher is the weight attributed to a market, the greater is the contribution that the market makes to the process of price discovery. The advantage of the measure is that the contribution is defined as a function of the error correction coefficients α, such that common factor weights are readily accessible after estimating a linear VECM.[13] A set of empirics adopt the CFW to examine the contribution made by spot and futures markets to the process of price discovery. For example, Booth et al. (1999) reveal that the price discovery role is shared equally by the DAX 30 spot and futures based on the similar weights estimated from each market, whereas Theissen (2012) and Schlusche (2009) record that the DAX 30 futures leads the underlying spot as the former assigns a substantially larger contribution to price formation. Theissen (2012) extends the CFW metrics by allowing for the presence of arbitrage opportunities, and concludes a major contribution of the DAX 30 futures.

Nevertheless, the CFW has been criticised for generating biased estimates of the true price discovery parameters (Hasbrouck, 2002) and neglecting innovation variances (Lien and Shrestha, 2009). A different avenue to quantify the information content of stock index and index futures prices is the information share (IS) developed by Hasbrouck (1995). The method is again established on the basis of the linear VECM, but considers its vector MA (VMA) representation. The IS of market i is defined as follows:

$$IS_i = \frac{\boldsymbol{\psi}_i^2 \boldsymbol{\Omega}_{ii}}{\boldsymbol{\psi}\boldsymbol{\Omega}\boldsymbol{\psi}'}$$

where $\boldsymbol{\psi}$ is an innovation coefficient in the VMA representation, and $\boldsymbol{\Omega}$ denotes a diagonal covariance matrix. When $\boldsymbol{\Omega}$ is not diagonal, the IS of market i can be calculated as follows:

[13] The CFW in nature is a Stock-Watson common stochastic trend plus an additively separable idiosyncratic transitory disturbance, and thus it is useful when establishing the innovations in the implicit efficient price from the full innovation vector (de Jong, 2002).

$$IS_i = \frac{[(\boldsymbol{\psi}\mathbf{F})_i]^2}{\boldsymbol{\psi}\boldsymbol{\Omega}\boldsymbol{\psi}'}$$

where $\mathbf{F}$ is the Cholesky decomposition of $\boldsymbol{\Omega}$, i.e. $\mathbf{F}$ is the lower triangular matrix such that $\boldsymbol{\Omega}=\mathbf{F}\mathbf{F}'$.

The IS of a market is the proportion of variance in the common factor that is attributable to the innovations in that market (Baillie et al., 2002). Empirical studies suggest that the IS gives a proper indicator of the amount of information impounded by a market in face of perturbation. For example, Tse (1999) adopts the IS measure to investigate the relative leadership in the DJIA markets, and finds the leading role played by the index futures market. Tse et al. (2006) re-examine the question and obtain a slightly larger share allocated to the spot market. Chen and Gau (2009) report that the Taiwan spot market contributes most to price discovery relative to the corresponding futures, and the contribution is higher as the minimum tick size becomes smaller.

Yet the IS measure can only provide lower and upper bounds or a variation range, rather than a unique value, because the calculation of the IS depends on the ordering of each series. The fact that the bounds are often far apart when innovations of the series are highly contemporaneously correlated entices some papers to use the mean of the bounds to reduce ambiguity (e.g. Baillie et al., 2002; Chen and Gau, 2009; Guo et al., 2013). Alternatively, the problem can be overcome by the work of Lien and Shrestha (2009) who propose a distinct linear factor structure in the computation process, and generate a measure called modified IS (MIS) that can output a unique measurement of the information content of asset prices. They compare the performance of the MIS and the IS in the S&P 500, FTSE 100, and Tokyo Stock Price Index (TOPIX) spot and futures markets, and find that the MIS outperforms the IS and that information dissemination takes place mostly in the futures. Both the IS and the MIS fit in with the study of spot and futures prices as the price series share the common stochastic factor. Nevertheless, it should be noticed that when the cointegrating relationship is not one-to-one (for example, across futures, options, credit default swaps and bond markets), the IS cannot be applied in that it relies on the identical row of $\boldsymbol{\psi}$. Lien and Shrestha (2014) further expand the compatibility of the MIS by introducing a generalised version of the IS (GIS). Independent of the ordering as well, the GIS merely requires the *n* series under scrutiny to be cointegrated with the number of cointegrating vectors equal to (*n*-1). Obviously this is common and thus the GIS can be employed to examine the interrelationships across a wide range of financial markets.

The debate on which method, the CFW or the IS, is superior does not end up with a clear answer,[14] probably because they are designed from different perspectives to measure different spheres of the cointegrated system. The CFW metrics centres on the components of the common factor and the error correction mechanism, whereas the IS measure looks into the contribution made by each market to the total variation in common trend innovations. Both models yield qualitatively similar results when residual correlation is negligible and residual variances are equal. In the case of highly correlated or heteroskedastic innovations, however, the results can be quite different (Baillie et al., 2002). It seems to make more sense to exploit the relationship between the CFW and the IS, that is, the results of both models are mainly derived from a common factor coefficient vector (ibid), and to combine them in practice to help in the understanding of the relative efficiency of each market in response to information. Guo et al. (2013) use both measures in the CSI 300 markets and confirm that the futures market dominates the price discovery process.

2.3.2 The volatility transmission process

The first-moment dynamics captured by the price discovery process tells only part of the story about the information transmission mechanism between stock index and index futures markets. In fact, a considerable amount of information is disseminated through higher moment dependencies between the two markets, which can be viewed as the most important feature of speculative price changes (Koutmos and Tucker, 1996). Second-moment transmission that involves dynamic interactions of conditional variances and covariances, in particular, becomes notably attractive as autoregressive conditional heteroskedasticity (ARCH) effects play a vital role in deciphering uncertainties over competitive market forces. However, compared with the

[14] The details of the debate can be found in Baillie et al. (2002), de Jong (2002), Hasbrouck (2002), Harris et al. (2002), Lehmann (2002), among others.

behaviour of conditional means, the behaviour of conditional variances has been less well understood in the literature, partly because economic theories on the time-varying conditional variances are very limited (Bollerslev et al., 1992), and partly because early empirics (e.g. Kawaller et al., 1987; Stoll and Whaley, 1990) overlook the important channel of information transmission in index futures markets.

2.3.2.1 Information flow and price volatility

The relation between information flow and price volatility should not be understated. In the simple parameterised model developed by Ross (1989), the variance of price change is proven to be identical to the variance of information flow in a no-arbitrage economy. This theorem, independent of the particular asset-pricing models being used, helps to shed light on the mechanism whereby the rate of information flow is directly related to price volatility. As such, focusing only on the first-moment dynamics could lead to specification errors and false inferences about the interactions between spot and futures prices (Chan et al., 1991). Besides, exploring the temporal dependencies of conditional variances may open the door to new insights. For example, the strong bidirectional dependence in intraday volatility between the S&P 500 spot and futures prices in Chan et al. (1991) implies that information originating from one market could forecast the rate of information flow in the other, which challenges the common interpretation that market-wide information tends to flow from futures to spot. The volatility transmission process also has important implications for the debate on the influence of futures trading on stock market volatility.

The link between information and volatility manifests itself via some stylised facts of price volatility. Volatility clustering characterises the behaviour that large price changes tend to be succeeded by large price changes with random signs (Mandelbrot, 1963). It is often analogous to "heat waves" - a high temperature in a place today is likely to be followed by a high temperature there tomorrow but not by a high temperature in another place (Engle et al., 1990). In the time plot of conditional variance series, the phenomenon is depicted by periods of perturbation alternating with periods of tranquillity, and it becomes more apparent as the frequency of data increases. Econometrically speaking, volatility clustering can be reflected by time-varying, market-specific autocorrelations between price changes, which suggest the persistence and predictability of conditional variances. One reason for the clustering is that the arrival of information flow is in clusters, triggering the ARCH effects in asset prices even if the market itself could be efficient. Another reason is that investors with heterogeneous information need time to adjust their expectations to a particular information shock. In either case, market dynamics enable the volatility process to be consistent with market efficiency (ibid).

The GARCH model proposed by Bollerslev (1986) overcomes some of the limitations of the ARCH model of Engle (1982) and provides a prominent framework to capture the tendency of volatility clustering. The model specifies the evolution of the conditional variance σ_t^2 as a linear function of lagged squared information shocks and lagged conditional variances. A typical, univariate GARCH (1, 1) model can be established as below:

$$u_t = \sigma_t \eta_t \tag{2.13}$$

$$\sigma_t^2 = \omega + a u_{t-1}^2 + b \sigma_{t-1}^2 \tag{2.14}$$

where $\omega>0$; $a\geq0$; $b\geq0$; $a+b<1$. u_t is the innovation or information shock at time t; σ_t is a time-varying, positive and measurable function of the information set at time t-1; η_t is a sequence of iid normal random variables with zero mean and unit variance; the ARCH parameter a measures the impact of shocks and the GARCH parameter b measures the extent of volatility persistence; $a+b<1$ is a necessary and sufficient condition for the existence of a finite unconditional variance (Tsay, 2005). The GARCH (1, 1) model is widely used to study the second-moment behaviour of asset prices, and the number of parameters that need to be estimated in the GARCH model is typically far less than that in the ARCH model. As the GARCH model recognises the contribution of the past information shock and that of the past conditional variance to the current conditional variance, volatility transmits from u_{t-1} or σ_{t-1} to σ_t^2, and then to the current information shock u_t, such that a large current innovation follows a large past innovation, giving rise to the phenomenon of clustering. The sum ($a+b$) also indicates the level of volatility persistence. For instance, the influence of historical shocks could be permanent when the sum equals 1 as in the integrated GARCH (IGARCH) model of Engle and Bollerslev (1986) (McMillan and Speight, 2003).

The effect of clustering is closely connected with fat tailedness, which means that asset prices tend to be leptokurtic. It can be shown that the excess kurtosis in the information shock u_t arises from the randomness in the conditional variance σ_t^2, or from the excess kurtosis in the conditional distribution of u_t, or from both (Bollerslev et al., 1994). Despite that the GARCH model provides a parsimonious modelling of the clustering, it does not adequately account for the leptokurtosis. In other words, the standardised residuals from the fitted model often appear to have fatter tails than the normal distribution, and the conventional standard errors for the estimated parameters obtained under the assumption of conditional normality of η_t tend to understate the true standard errors in the presence of leptokurtosis (Bollerslev et al., 1992). A common solution to the problem of excess kurtosis is to assume that η_t follows a more general distribution, such as a standardised *t*-distribution or a generalised exponential distribution, which could accommodate the fat tailedness, although recent studies using high-frequency data indicate that the tail behaviour of the GARCH model is too short even with the standardised *t*-distribution (Tsay, 2005).

Numerous studies (e.g. Chan et al., 1991; Tse, 1999) document a U-shaped volatility pattern - volatilities tend to be higher at the open and close - for stock index and index futures prices within each trading day. The pervasive evidence of the intraday pattern in volatility indicates that information accumulates at the open and close while the accumulation becomes slow during the middle of the day. Since information that arrives when markets are closed is very likely to be reflected in prices when the markets re-open (Bollerslev et al., 1994), liquidity investors with discretion over their trading time prefer exploiting that information together to exert minimal impact on market prices (Admati and Pfleiderer, 1988). Besides, the optimal portfolio to be held over non-trading periods is likely to be different from that over trading periods, and thus portfolio rebalancing trades could contribute to the volatility surge at the open and close (Brock and Kleidon, 1992). It is also recorded that price changes tend to be substantial following weekends and holidays, and are associated with forecastable events where important information is released. The GARCH model can be modified to allow for the time-related anomalies in volatility due to non-trading periods and predictable information releases (Bollerslev et al., 1994). For example, a constant conditional correlation (CCC) structure of Bollerslev (1990) can be imposed on the GARCH process in event study methodology (Bollerslev et al., 1992).

The negative link between current returns and future return volatility, introduced by Black (1976) as "predictive asymmetry", commonly referred to as "the leverage effect", implies that price changes tend to be larger in the case of bad news than those in the case of equally sized good news. Black (1976) and Christie (1982) maintain that bad news decreases the share prices of a company and so increases its debt to equity ratio, or leverage, lifting the riskiness (volatility) of the company. Likewise, market declines engender a higher aggregate leverage and thus higher stock market volatility. Although the leverage effect partially explains the asymmetric responses of the volatilities, it is inherently difficult to apply the effect to futures markets (Koutmos and Tucker, 1996; McMillan and Speight, 2003). The predictive asymmetry could also be the result of volatility feedback. Campbell and Hentschel (1992) hold that a large piece of news is likely to raise expected future volatility and thus the required rate of return on stocks. Stock prices therefore fall, and the negative impact of bad news is amplified whereas the positive impact of good news is attenuated. In particular, the (G)ARCH-in-mean model of Engle et al. (1987) incorporates the conditional variance into the conditional mean equation. The parameter of the conditional variance, called the risk premium parameter, is expected to be positive, indicating the fundamental risk-return tradeoff.[15] Empirically, Tao and Green (2012) report a significant volatility feedback effect through the positive risk premium parameter for the FTSE 100 spot and futures prices. Furthermore, Sentana and Wadhwani (1992) note that large price declines lead to more positive feedback trading[16] that increases with the level of stock price volatility, relative to equivalent price rises. The asymmetry is consistent with the fact that investors have to sell their

[15] An explicit tradeoff between expected return and variance is documented in many finance theories. For instance, under the assumption of risk aversion, the excess returns on all risky assets are proportional to the systematic risk measured by the covariances with the market portfolio in the traditional capital asset pricing model (Bollerslev et al., 1994).

[16] Sentana and Wadhwani (1992) split the noise traders into positive and negative feedback traders. Positive feedback traders buy assets after asset prices rise, while negative feedback traders buy after prices fall. They argue that positive (negative) feedback trading predominates in times of high (low) volatility.

holdings to meet obligations when a market falls and with the possibility that risk aversion declines rapidly with wealth. McMillan and Speight (2003) attribute the significant asymmetric responses of the quarter-hourly and hourly FTSE 100 index futures returns to the activities of feedback traders as they do not find evidence in favour of the volatility feedback.

The linear GARCH model, however, is unable to capture the asymmetry because the conditional variance is parameterised as a function of the magnitudes of the lagged squared information shock and the lagged conditional variance; the signs of these variables play no part within the symmetric framework. In the class of nonlinear GARCH models, the conditional variance depends not only on the magnitudes but also on their corresponding signs (Bollerslev et al., 1992), and thus can describe the asymmetric volatility effect. For example, Nelson (1991) develops the exponential GARCH (EGARCH) model where the conditional variance is a function of both the magnitudes and the signs of the lagged variables. Let σ_t^2 be the conditional variance as in equation (2.13), a simple univariate EGARCH (1, 1) model can be formulated as below:

$$\ln \sigma_t^2 = \omega + \lambda(u_{t-1} / \sigma_{t-1}) + a\left|u_{t-1} / \sigma_{t-1}\right| + b \ln \sigma_{t-1}^2 \tag{2.15}$$

where there are no constraints on the non-negativity of the coefficients ω, a and b. The above specification enables η_{t-1} (or u_{t-1}/σ_{t-1}) to impact the logarithmic conditional variance $\ln\sigma_t^2$ asymmetrically, and the impact is a linear combination of λ and a. For a positive shock, $u_{t-1}/\sigma_{t-1}>0$, the impact is ($\lambda+a$); for a negative shock, $u_{t-1}/\sigma_{t-1}<0$, the impact is ($-\lambda+a$) (Enders, 2010). Thus, a negative λ is required for negative shocks to trigger higher volatility. Compared with the linear GARCH, the EGARCH model is less restrictive as no constraints on a or b are needed, and thus the EGARCH model is a more general process that encompasses random oscillatory behaviour of asset return volatilities (Darrat et al., 2002). Besides, the conditional moments of the linear GARCH model may explode as shocks could persist in one norm and die out in another even when the model itself is strictly stationary and ergodic, making the persistence pattern difficult to discern; but the stationarity and ergodicity of $\ln\sigma_t^2$ can be easily checked (Nelson, 1990). The EGARCH process can be regarded as a weighted moving average of past volatility and return regression residuals and such an averaging process can reduce the time discrepancies in reporting and recording procedures between spot and futures prices (Darrat et al., 2002). Pagan and Schwert (1990) find that the EGARCH model performs better than other parametric models in sample and non-parametric models out of sample. Abhyankar (1995) adopts the univariate EGARCH model to generate the time series of conditional variances for hourly FTSE 100 spot and futures returns before examining the lead-lag relationship in volatility in a VAR framework.

Another asymmetric GARCH model commonly used is the GJR-GARCH model of Glosten et al. (1993). With zero as a threshold to differentiate positive from negative information shocks, a univariate GJR-GARCH (1, 1) model can be represented as:

$$\sigma_t^2 = \omega + a u_{t-1}^2 + \lambda I_{t-1} u_{t-1}^2 + b \sigma_{t-1}^2 \tag{2.16}$$

where the dummy variable I_{t-1}=1 if u_t<0 and 0 otherwise. For a positive shock, $u_{t-1}/\sigma_{t-1}>0$, $I_{t-1}=0$, the impact of the positive shock on σ_t^2 is a; for a negative shock, $u_{t-1}/\sigma_{t-1}<0$, $I_{t-1}=1$, the impact of the negative shock on σ_t^2 is $(a+\lambda)$ (Enders, 2010). In this way, provided that $\lambda>0$, a negative shock increases volatility more than a positive shock of the same magnitude. The linear GARCH can be seen as a special case of GJR-GARCH with $\lambda=0$. Suppose u_t follows a symmetric distribution, the necessary and sufficient condition for the existence of a finite unconditional variance is $a+b+0.5\lambda<1$ for the GJR-GARCH, which reduces to $a+b<1$ for the linear GARCH (Ling and McAleer, 2002). The close connection with the linear GARCH and the relative ease in forecasting as it is reasonable to assume the probability of a future shock of either sign being 0.5, make the GJR-GARCH model prevalent in the literature. Other types of asymmetric models include the quadratic GARCH (QGARCH) model of Sentana (1995), among others. McMillan and Speight (2003) apply the univariate GJR-GARCH and QGARCH models to the FTSE 100 spot and futures returns, and report that the volatility behaviour at hourly frequency is satisfactorily described by the asymmetric GARCH models.

2.3.2.2 Leads and lags in price volatility

The concept of Granger causality extended to second-moments is second-order causality and causality-in-variance. Granger et al. (1986) define second-order noncausality as:

$$E_t\left[(\mathbf{X_{1t}} - E\left[\mathbf{X_{1t}}\middle|\Omega_{t-1}^{\mathbf{X}}\right])^2\middle|\Omega_{t-1}^{\mathbf{X}}\right] = E_t\left[(\mathbf{X_{1t}} - E\left[\mathbf{X_{1t}}\middle|\Omega_{t-1}^{\mathbf{X}}\right])^2\middle|\Omega_{t-1}^{\mathbf{X_1}}\right]$$

where $\mathbf{X_t}$ is a n-dimensional matrix at time t, which can be partitioned into $\mathbf{X_t}=\{\mathbf{X_{1t}}, \mathbf{X_{2t}}\}$ with dimensions n_1 and n_2, respectively; Ω_{t-1} is the information set at time t-1 for $\mathbf{X_t}$ (or $\mathbf{X_{1t}}$). The definition of variance noncausality is slightly different. $\mathbf{X_2}$ does not cause $\mathbf{X_1}$ in variance means $V\left[\mathbf{X_{1,t}}\middle|\Omega_{t-1}^{\mathbf{X}}\right] = V\left[\mathbf{X_{1,t}}\middle|\Omega_{t-1}^{\mathbf{X_1}}\right]$, where $V[\cdot]$ denotes conditional variance (Comte and Lieberman, 2000). The difference between the two definitions lies in the conditioning information sets: $V\left[\mathbf{X_{1,t}}\middle|\Omega_{t-1}^{\mathbf{X_1}}\right] = E_t\left[(\mathbf{X_{1,t}} - E\left[\mathbf{X_{1,t}}\middle|\Omega_{t-1}^{\mathbf{X_1}}\right])^2\middle|\Omega_{t-1}^{\mathbf{X_1}}\right]$(Caporin, 2007). Variance noncausality exists if and only if there are both mean noncausality and second-order noncausality. Hence a sequential testing scheme is suggested that check causality-in-mean first; provided no relation is found then tests for second-order noncausality. If and only if both tests do not detect any causation one can conclude variance noncausality or no causality-in-variance (Caporin, 2007; Tchahou and Duchesne, 2013).

The causality-in-variance, or the lead-lag relationship in price volatility, is critical as volatility serves as another important information channel between markets, apart from price. The volatility interactions are especially important in the absence of causality-in-mean, in which case information can only transmit through the conditional variances and covariances of asset prices. In practice, the causality-in-variance is sometimes termed “volatility spillover”, which captures the fact that information shocks are not restricted in a market but can spread out to affect the volatility processes elsewhere. In contrast to volatility clustering, volatility spillover implies that sources of information shocks are not market-specific fundamentals (Mantalos and Shukur, 2010); rather, shocks are contagious from one market to the other such that volatilities become predictable on the basis of volatilities in the related markets, violating the Efficient Market Hypothesis. The spillover effect can be analogous to “meteor showers” - a meteor shower in one place may be followed by a meteor shower in another place (Engle et al., 1990). Zhong et al. (2004) split the spillover effect into short-run and long-run versions for Mexican spot and futures markets. The short-run spillover bears much resemblance to the interim adjustment of spot and futures prices, with temporal leads and lags in volatility; while the long-run spillover reflects the error correction effect under which previous departures from the cost of carry equilibrium are allowed to impact current conditional variances and covariances.

Research on the volatility interactions or spillovers is permeated by multivariate GARCH (MGARCH) specifications, the most obvious application of which is the study of the dynamics of volatilities and co-volatilities of several markets (Bauwens et al., 2006). Like the univariate GARCH models, the MGARCH models parameterise the conditional variance as a function of its lagged residuals suggesting volatility persistence within a market. Yet unlike the univariate GARCH models, the MGARCH models also encompass cross-market lagged innovations and conditional covariance in an effort to estimate cross-market volatility interactions. In this way, information contained in the volatility in one market can have predictive power for the volatility in the other market. Combined with the leverage effect, a bearish futures (spot) market is likely to be followed by higher spot (futures) market volatility than a bullish futures (spot) market. For example, applying a bivariate EGARCH (1, 1) model to daily S&P 500 spot and futures returns, Koutmos and Tucker (1996) record that a given futures market decline increases stock volatility 1.6326 times more than a futures market advance of equivalent size.

In general, the MGARCH models can be divided into three types (Bauwens et al., 2006). The first type directly generalises the standard univariate GARCH models and thus can involve an excessive number of unknown parameters which are difficult to interpret and may lead to computational burdens. Examples are VECH of Bollerslev et al. (1988) and BEKK of Engle and Kroner (1995). Yang et al. (2012) employ a BEKK specification with asymmetric basis terms to examine the volatility transmission mechanism between the CSI 300 spot and futures markets, and find strong bidirectional dependence in intraday volatility of both markets. Guo et al. (2013) re-consider the issue with a BEKK model, but find the CSI 300 futures leading the spot in volatility. However, Bauwens et al. (2006) suggest that the VECH and BEKK are too restrictive to be used to investigate volatility transmission across markets. The second type can be viewed as linear combinations of the univariate GARCH models, each of which needs not necessarily to be a linear GARCH model. The orthogonal GARCH model of Alexander and Chibumba (1997) belongs to the type and can be nested in the BEKK model such that its properties follow those of the BEKK model (Bauwens et al., 2006). Yet there are few empirical studies using the method in index futures markets. The third type combines the univariate GARCH models in a nonlinear fashion, exemplified by the CCC model of Bollerslev (1990). The model assumes that the conditional correlations are time-invariant and hence the conditional covariance is proportional to the product of the conditional standard deviation of each price series. The assumption considerably reduces the number of unknown parameters that need to be estimated, thereby making the model tractable, despite the fact that the constant correlation coefficients are not realistic as they are very likely to change over time. It is a common practice to impose constant correlations on the MGARCH models to simplify estimation. For example, Chan et al. (1991) assume a constant correlation matrix within a bivariate GARCH (1, 3) model to examine the volatility spillovers between the S&P 500 spot and futures markets and document a bidirectional spillover effect. Tse (1999) follows the practice with a bivariate EGARCH (1, 1) model in the DJIA markets but reports futures leading spot in volatility. The dominant role of futures market in volatility transmission is also obtained in the S&P 500 spot and futures markets by Koutmos and Tucker (1996), who modify the constant correlation specification with dummy variables measuring structural changes built in a bivariate EGARCH (1, 1) model. The constant correlation is also implied in the cost of carry relationship which predicts that the correlation between spot and futures prices should be constant and equal to unity, provided non-stochastic risk-free interest rate and dividend (ibid).

As a generalisation of the CCC model, the dynamic conditional correlation (DCC) model proposed by Engle (2002), Tse and Tsui (2002), and Christodoulakis and Satchell (2002) allows the conditional correlation matrix to be time-varying. To ensure the positive definiteness[17] of the conditional variance-covariance matrix, the DCC model imposes simple conditions on the model, such as the scalar parameters in Engle (2002) and Tse and Tsui (2002), and the Fisher transformation of the correlation coefficients in Christodoulakis and Satchell (2002). As an illustration, the DCC multivariate GARCH model of Engle (2002) employs a parsimonious parameterisation for the conditional correlation matrix $\mathbf{R_t}$:

[17] The conditional variance-covariance matrix in the MGARCH models must be positive definite. A square matrix is positive definite if it is symmetric and all of its eigenvalues are positive (Tsay, 2005).

$$\mathbf{H_t} = \mathbf{D_t R_t D_t} \tag{2.17}$$

$$\mathbf{R_t} = \mathbf{Q_t^{*-1} Q_t Q_t^{*-1}} \tag{2.18}$$

where, in a bivariate system, $\mathbf{H_t}$ is the 2×2 conditional variance-covariance matrix, whose elements are conditional variances and covariances estimated from univariate GARCH-class models; $\mathbf{D_t}$ is the 2×2 diagonal matrix of conditional standard deviations, or $\mathbf{D_t} = diag(\sigma_{1t}, \sigma_{2t})$; $\mathbf{R_t}$ is the time-varying conditional correlation matrix with 1 on the diagonal, conditional correlation coefficients $\rho_{12,t}$ off the diagonal; $\mathbf{Q_t} = (1-m-n)\bar{\mathbf{Q}} + m u_{t-1} u'_{t-1} + n\mathbf{Q_{t-1}}$, where $\bar{\mathbf{Q}}$ is the 2×2 unconditional correlation matrix of the standardised residuals, and m, n are scalar parameters that provide a GARCH-like dynamic structure for $\mathbf{Q_t}$: m captures the impact of past shocks and n captures the impact of past dynamic correlations; $\mathbf{Q}^* = diag(\sqrt{q_{11,t}}, \sqrt{q_{22,t}})$ is the 2×2 diagonal matrix that contains the square roots of the diagonal elements of $\mathbf{Q_t}$. For the positive definiteness of $\mathbf{H_t}$, it is sufficient to require $\mathbf{R_t}$ to be positive definite. For the positive definiteness of $\mathbf{R_t}$, I only need to ensure that $\mathbf{Q_t}$ is positive definite (Engle and Sheppard, 2001). The positive definiteness of $\mathbf{Q_t}$ and hence the positive definiteness of $\mathbf{H_t}$ is satisfied if m, n are non-negative, and have a sum less than 1. If m+n=0, the correlations are constant in time, and the DCC reduces to the CCC model of Bollerslev (1990). Given the positive definiteness of $\mathbf{Q_t}$, $\mathbf{Q}^*$ guarantees that $\mathbf{R_t}$ is a conditional correlation matrix with 1 on the diagonal, $\rho_{12,t}$ off the diagonal no larger than 1 in absolute value (Cappiello et al., 2006). The time-varying conditional correlation coefficients are calculated as $\rho_{12,t} = q_{12,t} / \sqrt{q_{11,t} q_{22,t}}$ in $\mathbf{R_t}$.

The scalars m and n constitute the major critique of the DCC model for they imply that all the conditional correlations obey the same dynamics, which can be hard to justify when the dimension N is high (Tsay, 2005; Bauwens et al., 2006). Nevertheless, the critique may be outweighed by the flexibility and tractability of the DCC model. If the conditional variances are modelled by a univariate GARCH (1, 1) process, Bauwens et al. (2006) show that the number of the parameters that need to be estimated in the DCC model is $(N+1)(N+4)/2$, far less than that in the VECH model. Engle and Sheppard (2001) suggest a two-step estimation procedure for the DCC model which requires the estimation of univariate GARCH models first and then the time-dependent correlation between the price series. The procedure is proved to generate consistent and asymptotically normal log-likelihood estimates and thus makes the model feasible. The DCC model has become a standard method in the literature for studying dynamic market co-movements. Tao and Green (2012) use a bivariate DCC model with a GJR-GARCH-in-mean formulation to study the co-movements between the FTSE 100 spot and futures markets. They report that the market relationships are closer and less variable after the cost-reducing reforms of market microstructure.

As an alternative to the MGARCH methodology, the cross-correlation function (CCF) test of Cheung and Ng (1996) is a diagnostic approach that makes use of the information contained in sample residual cross-correlations to detect causality-in-variance. This is again a two-stage procedure. Univariate conditional mean and conditional variance models are estimated in the first stage and the cross-correlation functions of the squared standardised residuals obtained from the first stage are calculated and tested in the second stage. Given that the distribution of the sample cross-correlations converges to standard normality, a normal test statistic or a χ^2 test statistic can be used to test the null hypothesis of variance noncausality. Compared with the MGARCH models, the two-stage CCF test is convenient to implement, especially when large numbers of series are present and long lags are expected, as the test does not involve the estimation of excessive parameters that may well lead to computational burdens. Pantelidis and Pittis (2004) demonstrate that inferences on causality-in-variance could suffer from severe size distortions if the possible effect of causality-in-mean is ignored. The CCF test is therefore appealing by which the causal patterns in both mean and variance can be determined simultaneously. The CCF test results can further provide helpful guidance on formulating a multivariate model. In the case of a small sample size, a modified test statistic of Koch and Yang (1986) can be used to approximate a χ^2 distribution accurately. Moreover, the CCF test enjoys fairly good finite-sample properties including considerable empirical power, robustness to asymmetric and leptokurtic errors, and insulation of the size of the test from volatility persistence. Nevertheless, the case of zero cross-correlations cannot be detected by the CCF test, and any misspecification resulting in autocorrelations in the models in the first stage can affect the size of the test, which is similar to the EGARCH and GARCH-in-mean models in that the full formulations must be correctly specified (Bollerslev et al., 1992). Selecting a wrong order of the test statistics could also dampen the performance of the test (Hafner and Herwartz, 2006).

The CCF test has been improved in several aspects. Wong and Li (1996) replace the assumption of independent residual series with a weaker condition. Hong (2001) modifies the uniform weighting structure in the test to a flexible weighting scheme where larger weights are assigned to lower-order lags to achieve better power. van Djik et al. (2005) suggest pre-testing for volatility breaks before performing the CCF test, because structural breaks in volatility could give rise to size distortions and hence unreliable inferences on the spillover effect. Rodrigues and Rubia (2007) extend the single volatility break to non-stationary volatility processes and theoretically justify the pre-testing procedure. Tchahou and Duchesne (2013) generalise the univariate CCF test to a multivariate framework from two perspectives: to obtain the asymptotic distributions of residual cross-covariance matrices; and to define transformed residuals and derive the asymptotic distributions of the cross-correlations of the transformed residuals. As a result, they propose new test statistics that reduce to the test statistics of Cheung and Ng (1996) in the univariate context.

Empirical studies using the CCF approach can be found in exchange rate markets (Hong, 2001), credit default swap markets (Tamakoshi and Hamori, 2013) and international stock markets (Tchahou and Duchesne, 2013). In index futures markets, Cheung and Ng (1996) apply the CCF test to the 15-minute S&P 500 spot and futures returns, and reveal a feedback relationship in conditional means and conditional variances. Tao and Green (2012) use the CCF test to examine the causal relationship in volatility in the FTSE 100 markets over two samples. They do not find any spillovers in the first sample and only find bidirectional volatility spillovers at lags 8 and 9 in the second sample, suggesting that information is largely impounded into the FTSE 100 spot and futures prices in a simultaneous manner.

2.3.3 The price and volatility dynamics across countries

One of the prominent features of globalisation is the increasing linkages and interactions among worldwide financial markets. Despite numerous papers on the interrelationships of stock markets,[18] research on the integration of index futures markets is far less abundant. Even so, it is held that the interdependencies of index futures markets has been dramatically enhanced by deregulatory policies, information-sharing mechanisms and advances in information technology (Booth et al., 1997). The trend of globalisation is clearly reflected by futures contracts with an international dimension. Dual- or triple-listed index futures contracts such as the Nikkei 225 futures contracts based on the same underlying index are actively traded instruments in more than one exchange, and these futures contracts act as important vehicles for the information linkages across the markets. To illustrate, a piece of news might be impounded into the Nikkei 225 futures prices in Chicago first, and then transfer to the Nikkei 225 futures prices in Osaka, causing the observed lead-lag relationships in their price and volatility (Fung et al., 2001).[19] The resulting temporal price differentials among the futures markets invite spread arbitrage activities that aim for a riskless profit (Board and Sutcliffe, 1996).[20] In this respect, spread arbitrage maintains the long-run equilibrium relationship between the domestic or home futures market where the futures contracts are traded in the same country as the stocks underlying the index (Osaka in this case), and the foreign or offshore market in whose country the futures contracts are traded but the stocks underlying the index are not (Chicago in this case). Given that spread arbitrage requires lower transaction costs, its no-arbitrage band is narrower than that of index arbitrage, and the link between domestic and foreign markets is tighter than the link between spot and futures markets (Board and Sutcliffe, 1996; Sutcliffe, 2006). Index futures traded on nearly the same underlying stocks provide a similar conduit for information transmission. For instance, both the Taiwan Morgan Stanley Capital weighted stock index (TiMSCI) and the Taiwan Stock Exchange Capitalisation Weighted stock index (TAIEX) measure the stock market conditions in Taiwan and the

[18] See, for example, Garbade and Silber (1979), Hamao et al. (1990), Koutmos and Booth (1995), and Grammig et al. (2005).
[19] As will be discussed below, this example is evidence supporting the international centre hypothesis.
[20] However, it is noteworthy that spread arbitrage is seldom riskless in practice. Despite that multiple-listed futures are based on the same index, they are not perfect substitutes, as differences exist in, *inter alia*, (futures) contract specifications, regulatory regimes, trading hours and transaction costs among the markets (Board and Sutcliffe, 1996).

correlation of their 5-minute returns can be greater than 97%. It is thus not surprising for their corresponding futures returns to be correlated at 99.9% (Roope and Zurbruegg, 2002). However, riskless arbitrage exploiting the price differentials among the four markets is not possible due to structural differences in contract specifications and variations in the component stocks of the underlying indices (Frino et al., 2013). Even if the underlying assets are different, e.g. the S&P 500 index and the FTSE 100 index (Booth et al., 1997), their interactions with the corresponding futures contracts still constitute the potential information linkages through cross-border price discovery and volatility transmission mechanisms, and the linkages can be more effectively traced than the stock market linkages alone due to the lack of nonsynchronous trading and fewer market frictions in futures markets (Sim and Zurbruegg, 1999).

In particular, the price and volatility dynamics between domestic spot/futures markets and foreign spot/futures markets shed critical light on the information role of each market, in the sense that new information generated in one market is very likely to affect the other market in a predictable way. This has important implications at least for exchange competition and asset management. The institutional differences between futures exchanges may attract much of the trading volume which was originally captured domestically to migrate to a competing foreign exchange, rendering the exchange at home redundant in information dissemination, i.e. it lags behind in reacting to new information, with fewer participants and less liquidity (Roope and Zurbruegg, 2002). This perception is called the order flow diversion hypothesis (Frino et al., 2013). Hence, the increasing exchange competition necessitates careful contract design and trading regulation on the basis of the knowledge of the interaction mechanism in informationally linked markets, through which an exchange may gain competitive advantage over other exchanges. On the other hand, for small markets that rely on global financial centres, and markets in the increasingly integrated financial environment, the influence of foreign market behaviour on the local spot-futures relationship can be tremendous. It follows that investors in those markets are suggested assigning a heavy weighting to foreign markets when capitalising on the mutual adjustments between domestic and foreign prices and volatilities in their strategies of asset allocation and risk management worldwide (Sim and Zurbruegg, 1999; Fung et al., 2001).

2.3.3.1 Home bias vs international centre

Two hypotheses regarding the information transmission mechanism between domestic and foreign markets are often examined in the literature: the home-bias hypothesis and the international centre hypothesis. The home-bias hypothesis states that the domestic market tends to reflect new information first, and then transmit the news to the foreign market. The rationale behind the hypothesis pertains to the "home market advantages" resulting from geographic proximity (Fung et al., 2001). For example, the home market of futures contracts locates near the underlying stock market (within the same country), so that domestic investors enjoy a priority in obtaining firm-specific information such as dividends and taxes compared with foreign investors (ibid). Another benefit is that domestic investors are better informed about local trading environment and regulatory regime, and thus they contribute to greater efficiency in trading assets and less noise at home. Moreover, domestic investors face far less trading hurdles such as currency fluctuations and non-overlapping trading hours than their foreign counterparts, further giving rise to the home-market bias. In contrast, the international centre hypothesis means that a foreign market, usually a global financial centre, should play a leading role in the information dissemination process. This is buttressed by the fact that an offshore venue generally provides more lenient and liquid trading conditions, e.g. lower entry barriers, fewer transaction costs, larger price/position limits, longer trading hours, bigger minimum price movements, etc. (Fung et al., 2001; Roope and Zurbruegg, 2002; Covrig et al., 2004), which is consistent with the transaction costs hypothesis. Besides, as a niche player, the foreign market is especially attractive to some international investors who manage risk by trading futures together with other financial instruments also available on that market. Due to differences in trading hours, a foreign market offers additional opportunities for arbitrage when the domestic market is closed (Board and Sutcliffe, 1996).

As such, it seems reasonable to conjecture that both domestic and foreign markets contribute significantly to the information transmission mechanism across borders (Covrig et al., 2004), but the relative extent of the contribution is an empirical issue. From the perspective of the price discovery process across markets, the CFW and the IS measures for information content are employed jointly to test the hypotheses, after model modifications to fit in the multivariate case. In the Nikkei 225 markets, for example, Covrig et al. (2004) use both measures to examine the contribution of the Osaka Exchange (OSE), the Singapore Exchange (SGX), and the underlying stock market to price discovery. They find that futures dominate the price formation process relative to spot in each market; in addition, 46% of the common factor weights can be attributed to the OSE and 33% to the SGX. Although the evidence suggests that the price discovery function is mainly assumed by the domestic market, the contribution of the SGX is more revealing considering the low trading volume in the foreign market. The results from the IS metrics are consistent, with 39.15% contributed by the OSE and 34.09% by the SGX. The relative importance of the SGX is argued to be due to lower transaction costs and longer trading hours, plus the trading system of open outcry. Similar evidence is found by Guo et al. (2013), who use the two measures jointly for the CSI 300 spot, futures in China and the FTSE China A50 spot, futures in the SGX, and corroborate the primary role of China as the domestic market in price discovery. Meanwhile they point out that the contribution made by the relatively thinly-traded Singaporean market is indeed substantial. Roope and Zurbruegg (2002) study the cross-border price dynamics between the Taiwan Futures exchange (TAIFEX) spot, futures in Taiwan and the TiMSCI spot, futures in the SGX. The CFW results show that each futures market leads its spot market, whereas the IS results show spot leading futures in Taiwan and such a relationship is subject to change.[21] However, both measures confirm that the SGX plays a major role in the price discovery, thereby supporting the international centre hypothesis.

Alternatively, Granger causality tests in the multivariate setting consist of block exogeneity test for short-run adjustments and the linear VECM for long-run causality.[22] Roope and Zurbruegg (2002) adopt the methodology and report a temporal feedback relationship among the four

[21] The variability of the relationship results from the large difference between lower and upper bounds in the IS measure and the high correlation between price movements in Taiwan (Roope and Zurbruegg, 2002).

[22] Kim et al. (1999) examine the price discovery process across the S&P 500, NYSE Composite, and MMI futures, and across their respective spot indices. However, the Johansen trace test shows that no cointegration exists across the futures markets, or across the spot markets, so that they adopt variance decomposition and impulse response functions from a VAR model without cointegration constraints. They report that the S&P 500 futures leads the other futures and the MMI index leads the other indices in the price discovery, consistent with the prediction of the transaction costs hypothesis.

Taiwan-related markets, i.e. the TAIFEX spot, futures and the TiMSCI spot, futures. The error correction coefficients, however, indicate that the spot leads the futures in each market, and the two stock indices respond to information at approximately the same speed in the long run. Guo et al. (2013) report bidirectional causality between the CSI 300 spot, futures in China and the FTSE China A50 spot, futures in the SGX, and highlight the key function of China as the domestic market. With the Granger causality test, Shyy and Shen (1997) investigate the Nikkei 225 futures contracts in the OSE and the SGX. Although they do not conclude clear directions of any causal relationships, the information flow seems more evident from the OSE to the SGX than the other way round in the short run.[23] In contrast, Booth et al. (1996) find that none of the trading markets of the Nikkei 225 futures contracts, i.e. the OSE, the SGX, and the Chicago Mercantile Exchange (CME), can be regarded as a main source of information flow, implying that each market is informationally efficient. Furthermore, after the reduction in the futures transferring tax from 0.05% to 0.025% in Taiwan, the TAIFEX futures experienced an improved information advantage relative to the TiMSCI futures in the SGX (Chou and Lee, 2002; Hsieh, 2004), which suggests that the information role of markets is susceptible to regulatory reforms pertinent to transaction costs. Frino and West (2003) directly test the transaction costs hypothesis for the Nikkei 225 futures listed on the OSE and the SGX, and demonstrate that the lower transaction cost structure at least stemming from negotiable brokerage commissions and less margin requirements in the offshore market induces the SGX futures prices to lead the OSE futures prices.

In terms of price volatility behaviour, it is held that stock volatilities are usually higher during trading hours when more public and private information and noise occur than non-trading hours (e.g. Fama, 1965; French and Roll, 1986). But it is not clear whether the argument holds in futures markets. Booth et al. (1996) therefore compare trading time variances with non-trading time variances in the three Nikkei 225 futures markets. For the OSE and the SGX, the argument is supported; whereas for the CME, the trading time variances are found to be lower than the non-trading time variances. Due to differences in time zones, the non-trading

[23] See Table 4(b) of Shyy and Shen (1997).

periods of the CME overlap the trading periods of the other two markets, and thus the result suggests that the three markets are driven by the same kind of information which is released during Japanese business hours. Shyy and Shen (1997) find that the Nikkei 225 futures returns at the opening of the OSE and the SGX are more volatile and serially correlated than at the close, but the differences of such behaviour between the two markets are not significant. Regarding the cross-border volatility spillovers, innovation accounting and impulse response analysis based on a VAR system are conducted by Booth et al. (1997), who consider the interaction of the S&P 500, the FTSE 100, the Nikkei 225 futures volatilities estimated by the method of Garman and Klass (1980) across the US, the UK and Singapore. The US and the UK are found to spread volatilities to each other, as well as cluster volatilities individually. In contrast, Japanese volatilities seem to depend only on its past values. Besides, a given shock from the US or the UK spills over to each other and then diminishes quickly, while a Japanese shock only affects its own volatilities and the impact can last for more than ten days. The MGARCH models are also used by several studies on the volatility transmission process across borders. Specifically, the quadvariate ECM-ARCH (1) model of Sim and Zurbruegg (1999) incorporates an error correction term into the conditional variance equation to explicitly allow for any potential relationship between disequilibrium and uncertainty in Australia and Japan. They report that Australian traders in either the SPI futures or the All Ordinaries Index (AOI) spot markets should take into account the price and volatility movements in the Nikkei 300 spot and futures markets in their risk perceptions, for the volatility spillover from Japan to Australia is unidirectional and significant, which is in line with the dependence that Australia has on the Japanese economy. The BEKK model of Guo et al. (2013) shows the leading effect of the CSI 300 spot, futures volatilities on the FTSE China A50 counterparts, respectively, which reaffirms the domestic market as a main source of information flow. Fung et al. (2001) construct a bivariate ECM-GJR-GARCH (1, 1) model to examine the Nikkei 225 futures volatilities in the OSE and the CME. Despite strong interactions in cross-market terms, the volatility contagion from the US to Japan is greater than the reverse, evincing the dominant role of the foreign market in transmitting information.

2.4 Conclusion

The spot-futures pricing relationship hitherto has been investigated from the perspectives of the pricing efficiency of futures contracts, and of the price and volatility dynamics between spot and futures markets within and across countries. The cost of carry relationship defines the no-arbitrage condition between spot and futures markets. In the presence of transaction costs and risks, however, it develops into a no-arbitrage band, and the pricing deviations from the no-arbitrage relation, or futures mispricing takes place frequently and persistently, signalling potential opportunities for index arbitrage. Based on the arbitrage decision rules, and econometric models such as the TAR models and the STAR models, the literature generally reaches a consensus that the profitability of index arbitrage activities can only be determined after allowing for the associated transaction costs and risks.

The cost of carry model implies that the spot-futures price differential, or basis, must be embodied in the framework that models the price discovery process between spot and futures markets, for the basis reflects the error correction mechanism between the two markets in the sense that any present departures from the cost of carry relationship will be corrected in the next stage so that spot and futures prices move closely together in the steady state. As such, the linear ECM is appropriate for studying the short-run adjustments and long-run equilibrium of spot and futures prices. More advanced models such as the TECM and the STECM are designed to capture the nonlinear adjustment mechanisms in spot and futures markets. The TECM extends the constant cointegration in a linear ECM to threshold cointegration, such that spot and futures prices follow a stepwise adjustment pattern and the error correction mechanism is regime-dependent - only when a specific transaction cost threshold is crossed can arbitrage be activated to remove disequilibrium. This is based on the assumption that investors are homogeneous. If investors are assumed to be heterogeneous, in the aggregate they may not transit between the regimes discontinuously; rather, the whole market is more likely to adjust in a gradual and smooth manner. Taking the line of reasoning as its basic spirit, the STECM may be more suitable for studying market reactions as a whole.

An increasing number of papers hold that cointegration is consistent with causality in price series, and thus leads and lags in spot and futures prices can constitute evidence supporting the cost of carry model, rather than refuting it. Theories generally predict that price leadership should take place in a futures market, or in other words, a piece of news is more likely to be impounded into futures prices first and then transfer to the underlying spot prices, in that the spot market is usually characterised by nonsynchronous trading, higher transaction costs, short-selling restrictions, concentration of unsystematic information, and less efficient trading systems. This is reinforced by numerous empirical studies with conforming evidence from a wide range of markets. However, several papers generate different results, such as spot dominating futures in the process of price discovery, suggesting that the price dynamics in the real world may be more complex than the theoretical prediction.

The volatility of spot and futures prices provides another conduit for information transmission, apart from the price. Spot and futures variances exhibit conditional heteroskedasticity, characterised by volatility clustering, fat tailedness, intraday fluctuations, predictive asymmetry, and volatility spillover. In particular, the volatility spillover effect taking the form of leads and lags in volatility suggests that information contained in the volatility in one market has predictive power for the volatility in the other market, showing the information transmission between spot and futures markets through the volatility linkage. The MGARCH models are prevalent in the empirical research investigating the volatility interactions, as they are proved to be successful in describing the dynamics of volatilities and co-volatilities. For example, the DCC multivariate GARCH model allows the conditional correlation matrix to vary over time; meanwhile it maintains tractability and feasibility through a two-step estimation procedure. An alternative method is the CCF test which makes use of the information contained in sample residual cross-correlations and has been performed in a few papers. The empirical evidence of the volatility spillovers is supported in several markets, but rejected in others probably because in those markets information is reflected in spot and futures prices simultaneously.

Beyond national borders, the price and volatility dynamics between domestic spot/futures markets and foreign spot/futures markets constitute the informational linkages across countries. Both the domestic and the foreign markets can contribute to the international information dissemination mechanism in theory, but their relative degree of the contribution is an empirical issue. The Granger causality test and the information content method are modified in the multivariate setting to explore the cross-border price dynamics, and the MGARCH models are ubiquitously adopted to examine the transnational volatility transmission process. Although the literature is not unanimous in the location of the information leadership across countries, most works recognise the important functions of foreign futures exchanges and the international linkages and interactions among the related futures markets.

Chapter 3

The Nikkei 225 stock index and index futures markets

3.1 Introduction

This chapter aims to introduce the Nikkei 225 stock index and index futures markets, and provide essential institutional and background information for the subsequent empirical chapters. The chapter is organised in the following order. A brief history of the triple-listed Nikkei futures contracts is given below. Section 3.2 introduces the Nikkei 225 stock index market. Section 3.3 analyses the main differences among the Nikkei 225 futures contracts. Section 3.4 concludes the chapter.

On 3 September 1986, the first Nikkei 225 futures contract in the world was launched in the Singapore International Monetary Exchange (SIMEX), later merged to the Singapore Exchange (SGX). Unlike all other index futures contracts at that time, whose underlying asset was a national stock index in the same country, the Nikkei futures contract was based on the Nikkei Stock Average (the Nikkei 225), which is the premier barometer of stock markets in Japan. SGX therefore became the world's first offshore exchange for index futures contracts. It remained the only marketplace for index arbitrage between Nikkei spot and futures until 3 September 1988, when the Osaka Securities Exchange, now the Osaka Exchange (OSE), started to trade Nikkei 225 futures contracts. Due to some similarities in contract specifications and overlapping in trading hours, arbitrage between the OSE futures contracts and the SGX futures contracts began to attract scores of investors, including Nick Leeson whose trading ultimately led to the insolvency of Barings Bank. In a further development the Chicago Mercantile Exchange (CME) introduced Nikkei 225 futures contracts on 25 September 1990, in response to the increasing importance of the Japanese economy and the pressing need for risk management tools among US investors. Therefore the unique feature of the Nikkei futures contracts is that they are simultaneously listed on three futures exchanges with one common stock market.

3.2 The Nikkei 225 index

The Nikkei 225 index consists of 225 blue-chip common stocks listed on the First Section of the Tokyo Stock Exchange (TSE). In June 2014, the market capitalisation of the constituent stocks amounted to $4.49 trillion, covering 64% of that of all stocks in the First Section of the TSE.[24] Similar to the Dow Jones Industrial Average (DJIA), the Nikkei 225 is a price-weighted index calculated by summing up the prices of all constituent stocks adjusted by presumed par values and dividing the summation by a divisor which changes from time to time to maintain the continuity of the index in cases of stock splits, reverse splits, component changes, etc. The constituent stocks include companies such as Toyota, Sony, Mitsubishi and Fast Retailing. The Nikkei index is calculated every 15 seconds from 4 January 2010 (and every 1 minute before then) during the trading hours of the TSE, and reported to two decimal places, by Nikkei Inc. Figure 3.1 graphs the historical daily closing price of the Nikkei 225 index from 3 September 1986 to 31 December 2014. Following the bubble era in the late 1980s when the Nikkei index rose to historically high levels, there are several periods in which the index is decreasing. The first period is the Japanese stock market crash in the early 1990s. The second is the Japanese "Big Bang" period from November 1996 to March 2001, although the decrease lingers on until early 2003.[25] The third is the credit crunch and global financial crisis period from 2007 to 2012, which envelops the Japan earthquake and Fukushima nuclear crisis in March 2011.

Trading of stocks in the First Section in the TSE was on the floor before 30 April 1999, and after that transactions were computerised and the current electronic trading system is called Arrowhead. The TSE opens during 9.00-11.30 (morning session), 12.30-15.00 (afternoon session) (Japan Standard Time, JST). The TSE is an auction or order-driven market, traditionally with two types of members: regular members and saitori members (Takagi, 1989). Regular members are securities companies that trade on proprietary accounts or on customers' accounts

[24] Data are from Nikkei Inc.

[25] The Japanese "Big Bang" is a five-year financial deregulatory reform proposed by Japan's government in November 1996, aimed at eliminating all partitions in Japanese financial markets no later than 2001. During the "Big Bang" period, a series of policies came into effect to remove barriers and increase competition among financial intermediaries. A notable example is the full deregulation of brokerage commission rates in 1 October 1999, and from then on the commission rates in Japan were no longer fixed but negotiable for all transactions (Liu, 2010; Flath, 2014).

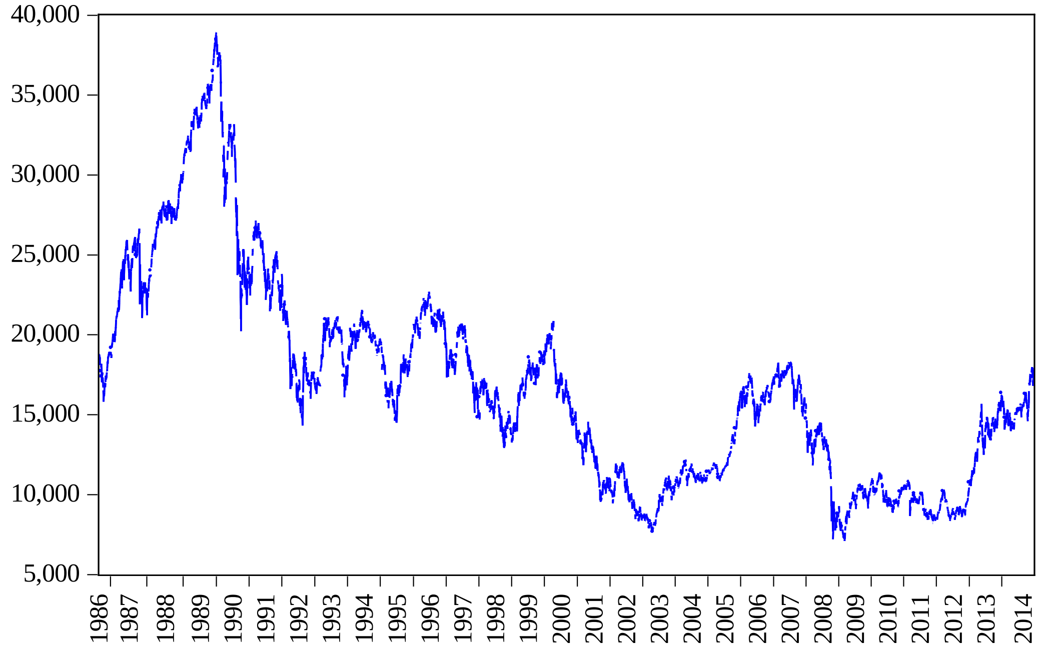


Figure 3.1 The Nikkei 225 index

Notes: This figure plots the daily closing price of Nikkei 225 index during the period 03/09/1986-31/12/2014. Data are from Thomson Reuters Eikon.

in the exchange. Saitori members are market specialists who act as intermediaries between regular members and they are not allowed to trade for their own account. Now all members are called general trading participants and there are 93 general trading participants in the TSE.[26] Trading is conducted using limit orders with specific execution prices and market orders without specific execution prices. The auction rules are based on the principles of price priority and time priority. The first priority is price, which means that market orders take precedence over limit orders, and for limit orders, the highest bid and lowest offer prices are matched before other orders. The second priority is time, which means that earlier accepted orders have priority over later accepted orders given the same execution price. The stock opening prices (including initial prices at the resumption of trading after trading halts) and closing prices of each trading session are determined by the Itayose (call auction) method which uses the price priority principle only to clear the market. The stock prices in the rest of the trading sessions are determined by the

[26] After the establishment of Japan Exchange Group by the OSE, TSE and other institutions on 1 January 2013, apart from general trading participants, there are futures, etc. trading participants and government bond futures, etc. trading participants; as their names suggest, the latter two are allowed to trade derivatives rather than stocks.

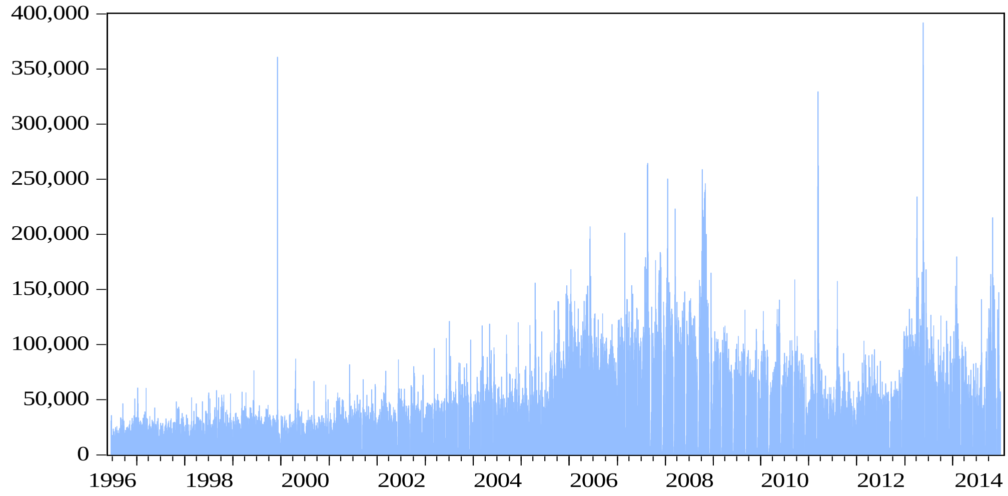
Zaraba (continuous auction) method which uses both principles. Regular transactions account for more than 99% of all transactions and settlement is due on the third business day following the transaction date (T+3).

3.3 Differences among the Nikkei 225 futures contracts

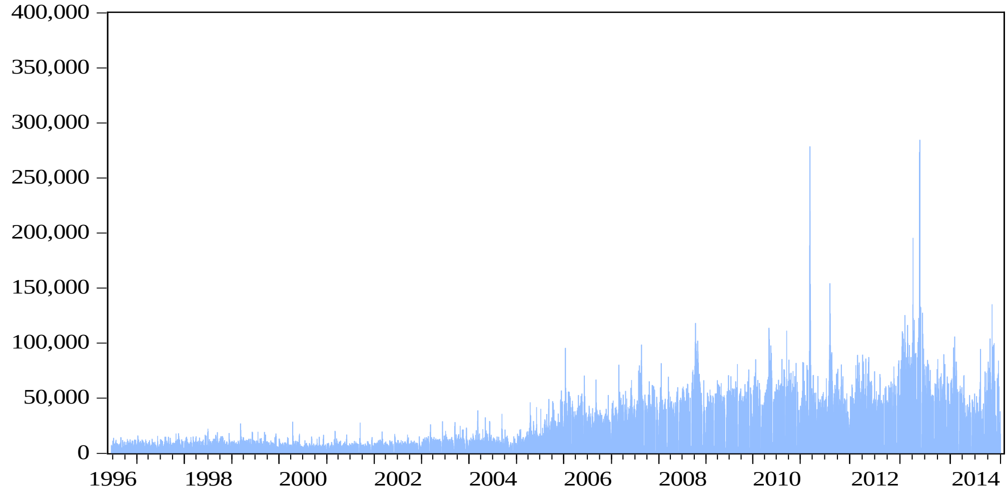
Despite sharing the same stock market, the three Nikkei 225 futures contracts differ in many aspects. The most striking difference is in trading volume. Figure 3.2 shows the daily number of contracts traded on the three exchanges. Clearly, the OSE Nikkei futures contracts are the most heavily traded, with a daily average volume of 54,181 contracts. Given that the SGX futures contracts are half the size of the OSE futures contracts, the SGX volume is divided by two to facilitate direct comparison with the OSE volume. The adjusted SGX volume is much smaller, on average about 26,777 contracts are traded daily. The CME futures contracts are denominated in US dollars and thus the CME volume is unadjusted,[27] but from the figure it is still evident that the CME futures contracts are the most thinly traded, on average about 6,767 contracts are traded daily. The OSE has been the largest market over the course of years, while the offshore exchanges (SGX and CME) are smaller in terms of trading volume.

Another difference is in trading hours. The three exchanges are located in different time zones and the three Nikkei futures contracts are traded within different time periods. The OSE opens 9.00-15.15, with an overnight session 16.30-3.00 (JST). The SGX opens 7.45-14.25, with an overnight session 15.15-2.00 (Singapore time, SGT), corresponding to 8.45-15.25 and 16.15-3.00 (overnight) in terms of JST. Hence, the trading hours of the two markets are almost overlapping, and the SGX opening time is longer by 40 minutes. The longer trading time of the SGX may be important to liquidity investors and research supports the contribution of the extra minutes of the SGX to daily price changes (Covrig et al., 2004). The CME futures contracts are traded on both open outcry and electronic (Globex) systems during 1995-2015. The CME open

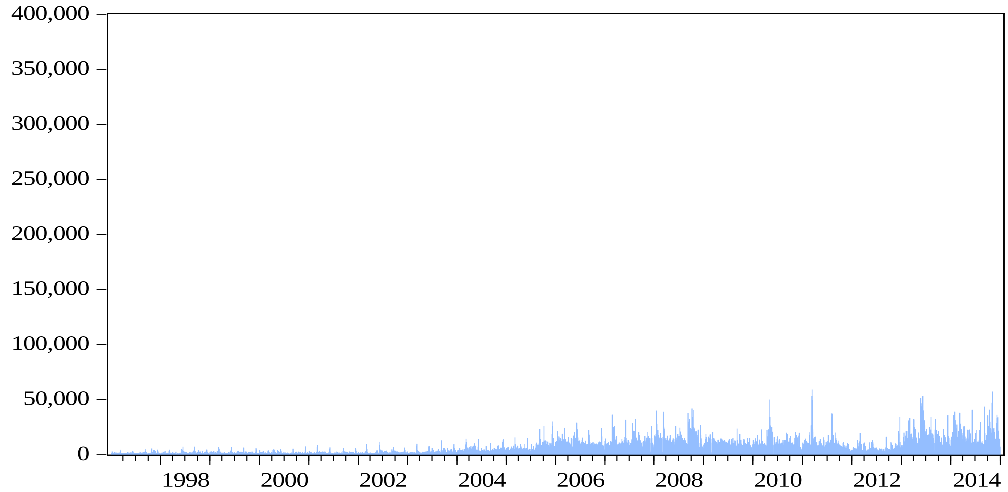
[27] The CME futures contracts have a contract size of 5 dollars. If applying an exchange rate of 107.55 yen per dollar, which is the average yen-dollar middle rate during 1997-2014, the CME contract size amounts to about 54% of the OSE contract size. This accentuates the difference in volume between CME and the other two exchanges.



(a) OSE



(b) SGX

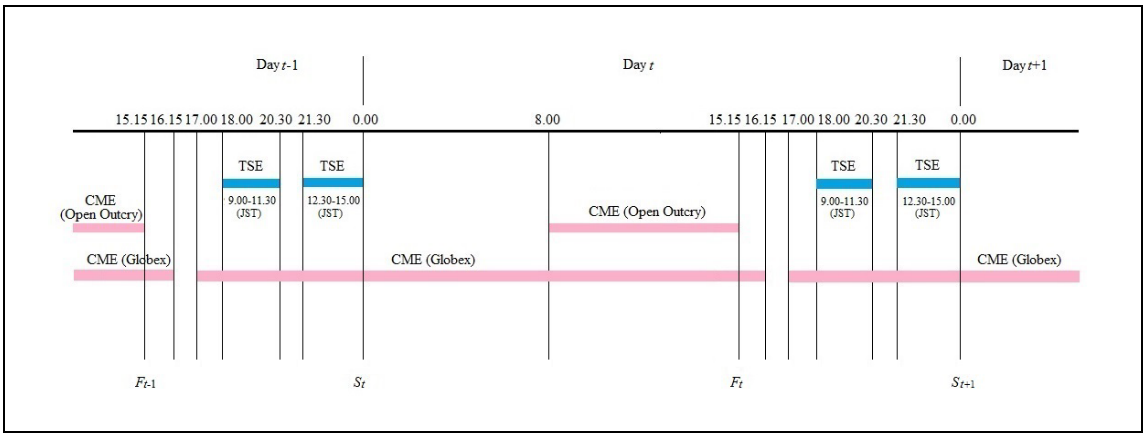


(c) CME

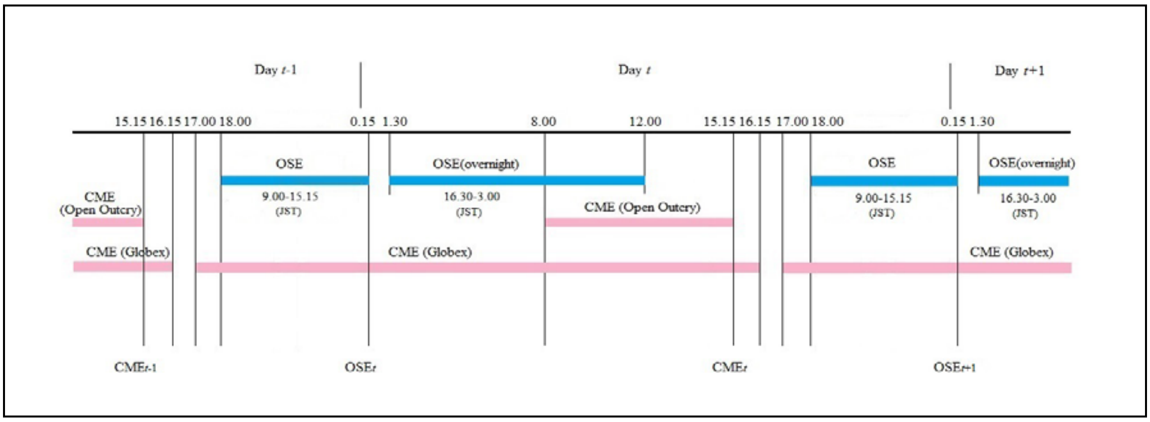
Figure 3.2 Trading volumes of the Nikkei 225 futures contracts

Notes: (a)-(c) graph the daily number of contracts traded on the Nikkei futures markets over the period 20/06/1996-31/12/2014 (OSE and SGX); 01/01/1997-31/12/2014 (CME). The SGX contracts shifted from open outcry to electronic trading on 01/11/2004, and thus the SGX volume is the number of the contracts traded on the floor before 01/11/2004, and the number of the contracts traded electronically after the date. The SGX volume is halved to facilitate direct comparison with the OSE volume. The CME adopts both open outcry and electronic trading during the period and the CME volume is the total number of the contracts traded on both systems. Data are from Datastream, OSE, SGX and CME.

outcry opens 8.00-15.15 (Central Standard Time, CST), which is equivalent to 23.00-6.15 (JST). As shown in Figure 3.3, there is no overlap in trading hours between the spot market and the CME open outcry, and only a short overlapping interval from 23.00 to 3.00 (JST) (or from 8.00 to 12.00 in CST) between the OSE (or SGX) and the CME open outcry. Globex trades from 17.00 to 16.15 the next day (CST), which envelopes the opening times of the other Nikkei markets. Although the CME Globex alleviates the effect of time zones, it is still likely that the OSE and SGX are more closely linked with each other by arbitrage which is essentially not affected by time differences, than any one of them with the CME. Further discussions are provided in section 4.2.4, Chapter 4.



(a) TSE and CME



(b) OSE and CME

Figure 3.3 Trading hours of the Nikkei 225 futures contracts

Notes: (a) illustrates the trading hours of the TSE and CME; the bottom line shows the time when futures settlement price (F) and stock closing price (S) are generated. (b) illustrates the trading hours of the OSE (including the overnight session) and CME; the bottom line shows the time when the OSE, CME settlement prices are generated. The trading hours of the OSE and SGX are almost overlapping, and thus only the trading hours of the OSE and CME are compared in (b). The time is CST unless otherwise marked. The subscripts t-1, t and t+1 indicate the timing differences. Trading hours are presented as of 31/12/2014.

Table 3.1 The Nikkei 225 futures contracts

	OSE	SGX	CME
Underlying asset	Nikkei 225	Nikkei 225	Nikkei 225
Launch date	03/09/1988	03/09/1986	25/09/1990
Contract size	Index×¥1,000	Index×¥500	Index×$5
Tick size	10 index points (¥10,000)	5 index points (¥2,500); 1 index point (¥500) for strategy trades	5 index points ($25)
Contract months	Nearest 3 for Mar and Sept; nearest 10 for Jun and Dec	Nearest 6 for serial months; nearest 20 for Mar, Jun, Sept, Dec	Mar, Jun, Sept, Dec
Trading hours	9.00-15.15, 16.30-3.00 (JST)	7.45-14.25, 15.15-2.00 (SGT)	Floor trading: 8.00-15.15 (CST) Screen trading: 17.00-16.15 (CST)
Daily price limits	8%, 12%, 16% up/down of a base price calculated by the OSE	1,000 points, 1,500 points, 2,000 points up/down of the previous settlement price for the front quarter month of the SGX contract	8%, 12%, 16% up/down of a futures fixing price calculated by the CME
Circuit breaker	10% up/down of the price limit range; duration 10 minutes at least	No trading halts	No trading halts
Margins per unit	¥720,000	Initial margin: ¥396,000 Maintenance margin: ¥360,000	Initial margin: $3,600 Maintenance margin: $3,600 [a]
Mutual offset	No mutual offset	Mutual offset with the CME	Mutual offset with the SGX
Trading mechanism	Screen trading	Floor trading (before 01/11/2004) Screen trading (after 01/11/2004)	Floor trading and screen trading [b]
Last trading day	The business day prior to the settlement date	The business day prior to the settlement date	The business day prior to the settlement date
Final settlement day	Second Friday of the contract month	Second Friday of the contract month	Second Friday of the contract month
Final settlement price	Special quotation based on the total opening prices of each constituent of Nikkei 225 index on the settlement date	Special quotation based on the total opening prices of each constituent of Nikkei 225 index on the settlement date	Special quotation based on the total opening prices of each constituent of Nikkei 225 index on the settlement date
Settlement procedure	Cash settlement	Cash settlement	Cash settlement

Notes: The table presents the details of the Nikkei futures contracts traded on the OSE, SGX and CME as of 31/12/2014. [a] The CME margin levels are for hedgers or CME members. [b] The CME closed the floor trading system for the Nikkei contracts on 19/06/2015. Data are from the OSE, SGX and CME.

There are also differences in the details of the Nikkei futures contracts and regulatory policies. Table 3.1 provides a summary. First, denominated in yen, the OSE futures has a contract size (Nikkei index price×¥1,000) that is twice the contract size of the SGX futures (Nikkei index price×¥500). The smaller contract size of the SGX futures allows lower capital requirements and risks which may appeal to investors with capital constraints and/or risk aversion. In contrast, the CME contract has a multiplier of $5 and is transacted and settled in dollars. This special arrangement introduces currency risk to the arbitrage between the CME and any other Nikkei market, as the CME investors would frequently convert currencies and expose their arbitrage positions to the yen-dollar exchange rate fluctuations. It follows that the OSE and SGX should be more integrated through arbitrage activities aloof from the currency risk. Also, CME futures price deviations (mispricing) could be larger in size and quantity due to exchange rate fluctuations than the OSE and SGX mispricing.

Second, the minimum price movement, or tick size, of the OSE contract is 10 index points, while the tick size of the SGX, CME contracts are 5 index points. The SGX allows an even smaller tick size of 1 index points for strategy trades. The tick size is closely related to trading volume and transaction costs. The OSE has the largest trading volume from Figure 3.2, which can be attributable to the large tick size of the OSE contract. However, finer tick sizes encourage more continuous price changes and narrower bid-ask spreads. Covrig et al. (2004) estimate the average percentage bid-ask spread on the OSE to be 0.069%, compared with that on the SGX to be 0.040%. Given that the bid-ask spread is a main component of transaction costs, the offshore exchanges (the SGX and CME) are likely to offer lower transaction costs for Nikkei investors.

Third, the OSE futures contracts have had a computerised trading system from the inception of the contracts. The SGX futures contracts used open outcry, but officially shifted from open outcry to electronic trading on 1 November 2004. The shift of the trading systems is smooth, without exerting a material effect on the SGX futures prices. This is because the SGX investors were given time to adapt to the electronic trading system (ETS) in overnight sessions and there was a period when both systems were available for trading. The ETS started to rival open outcry in volume from 1 November 2004, and shortly afterwards the ETS dominated and became the only trading mechanism. The CME futures contracts were traded on the floor from its inception. The electronic trading platform CME Globex was introduced on 25 June 1992 and stock index products began to trade on Globex from 1995. Up until 2015, both open outcry and Globex were available for the CME Nikkei futures contracts. The CME closed the open outcry system on 19 June 2015 for most stock index futures products including the Nikkei contracts, as a result of the decline in futures volumes on the system.

Fourth, in terms of key regulatory policies, while all the three exchanges use price limits, the OSE employs a circuit breaker which is a cooling-off system triggered when a price stays at a price limit or within 10% of the price limit range for 1 minute. Once the circuit breaker is triggered, trading will be halted for at least 10 minutes. After the trading halt, trading will be resumed with the initial price determined by the Itayose method, and the price limit will be expanded. There are no trading halts in the SGX and CME. Besides, the OSE charges the highest margin for trading one contract, which is almost twice that charged by the SGX (partly because of the larger contract size in the OSE). If the CME margin $3,600 is converted to yen by an exchange rate of 107.55 yen per dollar, the average yen-dollar middle rate during 1997-2014, it is about ¥387,180, which is also lower than the OSE margin cost. Furthermore, the SGX, CME Nikkei futures contracts can be traded through the Mutual Offset System (MOS) which is a mutual agreement between the SGX and CME. The MOS allows investors to enter a position in either exchange and clear that position in either the SGX or CME without additional cost. Compared with the OSE, the offshore exchanges (the SGX and CME) provide a more lenient trading environment for Nikkei investors.

3.4 Conclusion

To summarise, Figure 3.4 (the same as Figure 1.1) provides a chronological view of the major historical events in the Nikkei markets. Most studies on the Nikkei markets were published in the early 1990s-early 2000s. In the subsequent empirical chapters, I will study the Nikkei markets with a comprehensive new 19-year sample period which includes a pre-crisis period and a post-crisis period divided by the 2008 global financial crisis and therefore is able to cover

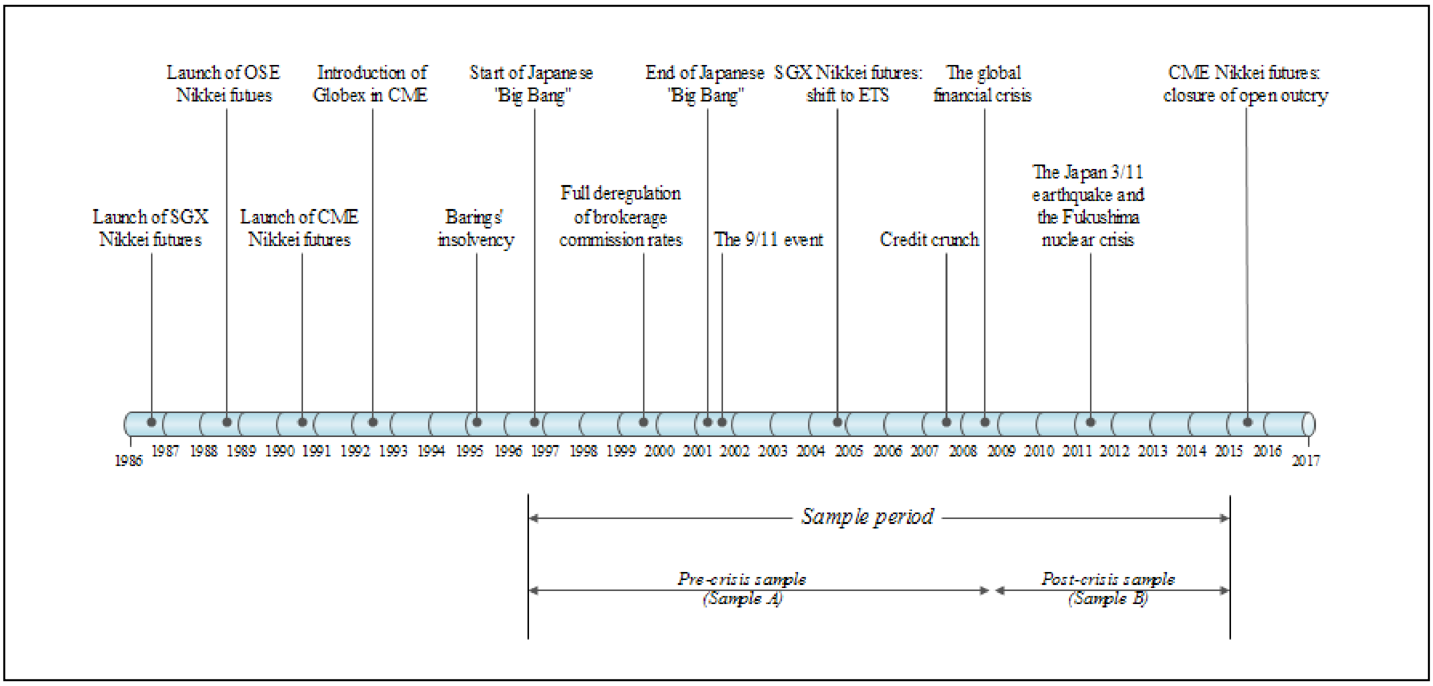


Figure 3.4 Major historical events in the Nikkei markets

Notes: This figure displays major historical events in the Nikkei markets in chronological order. The whole sample period of the dissertation is 20/06/1996-31/12/2014 (OSE and SGX); 01/01/1997-31/12/2014 (CME). The pre-crisis period (sample A) is during 28/06/1996-09/10/2008 (OSE, SGX); 09/01/1997-12/09/2008 (CME). The post-crisis period (sample B) is during 04/11/2008-31/12/2014 (OSE, SGX); 02/12/2008-31/12/2014 (CME).

a series of recent major historical events, reflect the quickly changing market conditions, and compare the cross-border mispricing, price and volatility dynamics before and after the 2008 global financial crisis.

The unique characteristics of the Nikkei futures contracts and the key institutional differences can be summarised as the following.

a) Triple-listing: the Nikkei futures contracts are traded on the OSE, SGX and CME, sharing a common stock market in the TSE.

b) Market sizes: The OSE is the largest market and the OSE futures contracts are the most heavily traded, while the SGX and CME are smaller in terms of trading volume.

c) Time differences: the three futures exchanges are located in different time zones. For example, the time used in the CME is 15 hours behind the time used in the OSE.

d) Currency denominations: trading and settlement on the CME involve US dollars while trading and settlement on the underlying stock market, the OSE and the SGX involve Japanese yen.

e) Trading mechanisms: the OSE contracts have had been traded electronically, but the SGX contracts shifted from open outcry to electronic trading and the CME adopted both open outcry and electronic trading during my sample period.

f) Transaction costs: there are differences in the Nikkei contract specifications and regulatory policies among the three exchanges. Generally speaking, the SGX and CME offer lower transaction costs and a more lenient trading environment for Nikkei investors.

g) Dividend practices: the special dividend payout practices of Japanese firms which will be investigated in depth in Chapter 4.

No previous research has fully considered the unique features of the three Nikkei futures and the key institutional differences listed above. I will study them in detail and allow for them in examining the spot-futures pricing relationship, market dynamics and the level of integration in and across the Nikkei futures exchanges in the subsequent empirical chapters.

Chapter 4

Cost of carry, mispricing and index arbitrage in the Nikkei 225 futures markets

4.1 Introduction

The cost of carry relationship defines the equilibrium between spot and futures markets. By this relationship, there should be a theoretical (or fair) futures price at any particular point in time, and any deviations from the theoretical price are measured as "mispricing". The basic arbitrage decision rule states that it may not be possible to exploit mispricing profitably if the mispricing lies within no-arbitrage bounds determined by transaction costs (section 2.2.3, Chapter 2). For this reason, the economic significance of mispricing, or whether it represents profitable arbitrage opportunities, is of particular interest in practice. Based on one common stock index market (Tokyo Stock Exchange, TSE), the Nikkei 225 stock index futures contracts are traded on three equivalent yet different markets: Osaka Exchange (OSE), Singapore Exchange (SGX) and Chicago Mercantile Exchange (CME). Knowledge of the cost of carry relationship and the behaviour of mispricing in the three Nikkei futures markets is therefore invaluable for investors around the world.

Recall from Chapter 2 that the standard cost of carry model of Cornell and French (1983a; 1983b) is given by:

$$F_t^* = S_t e^{(r-d)(T-t)} \tag{2.1}$$

where F_t^* is the theoretical (or fair) futures price at time t, S_t is the spot price at time t, (r-d) is the net cost of carry for the underlying stocks in the index. That is, the single, constant, risk-free interest cost r minus the known, constant, continuous dividend yield d. T is the maturity date of the futures contract and (T-t) is time to maturity, or the number of calendar days remaining in a futures contract until expiration. And the mispricing is defined as the difference between the actual (F_t) and the theoretical futures prices, normalised by the index value (MacKinlay and Ramaswamy, 1988):

$$Mis_t = \frac{F_t - F_t^*}{S_t} = \frac{[F_t - S_t e^{(r-d)(T-t)}]}{S_t} \tag{2.4}$$

While the two equations are widely used to study the behaviour of mispricing, they cannot be applied directly to the Nikkei futures contracts. This is because the triple-listing nature of the Nikkei contracts and key institutional differences among the Nikkei exchanges contribute to the special characteristics of the Nikkei futures contracts, such as dividend lumpiness, currency risk and different trading hours, and these characteristics require tailored formulas for the Nikkei contracts. However, previous research does not fully consider these characteristics, and yet ignoring them may lead to significant biases in the calculation of Nikkei futures mispricing. Besides, there is little research on the international dynamics of Nikkei futures mispricing - in particular, the speed of market responses to a given mispricing, or "propensity-to-arbitrage" (Taylor, 2007), such that the dynamic behaviour of mispricing remains unclear to market participants in the three Nikkei exchanges. In addition, extant studies on the static behaviour of Nikkei mispricing were mostly published in the 1990s; obviously they need to be updated to enable a deeper understanding of the quickly changing market conditions and the impact of the 2008 global financial crisis. The above considerations motivate this chapter.

The aim of this chapter is to investigate the static and dynamic behaviour of Nikkei futures mispricing using modified versions of the cost of carry model, to explore the index arbitrage activities in the Nikkei markets. Specifically, this chapter addresses the question whether the mispricing, if any, represent profitable arbitrage opportunities for investors in the three Nikkei futures markets. The starting point is to modify the standard cost of carry model by taking into account the unique dividend payout practices of Japanese firms, the yen-dollar exchange rate fluctuations, and the different trading hours among the Nikkei exchanges. The chapter also allows for the effect of transaction costs to analyse the Nikkei futures mispricing net of transaction costs. With a comprehensive new 19-year data range and (non-)parametric methods, the chapter presents systematic evidence on the static behaviour of Nikkei mispricing, including magnitude, sign, persistence, path dependence, and the relationship of Nikkei mispricing with a set of variables. The dynamic behaviour of Nikkei mispricing is addressed by describing the Nikkei mispricing with an exponential smooth transition autoregressive (ESTAR) model, and the smoothness parameter in the ESTAR specification provides an estimate of the propensity-to-arbitrage. At the stage of modelling, the whole sample is split into a pre-crisis period and a post-crisis period, such that the international dynamics of Nikkei mispricing can be compared before and after the 2008 global financial crisis. The chapter further interprets the heterogeneous arbitrage behaviour by analysing the ESTAR model parameters, and reveals that the effect of heterogeneity may be weaker than the effect of transaction costs in the Nikkei markets.

The chapter contributes to the literature in the following ways. First, the chapter takes into consideration the triple-listing nature of the Nikkei futures contracts and key institutional differences among the Nikkei exchanges in studying the cost of carry, mispricing and index arbitrage in the Nikkei markets. No previous research on the Nikkei futures pricing has considered the unique features of the Nikkei futures and the institutional differences as comprehensively as this chapter. The chapter finds that the effects of the dividend and currency risks are strongly significant on the pricing of the Nikkei futures contracts, while the effect of the time differences is insignificant. Based on this, it modifies the standard cost of carry model for each Nikkei contract. It also allows for the effect of transaction costs when examining the Nikkei futures mispricing. In this way, the chapter extends the work of Brenner et al. (1989a; 1989b; 1990), Board and Sutclifffe (1996) in modifying the standard cost of carry model for dual- or triple-listed index futures contracts, and therefore deepens understanding the impact of divided lumpiness and currency risk on the spot, futures and mispricing. Second, this chapter substantially and significantly updates literature on the static behaviour of Nikkei mispricing, using a comprehensive new 19-year sample period and (non-)parametric methods. Third, there has been little published work on the dynamic behaviour of Nikkei mispricing as smooth transition models have never been applied to the three Nikkei futures markets. The chapter examines the dynamics of Nikkei mispricing by an ESTAR model to disentangle different market responses to a given Nikkei mispricing. With the ESTAR model, it further investigates the level of heterogeneity in index arbitrageurs in the three Nikkei markets.

The rest of the chapter is structured as follows. Section 4.2 modifies the standard cost of carry model for each of the Nikkei futures contracts, allowing for dividend risk, currency risk, different trading hours and transaction costs. Section 4.3 describes data and analyses the static behaviour of Nikkei mispricing. Section 4.4 provides methodology of the ESTAR modelling, empirical results about the dynamic behaviour of Nikkei mispricing from the perspective of the propensity-to-arbitrage, and interpretations of the ESTAR parameters as to heterogeneous index arbitrage activities. Section 4.5 discusses the main findings and concludes the chapter.

4.2 The Pricing of Nikkei 225 futures contracts

In this section, different versions of the cost of carry model will be applied to the Nikkei 225 futures contracts traded on the OSE, SGX and CME to find out the most appropriate model for each market. A few general assumptions that apply throughout the section are listed below, although specific assumptions will also be set out in context.

1) Arbitrage positions are not unwound early but held to maturity.

2) There are no restrictions on short sales in the TSE.

3) Initially, there are no transaction costs. This assumption will be relaxed in section 4.2.5.

4) There are no taxes on gains or losses on the arbitrage positions.

4.2.1 The dividend payout practices in Japan

The institutional features of Japanese firms help to form their unique dividend payout practices that impact the theoretical prices of the Nikkei futures contracts through the dividend streams on the underlying index. First, the code law system in Japan puts low emphasis on individualism but high emphasis on uncertainty avoidance (Ho, 2003). In the past, Japanese executives regarded dividends as a cost to their businesses rather than as a reward for shareholders, and thus they intentionally kept dividend payouts low and stable. Although financial reforms in the 1990s, especially the Japanese “Big Bang”,[28] encouraged firms to increase dividend payments to attract investors, Japanese dividend payout rates remain at a low level, both in absolute and relative terms (Flath, 2014). Slight adjustments of dividends take place occasionally, but because Japanese firms are sensitive to adverse circumstances, they are more liable to reduce than to raise the amount of dividend payouts. Group influence on member firms is also widespread, as can be evidenced by clustered ex-dividend dates, i.e. a multitude of firms choose to go ex-dividend on the same day. Second, business group affiliation, or keiretsu, means that firms are integrated by long-term financial and non-financial ties, horizontally around a main bank or vertically around a core manufacturing firm, or mixed (Aggarwal and Dow, 2012), giving rise to concentrated ownership and prevalent cross-shareholdings. Many dividend studies support that the practice decreases information asymmetries and agency costs in keiretsu firms, providing some grounds for the low dividend payouts in Japan. Reforms have taken place in the 1990s to reduce the size and power of keiretsu, but their influence is still strong. Third, a few main banks act as the principal sources of corporate finance. The dual role of these banks, as creditors and shareholders, are not perfect substitutes, and they tend to take a conservative accounting approach in valuing assets and liabilities of the related firms, resulting in creditor protection in a credit-based system and depressed demands for dividends (Ho, 2003).

There are several important dates for Japanese dividend payments. The ex-dividend date is the third business day before the record date, which is 31st March for year-end dividends, and 30th September for interim dividends. Declaration date is around two months after the ex-dividend dates. Ordinary shareholders’ meetings are held to discuss and approve dividend proposals in late June, usually one business day before the dividend payment date. Similarly, meetings of board of directors are held in November for interim dividend issues. The dividend payment date, or effective date, varies from company to company, but generally it is in June for year-end dividends, and in December for interim dividends. Unlike firms in the US or the UK, Japanese

[28] The Japanese “Big Bang” is a five-year financial deregulatory reform proposed by Japan’s government in November 1996, aimed at eliminating all partitions in Japanese financial markets no later than 2001. During the “Big Bang” period, a series of policies came into effect to remove barriers and increase competition among financial intermediaries (Flath, 2014).

firms tend to announce dividends after the ex-dividend dates and shortly before the annual meeting of shareholders. This means that investors on the ex-dividend date have to forecast future dividend inflows on the index to be received on the payment date over a period of about two months, which may introduce dividend uncertainty to index arbitrage activities.

In the past, only a small portion of Japanese firms paid out dividends twice a year (Kato and Loewenstein, 1995). The regulatory changes in the 1990s made it easier for firms to increase the frequency of dividend payments, such that more and more firms listed on the TSE began to distribute dividends semi-annually. For my sample from 1996 to 2014, generally speaking, Japanese firms pay out dividends twice a year. Since most firms set March as the end of a fiscal year, they go ex-dividend in March and pay year-end dividends in June. Another ex-dividend date is in September, the end of the second quarter of a fiscal year, after which many firms pay out interim dividends in December.

As to dividend size, despite the evidence of low and stable dividend flows on the Nikkei index in the early literature (e.g. Brenner et al., 1989a; 1989b; 1990), recent studies document a steady growth of dividend payouts in non-horizontal keiretsu firms (Ferris et al., 2006). Dividend yields have been gradually increasing as well. Statistics indicate that the average annualised dividend yield of the Nikkei index was 0.76% from 1996 to 1999, 1.09% in the 2000s, and 1.78% from 2010 to 2014.[29] These can be roughly compared with the data in Kato and Loewenstein (1995), in which the average dividend yield of the 1,203 firms listed on the First Section of the TSE was 0.69% by 1990. The slowly growing trend is probably motivated by the regulatory changes in the 1990s and 2000s. For example, the TSE now requires that firms pay a minimum amount of dividends in each of the three years before listing, and that once they are listed, they should commit to continuing the payouts (Aggarwal and Dow, 2012). For most Japanese firms, the relative sizes of the year-end dividends and the interim dividends are equal: they each take up 50% of total dividends on average. In other words, the annual dividends are usually split evenly in June and December.

[29] Data are from Thomson Reuters Eikon.

The new Corporation Law of Japan went into effect on 01/05/2006. Under the law, Japanese firms are permitted to pay interim and year-end dividends at any time during a fiscal year, and are permitted to choose flexible dividend payments, subject to certain limits on retained earnings and approval of shareholders. This may explain the more flexible dividend payout practices in Japan in recent years. For example, firms sometimes adjust dividends to corporate earnings and the business environment, alter their dividend payment dates, and use share repurchase as an alternative method of profit distribution. However, the general tendency of Japanese dividend payouts has not changed much. For the most part, firms continue to adopt a steady and sustained dividend policy to seek medium-term or long-term growth, and thus tend to maintain a prudent, conservative attitude towards the allocation of surplus. The common practice of evenly paying year-end dividends in June and interim dividends in December has been followed at least over the sample period. In addition, cash has always been the dominant form of dividend payouts in Japan.

4.2.2 Dividend lumpiness

In view of the unusual dividend payout practices, dividends of the constituents of Nikkei 225 index are treated based on a few simplifying assumptions as below:

a) Investors have perfect foresight - they are able to accurately forecast future dividends which is the same as actual, ex-post dividends;
b) Dividends are certain;
c) Dividends are only paid in the last 10 trading days in June and the first 10 trading days in December;
d) Dividends are exempt from tax.

Given the stable and predictable dividend flows on the Nikkei index over the sample period, assumption a) is justified as this study uses an implied dividend series, computed from the historical dividend yield of the index, as a proxy for the ex-post aggregate dividends. Of course, investors may incur forecasting errors in the real world, but the risks of such errors are not likely to be important, as demonstrated by Yadav and Pope (1994). One might argue that the practice that Japanese firms tend to announce dividends after the ex-dividend dates induces dividend uncertainty. Nevertheless, assumption b) may still survive because of the availability of ex-ante dividend forecasts by the firms,[30] and the stability and predictability of their dividend payouts. Moreover, since only the nearest contracts are used to compile the futures series, dividend uncertainty may be small during the short time to maturity (Yadav and Pope, 1994; Tao, 2008). Assumption c) is based on a sample consisting of 35 companies randomly selected from the constituents of Nikkei 225 index. Historical dividend payment dates of the companies are traced back as far as possible, although the payment dates in the sample period of the chapter are inspected with special attention. It is found that most of the companies paid out dividends in June and December, and their dividend payment dates are clustered in the second half of June and the first half of December. The 10-working-day range is selected to remove weekends and to take into account possible slight changes made by firms as to the timing of their payouts over the years. Under the new Corporation Law of Japan, dividend payouts in Japan become more flexible, and firms are allowed to declare dividends at any time of a fiscal year, subject to certain criteria. While some of the sample companies amended their payment dates in recent years, assumption c) is generally held for the majority of the companies in most years in the sample period. As to tax on dividends, 50% of the total amount of dividends received is tax deductible for corporations. The remaining 50% subjected to a withholding tax rate of 20% from 1996 to March 2003, 10% from April 2003 to December 2013, and then 20% from January 2014.[31] Since cross-shareholding is prevalent in Japan, dividends paid by firm A to firm B and dividends paid by firm B to firm A could offset each other to some extent, leaving the taxable amount small. Even if tax is levied on that amount, given the low and stable dividend payouts of Japanese businesses, the magnitude of the tax could be smaller. Thus, the effect of the dividend tax is decided to be ignored as in assumption d), for the imposition of tax may complicate the cost of carry model, given the frequent tax reforms during the 19 years under consideration.

[30] Japanese firms publish dividend forecasts on average 17.67 days before the ex-dividend dates (Kato and Loewenstein, 1995), and any revisions to these forecasts, to which investors can refer.
[31] Data are from the TSE and Ministry of Finance, Japan.

Following Brenner et al. (1989a; 1989b; 1990), Gay and Jung (1999), I use an adjusted cost of carry model for the Nikkei futures contracts traded on the OSE and SGX:

$$F_t^* = S_t e^{r_t(T-t)} - \sum_{p=t}^{T} D_p e^{r_p(T-p)} \tag{4.1}$$

where F_t^*, S_t, $(T\text{-}t)$ are theoretical (or fair) futures price, spot price, time to maturity, respectively; r_t is the annualised gensaki treasury bill overnight rate divided by 365; D_p is the aggregate dividends on the Nikkei index paid at time p, $p \in [t,T]$, so that the dividend term, i.e. the second term on the right-hand-side of equation (4.1), measures the future value at time T of the accumulated dividend payments on the index. Since D_p is not directly available, it is proxied by an implied dividend series which is the product of the annualised dividend yield of the Nikkei index and the index closing price. The implied dividend series is then converted into a daily series following assumption c). To be more specific, it is divided by 2 to become year-end dividend series and interim dividend series, and then by 10 so that the outcome is the daily dividend amount paid on the index in the 10-day window in June or December. The daily dividend amount series is credited to futures' maturity date on each of the proposed dividend payment dates, and summed over time to create the dividend term.

For comparison, the standard cost of carry model, equation (2.1), is constructed for the same futures contracts, with r_t as the annualised gensaki treasury bill overnight rate, and d_t as the annualised dividend yield of the Nikkei index, both of which are divided by 365 to become daily rates. The standard model is denoted as COC1; equation (4.1) is denoted as COC2. Panel A of Table 4.1 shows the results of paired t-tests and Wilcoxon signed rank tests for the differences between the two models, in terms of theoretical futures price and futures mispricing.[32] The null hypothesis is that the means (medians) of the differences are zero. The mean (median) difference of theoretical futures price in the OSE is about 20 (18) yen; the mean (median) difference of mispricing in the OSE is about 0.16% (0.14%). The counterpart values in the SGX are similar. These statistics are all significant at the 5% level, suggesting that the null hypothesis can be

[32] Futures mispricing without transaction costs is computed using equation (2.4).

rejected in favour of the alternative that the mean (median) differences are significantly different from zero, and hence it may be appropriate to allow for the dividend payout practices of Japanese firms in the cost of carry model. As a further parametric test, the mispricing generated from COC1 is regressed on a constant and 20 dummy variables which represent the proposed 10 dividend payment dates in June and 10 dividend payment dates in December. If mispricing on the dividend payment dates is significantly different from mispricing on non-payment dates, the coefficients of the dummy variables should be significant. Table 4.2 provides the regression results. Clearly, *t*-tests show that most of the coefficients of the dummy variables in the OSE and SGX are significant at the 5% (or 10%) level, and conventional *F*-tests indicate that the joint contribution of the 20 dividend payment dates is highly significant, which reinforces that dividend lumpiness significantly affects the Nikkei mispricing. However, it is puzzling that the 10th dividend payment date, i.e. the last trading day of June, is not significant in any market. In fact, 57 out of the 225 constituent stocks paid out dividends on that day in 2014, and the end of June usually sees the most clustered dividend payouts during a year. The insignificance may be associated with time-related anomalies such as the turn-of-the-month effect,[33] and thus the last trading day of June is still retained as one of the proposed dividend payment dates. Restricted versions of the regression are run to check the joint explanatory power of the June dummy variables and that of the December dummy variables, and *F*-statistics indicate that they are highly significant in each market.[34] In light of the above, for the pricing of the OSE and SGX Nikkei contracts, I can conclude that COC2 is superior to COC1 because the former takes into account the specific dividend payout practices in Japan, and therefore will be adopted to calculate mispricing in the rest of the study.

[33] Another 11 dummy variables which represent the last trading day of each calendar month except June are added to the regression model, and negative, significant variables are found in May, August and December. However, dividends are seldom paid on the last trading days of the three months, and the significance is more likely to be associated with time-related anomalies. The joint marginal contribution of the dummy variables is significant at the 10% level in the SGX, but not in the OSE. There is therefore weak evidence of the turn-of-the-month effect. See Appendix 4.1 for more discussions.

[34] An additional set of 40 dummy variables which represents the 10 trading days before and after the proposed dividend payment dates in June and December, respectively, is added to the regression model. The significance of these new dummy variables displays a general trend of fade-away around the proposed payment dates. See Appendix 4.2 for more discussions.

Table 4.1 Model selection for Nikkei 225 futures contracts

Panel A: Dividend risk and currency risk

		OSE	SGX	CME (original)	CME (past)	CME (future)
Differences in theoretical futures price (¥;$)						
COC1 vs COC2	Mean	-19.5812**	-19.7319**	-0.1994**	-0.1994**	-0.1994**
	Median	-17.9388**	-18.1174**	-0.1732**	-0.1732**	-0.1736**
COC2 vs COC3	Mean			18.2374*	18.2876**	18.5470**
	Median			29.6363	29.6642	28.3943
COC3 vs COC1	Mean			-18.0380*	-18.0882*	-18.3476**
	Median			-29.4162	-29.4977	-28.3631
Differences in futures mispricing (%)						
COC1 vs COC2	Mean	0.1592**	0.1605**	0.0017**	0.0017**	0.0017**
	Median	0.1376**	0.1387**	0.0013**	0.0013**	0.0013**
COC2 vs COC3	Mean			-0.0967	-0.0970	-0.0991
	Median			-0.2516*	-0.2532*	-0.2451*
COC3 vs COC1	Mean			0.0951	0.0953	0.0974
	Median			0.2499*	0.2519*	0.2429*

Panel B: Signed exchange rate effects (CME) [a]

		Positive exchange rate effect			Negative exchange rate effect		
		original	past	future	original	past	future
Differences in theoretical futures price ($)							
COC2 vs COC3	Mean	-459.6443**	-459.7624**	-452.7612**	435.9399**	435.9399**	430.3092**
	Median	-371.3157**	-371.5022**	-365.4715**	276.3951**	276.3951**	271.3176**
COC3 vs COC1	Mean	459.8501**	459.9681**	452.9657**	-435.7461**	-435.7461**	-430.1144**
	Median	371.6221**	371.7392**	365.5612**	-276.1826**	-276.1826**	-271.0455**
Differences in futures mispricing (%)							
COC2 vs COC3	Mean	3.4830**	3.4841**	3.4319**	-3.2257**	-3.2257**	-3.1840**
	Median	2.8860**	2.8871**	2.8179**	-2.2508**	-2.2508**	-2.2337**
COC3 vs COC1	Mean	-3.4847**	-3.4858**	-3.4336**	3.2241**	3.2241**	3.1824**
	Median	-2.8855**	-2.8874**	-2.8193**	2.2499**	2.2499**	2.2303**

Table 4.1 continued

Panel C: Different trading hours (CME)

			COC1	COC2	COC3
Differences in theoretical futures price ($)					
	Past vs Future	Mean	0.0608	0.0608	0.3201
		Median	0.0000	0.0000	0.0000
	Past vs Original	Mean	0.0000	0.0000	0.0000
		Median	0.0000	0.0000	0.0000
	Future vs Original	Mean	-0.0608	-0.0608	-0.3201
		Median	0.0000	0.0000	0.0000
Differences in futures mispricing (%)					
	Past vs Future	Mean	-0.0005	-0.0005	-0.0026
		Median	0.0000	0.0000	0.0000
	Past vs Original	Mean	0.0099	0.0099	0.0099
		Median	0.0485	0.0485	0.0485
	Future vs Original	Mean	0.0104	0.0104	0.0125
		Median	0.0498	0.0498	0.0512

Notes: This table compares different versions of the cost of carry model for Nikkei 225 futures contracts traded on the OSE, SGX and CME, in terms of differences in theoretical futures price and mispricing calculated from COC1, COC2 (OSE, SGX, CME) and COC3 (CME). The mean differences are tested by paired *t*-tests; the median differences are tested by Wilcoxon signed rank tests. The null hypothesis is that the mean (median) differences are zero. Panel A compares the models in pair for the three futures contracts. Panel B compares the models in pair for the CME futures contracts, after positive and negative exchange rate effects are separated. The CME results are listed in the order of original view, past view and future view. Panel C compares the three views in pair by each cost of carry model for the CME futures contracts. Negative signs are due to the order of comparison: all the differences are calculated by subtracting the theoretical futures price or mispricing in the second model (or view) from that in the first model (or view). Theoretical futures price is in yen for the OSE and SGX futures contracts; in dollars for the CME futures contracts. Mispricing is in percentage. [a] 12 trading days with zero exchange rate effect are randomly included in the tests on the positive and negative exchange rate effects, half in each category. **denotes significance at the 5% level. *denotes significance at the 10% level.

Table 4.2 Dividend payment dates and dividend lumpiness

Coefficient	OSE			SGX		
	Unrestricted	Restricted		Unrestricted	Restricted	
		Jun dummies	Dec dummies		Jun dummies	Dec dummies
β_0	0.0009**	0.0010**	0.0010**	0.0010**	0.0011**	0.0011**
β_1	0.0027**	0.0026**		0.0029**	0.0028**	
β_2	0.0026**	0.0025**		0.0029**	0.0028**	
β_3	0.0012*	0.0011		0.0013**	0.0012*	
β_4	0.0011*	0.0011*		0.0016**	0.0015**	
β_5	0.0015**	0.0014*		0.0015**	0.0014**	
β_6	0.0006	0.0005		0.0010*	0.0009	
β_7	0.0020**	0.0019**		0.0023**	0.0022**	
β_8	0.0020**	0.0019**		0.0023**	0.0022**	
β_9	0.0018**	0.0017**		0.0016**	0.0015**	
β_{10}	-0.00001	-0.0001		-0.0004	-0.0005	
β_{11}	0.0030**		0.0029**	0.0023**		0.0023**
β_{12}	0.0013*		0.0012	0.0014**		0.0014**
β_{13}	0.0029**		0.0028**	0.0029**		0.0028**
β_{14}	0.0020**		0.0019**	0.0015**		0.0014**
β_{15}	0.0024**		0.0024**	0.0028**		0.0027**
β_{16}	0.0023**		0.0022**	0.0022**		0.0021**
β_{17}	0.0029**		0.0029**	0.0026**		0.0025**
β_{18}	0.0012**		0.0012**	0.0014**		0.0013**
β_{19}	0.0022**		0.0022**	0.0022**		0.0021**
β_{20}	0.0025**		0.0024**	0.0022**		0.0022**
F-statistic	7.1521**	9.5780**	5.2105**	6.0785**	7.2182**	5.3713**
R^2	0.0306			0.0258		
No. of obs	4554			4603		

Notes: This table provides the results of an ordinary least squares (OLS) regression of the mispricing calculated from the standard cost of carry model, equation (2.1), on 20 dummy variables that represent the proposed dividend payment dates, i.e. the last 10 trading days in June and the first 10 trading days in December, for Nikkei 225 futures contracts traded on the OSE and SGX. The regression model is:

$$Mis_t = \beta_0 + \sum_{p=1}^{20} \beta_p D_p + \varepsilon_t$$

where Mis_t is the futures mispricing calculated from equation (2.1); β_0 is a constant term; ε_t is an error term; D_p=1 if the day is the p^{th} dividend payment date, 0 if otherwise; β_p is the coefficient of the corresponding dummy variable. The proposed dividend payment dates are in ascending order: p=1 for the 1st dividend payment date (the 10th trading day counted backwards in June), p=11 for the 11th dividend payment date (the 1st trading day in December), etc. The unrestricted versions of the regression are estimated with the 20 dummy variables. The restricted versions of the regression are estimated with the 10 June dummy variables (D_1 to D_{10}) and the 10 December dummy variables (D_{11} to D_{20}). ** denotes significance at the 5% level. * denotes significance at the 10% level.

4.2.3 Currency risk

CME Nikkei futures contracts are traded on the Nikkei index, but have a contract multiplier of 5 dollars and are denominated in dollars. This feature makes the CME Nikkei futures contracts a quanto, as trading and settlement involve dollars while trading and settlement on the underlying stock market, the TSE, involve yen. Obviously, this special arrangement introduces currency risk to the index arbitrage, as arbitrageurs would have to convert currencies and expose their arbitrage positions to yen-dollar exchange rate fluctuations. In this regard, the cost of carry model should also allow for the effect of such risk on the CME Nikkei futures contracts, so that the theoretical futures price and mispricing generated from the cost of carry model could reflect the higher risk and compensation required by investors in the CME. The dividend assumptions discussed in section 4.2.2 still apply, but extra assumptions are needed for the CME Nikkei futures contracts:

e) Investors in the CME are from the US. They observe US holidays and use the financial markets in the US. Central Standard Time (CST) is applied each trading day.

f) The trading hours of the CME and TSE are overlapping. This will be relaxed in section 4.2.4.

To make things simple, it is necessary to differentiate futures and stock prices from the actual costs of the arbitrage positions. Futures and spot prices are usually expressed as indices, which are pure numerical values without regard to currency denomination. However, the actual cost is the amount of money invested on the futures (spot) contracts; it equals the contract multiplier times the futures (spot) price, and thus is denominated in dollars (yen). Let the futures price be F_t, the spot price be S_t, and their respective actual costs in the futures and spot markets be G_t and H_t. When the futures contracts mature at time T, gains or losses on the CME Nikkei futures contracts depend on the difference between G_t and G_T, and G_T does not equal H_T, because G_T=mF_T, or G_T=mS_T; but H_T is the yen equivalent of mS_T, where m is the dollar multiplier.

The derivation and notation below is based on the framework of Board and Sutcliffe (1996). Suppose that, at time t, a typical investor in the CME Nikkei futures market shorts a futures contract, at the cost of G_t; borrows money at risk-free interest rate r_t and uses it to long a unit of stock (or portfolio) in the TSE, at the cost of H_t. All dividends K_p received at time p on the stock position are converted to dollars and invested at the risk-free rate r_p. The dividend amount received on the Nikkei index itself is D_p, and $D_p = K_p/m$. At maturity T, the investor repurchases the futures contract and sells the stock at costs G_T and H_T, respectively. She also pays back the loan and gains the dividends invested earlier with interest.

Denote c_t, c_p, and c_T as the yen value of one dollar at time t, p, and T, respectively. The cash flows to the investor at different times can be tabulated as follows:

Table 4.3 Long arbitrage in the CME

	Time t	Time T
Short futures	0	$G_t - mS_T$
Borrowing	$\frac{H_t}{c_t}$	$-\frac{H_t}{c_t}e^{r_t(T-t)}$
Long stock	$-\frac{H_t}{c_t}$	$\frac{H_T}{c_T}$
Dividends	0	$\sum_{p=t}^{T}\frac{K_p}{c_p}e^{r_p(T-p)}$
Net cash flows	0	$G_t - mS_T - \frac{H_t}{c_t}e^{r_t(T-t)} + \frac{H_T}{c_T} + \sum_{p=t}^{T}\frac{K_p}{c_p}e^{r_p(T-p)}$

Notes: A long arbitrage requires buying stock and selling futures at time t; then selling the stock and repurchasing the futures at time T. A short arbitrage requires selling stock and buying futures at time t; then buying back the stock and selling the futures at time T.

The no-arbitrage condition requires that this index arbitrage strategy generate zero net cash flows at time T. Or:

$$G_t - mS_T - \frac{H_t}{c_t}e^{r_t(T-t)} + \frac{H_T}{c_T} + \sum_{p=t}^{T}\frac{K_p}{c_p}e^{r_p(T-p)} = 0 \qquad (4.2)$$

Rearranging equation (4.2) gives

$$G_t = \frac{H_t}{c_t} e^{r_t(T-t)} - \sum_{p=t}^{T} \frac{K_p}{c_p} e^{r_p(T-p)} + mS_T - \frac{H_T}{c_T} \tag{4.3}$$

Board and Sutcliffe (1996) show that $H_t=mS_tc_t$, $H_T/H_t=S_T/S_t$. Since the futures and spot prices are usually reported as index values, equation (4.3) is rewritten in terms of index values as below:

$$F_t^* = S_t e^{r_t(T-t)} - \sum_{p=t}^{T} \frac{D_p}{c_p} e^{r_p(T-p)} + S_T \left(1 - \frac{c_t}{c_T}\right) \tag{4.4}$$

The first two terms on the right-hand-side of equation (4.4) constitute a cost of carry model adjusted for dividend lumpiness. However, each dividend received on the index needs to be converted to dollars on each dividend payment date p by dividing the dividend by c_p, the yen price of dollars at time p. The last term is the rate of change in the exchange rate between time t and time T, adjusted by the spot price at time T. Equation (4.4) displays the sources of currency risk contained in the CME Nikkei futures prices: exchange rate fluctuations on dividend payment dates p and futures' maturity date T, and the spot price at maturity T. Since these important variables are uncertain as of time t and cannot be perfectly hedged, index arbitrage activities in the CME Nikkei futures market are not strictly risk-free. Hence, equation (4.4) actually gives a nearly fair price for the CME Nikkei futures contracts. It is denoted as COC3 for comparison with the other two versions of the cost of carry model.

COC3 is constructed for the CME Nikkei futures contracts. The risk-free interest rate is proxied by the annualised federal funds effective rate converted to a daily rate. The yen-dollar exchange rate is fixed at noon in New York (approximately 11.00am in the CME) each trading day, and is used to represent the rate to which investors refer throughout the day. For comparison, COC1 and COC2 are also built for the same CME futures contracts, yet with modifications.[35] Specifically, d_t is converted to its dollar equivalent in COC1, by dividing the dollar-denominated implied dividend series by the index closing price. Besides, r_t and d_t are converted to daily rates. In COC2, daily dividends received on the index are converted to dollars using the corresponding exchange rate on that day.[36]

[35] The cost of carry models are built for the CME Nikkei futures contracts without regard to the effect of the different trading hours between the CME and the TSE. In other words, each model is actually in an original view that ignores a 1-day time lag between the stock closing price and the futures settlement price. See section 4.2.4 for discussions of this effect.

[36] See Table 4.4 for these specifications.

As shown in Panel A of Table 4.1, like the OSE and SGX Nikkei futures contracts, the mean (median) differences of the CME Nikkei futures contracts between COC1 and COC2 in theoretical futures price and mispricing are significant at the 5% level, which confirms that the lump-sum adjustment of dividends is appropriate. Paired *t*-tests show that the mean differences in theoretical futures price between COC2 and COC3, and between COC3 and COC1 amount to about 18 dollars, and are all significant at the 10% level. Wilcoxon signed rank tests show that the median differences in mispricing between COC2 and COC3, and between COC3 and COC1 are 0.25%, which are also significant at the 10% level. One might notice that the median difference in theoretical futures price and the mean difference in mispricing are not significant. This is probably because the exchange rate effect measured by the last term on the right-hand-side of equation (4.4) could be positive or negative each trading day. For the whole sample, the positive effect of the exchange rate on some days could offset the negative effect of the exchange rate on other days. Given that the only difference between COC3 and COC2 is the exchange rate effect, and COC2 and COC1 produce similar (yet significantly different) results, the differences between COC3 and COC2 (COC1) over the sample period may not be as significant as expected.

The necessity of the currency risk adjustment is further checked by running an OLS regression of the last term on the right-hand-side of equation (4.4) on a constant. If the exchange rate effect is significantly different from zero, the constant should be significant. The regression result suggests a constant of -18.2374, with *t*-statistics -1.9586 and *p*-value 0.0502. It is likely that currency fluctuations indeed impact the fair price of the CME contracts. As a further test, positive exchange rate changes are separated from negative exchange rate changes, and paired *t*-tests and Wilcoxon signed rank tests are repeated for the model differences in theoretical futures price and mispricing. The results are provided in Panel B of Table 4.1. The differences between the models are much larger in magnitude, and more importantly, they are all strongly significant. Taken together, the significant differences in Table 4.1 indicate that ignoring the special dividend payout practices and exchange rate fluctuations may lead to significant biases in the pricing of the CME Nikkei futures contracts. As such, COC3 may be more suitable for the CME contracts.

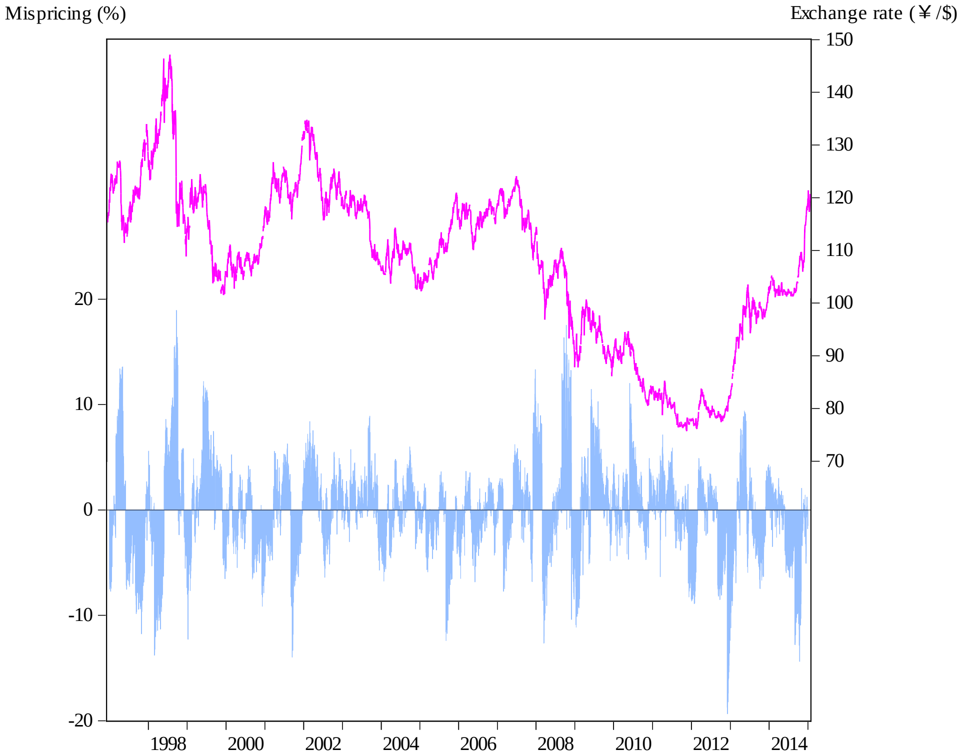


Figure 4.1 Signed mispricing and exchange rate fluctuations

Notes: The figure illustrates the implication of the cost of carry model adjusted for dividend and currency risks, in terms of the relation between the sign of mispricing and the tendency of the yen-dollar exchange rates. The CME mispricing calculated from COC3 is assigned to the left axis; the exchange rate is assigned to the right axis. Mispricing is in percentage; the exchange rate is expressed as yen per dollar.

The no-arbitrage argument predicts that if the yen appreciates relative to dollar over the life of the CME futures contract, the actual futures price will tend to exceed its theoretical price, in that investors with stock positions would profit from the conversion of yen to dollar at maturity of the futures contract. It follows that futures should be overpriced in the CME to maintain the no-arbitrage condition. Likewise, underpricing should be associated with a depreciation of the yen relative to dollar over the life of the contract. Figure 4.1 plots together the yen-dollar exchange rate and the futures mispricing computed from COC3. Clearly, overpricing tends to predominate during the periods of 1998-1999, 2002-2004 and 2007-2011, when yen showed a general tendency to increase in value relative to dollar. The reverse is true when yen depreciated.

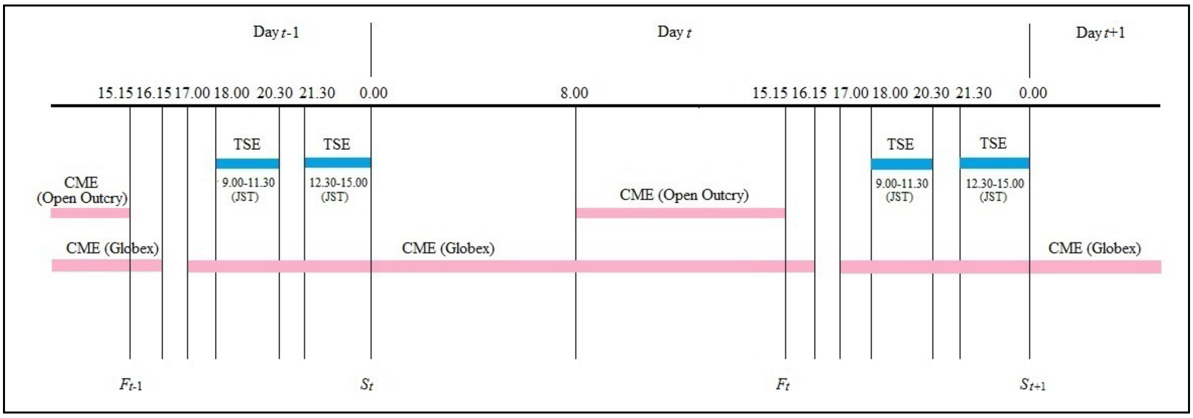
The subsequent analysis on the sign of the CME mispricing indicates that overpricing dominates the CME over the sample period (Table 4.7), which is consistent with the overall tendency of the appreciation of yen relative to dollar. For comparison, the mispricing generated from COC2 is also checked for its sign. In the periods of 1998-1999, 2002-2004 and 2007-2011, 1,077 overpricings are found against 1,445 underpricings; over the whole sample, 1,826 overpricings are found against 2,713 underpricings. Since COC2 also implies overpricing associated with yen appreciation due to the conversion of dividends, the preponderance of underpricing from COC2 contradicts the general tendency of the appreciation of yen relative to dollar, and thus suggests that COC2 by lack of the currency risk adjustment may not be correct in pricing the CME futures contracts. In contrast, COC3 is consistent with the conjecture that arbitrageurs require more overpriced (underpriced) futures contracts in response to higher risk of yen appreciation (depreciation) relative to dollar, and that currency fluctuations markedly influence the CME mispricing. It follows that COC3 will be used for the CME Nikkei futures contracts in the rest of the study.

4.2.4 Different trading hours

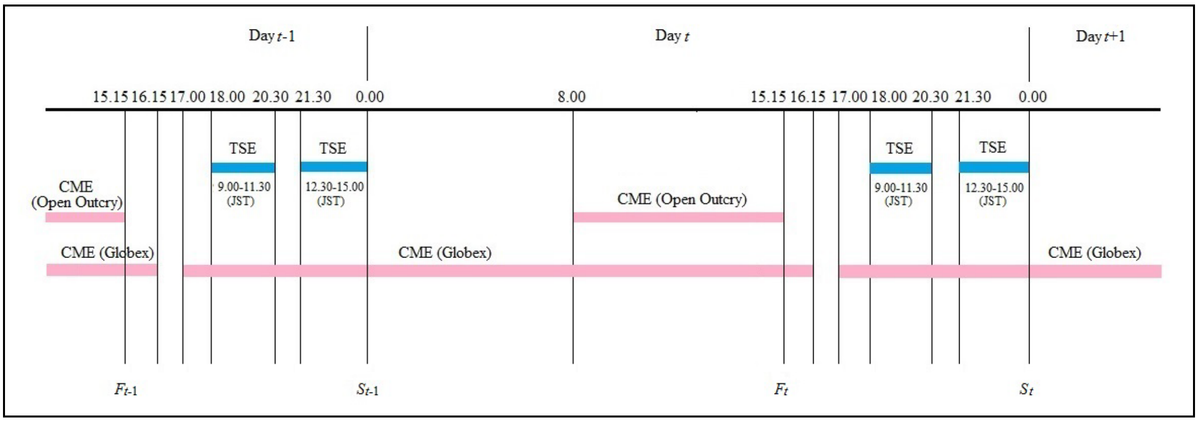
The above logic rests on the assumption that the spot market, TSE, and the futures market, CME, have simultaneous trading hours. Before 1995 when CME stock index products started to trade on an electronic trading platform called Globex, this assumption was not realistic.[37] As the CST used in Chicago is 15 hours behind the JST used in Tokyo,[38] the opening hours of the TSE, 9.00-11.30, 12.30-15.00 (JST), correspond to 18.00-20.30, 21.30-0.00 (CST), and they do not overlap with the opening hours of the open outcry system in the CME, 8.00-15.15 (CST). Figure 4.2 illustrates the non-overlapping trading hours of the TSE and the open outcry system in the CME.

[37] The CME Globex trading platform was first introduced to exchange rate and interest rate products in 1992 and then to stock index products in 1995.

[38] The CME observes Central Daylight Time (CDT) which was between the first Sunday in April and the last Sunday in October until 2006, and is between the second Sunday in March and the first Sunday in November from 2007, during which clocks are turned forward by 1 hour, such that the time gap between the TSE and the CME reduces to 14 hours. As a result, the common trading hours of the two markets are 19.00-21.30, 22.30-1.00 (CST). But this does not affect the existence of the time lag between the stock closing price and the futures settlement price.



(a) TSE perspective



(b) CME perspective

Figure 4.2 Trading hours of the CME futures and the underlying spot markets

Notes: The figure illustrates the trading hours of the CME and TSE, and any overlapping between their trading hours on a typical trading day *t* as of 31/12/2014. The bottom line shows the time when futures settlement price (*F*) and stock closing price (*S*) are generated, from the perspectives of the TSE (a) and CME (b). The subscripts *t*-1 and *t* indicate the timing differences. The time is CST unless otherwise marked.

One of the many contributions of the CME Globex trading system is that it extends the trading hours of the CME to nearly 24 hours a day. For Nikkei futures contracts, trading in Globex starts at 17.00 (CST) on day *t*-1 and closes at 16.15 (CST) on day *t*. This allows the typical investor in the CME to engage in the aforementioned long arbitrage strategy by shorting futures and longing stock, and doing the reverse during 18.00-20.30, 21.30-0.00 (CST), when the TSE and the CME open simultaneously, as shown in Figure 4.2. Index arbitrage between the TSE and the CME seems to be almost riskless once dividend lumpiness and currency fluctuations have been sufficiently accommodated. However, the different daily settlement time ranges in the two markets still introduce a time lag between stock closing price and futures settlement price, which may pose an additional risk to the arbitrage activities. From the perspective of the stock market (Figure 4.2(a)), the stock closing price S_t is generated in the afternoon closing auction at 15.00 (JST) or 0.00 (CST), whereas the futures settlement price F_t is derived during 15:14:30-15:15:00 (CST). It is assumed that S_t incorporates the spot market information up to 0.00 (CST) on day t, and F_t incorporates the futures market information up to 15.15 (CST) on day t. As riskless spot-futures arbitrage occurs when both markets are open, if information generated by the arbitrage activities in the common trading hours can be revealed and transmitted by market prices, the information contained in S_t is likely to match the information contained in F_t; yet the information contained in S_t leads the information contained in F_t by 1 trading day. Besides, dividends are usually paid during Japanese business hours, and thus D_p should be on the same day as the stock market.

Ideally, investors aiming for a riskless profit convert currencies at the spot exchange rate and invest money at the spot interest rate in the common trading hours. However, those data are not available. Instead, c_t is fixed at around 11.00 (CST), and r_t is supposed to be published before 15.15 (CST) on day t, each of which precedes the time when index arbitrage activities take place on day t. From the perspective of the CME investors (Figure 4.2(b)), there are two possible views as to the selection of the rates: a past view and a future view. The past view means that investors tend to consult historical rates in arbitrage activities - they trade in the common trading hours and use the rates released prior to the common trading hours, yet on the same day. Since c_t and r_t become available before trading commences on day t, they are likely to be applied to the stock closing price S_t, such that they convey the same kind of information as that in S_t. By contrast, the future view means that investors are able to forecast the rates for tomorrow, and arbitrage activities are based on the perfect foresight assumption: the rates forecasted and used by investors on day t-1 equal the actual rates on day t. Thus, c_t and r_t on day t can be known precisely on day t-1 in the arbitrage associated with S_{t-1}. Similarly, c_{t+1} and r_{t+1} are respectively used to convert and invest S_t, and so forth. Table 4.4 compares the two views with an original view that ignores the time lag between the stock closing price and the futures settlement price, regarding the selection of variables and modifications to COC1, COC2 and COC3 in each view.

Table 4.4 The cost of carry model in different views for the CME futures contracts

	Original view	Past view	Future view
Variables	S_t, F_t, D_p (d_t), c_t, r_t	S_t, F_{t+1}, D_p (d_t), c_t, r_t	S_t, F_{t+1}, D_p (d_t), c_{t+1}, r_{t+1}
COC1	$F_t^* = S_t e^{(r_t - d_t)(T-t)}$ [a]	$F_{t+1}^* = S_t e^{(r_t - d_t)(T-t)}$ [a]	$F_{t+1}^* = S_t e^{(r_{t+1} - d_t)(T-t)}$ [b]
COC2	$F_t^* = S_t e^{r_t(T-t)} - \sum_{p=t}^{T} \frac{D_p}{c_p} e^{r_t(T-p)}$	$F_{t+1}{}^* = S_t e^{r_t(T-t)} - \sum_{p=t}^{T} \frac{D_p}{c_p} e^{r_t(T-p)}$	$F_{t+1}{}^* = S_t e^{r_{t+1}(T-t)} - \sum_{p=t}^{T} \frac{D_p}{c_{p+1}} e^{r_{p+1}(T-p)}$
COC3	$F_t^* = S_t e^{r_t(T-t)} - \sum_{p=t}^{T} \frac{D_p}{c_p} e^{r_p(T-p)} + S_T\left(1 - \frac{c_t}{c_T}\right)$	$F_{t+1}{}^* = S_t e^{r_t(T-t)} - \sum_{p=t}^{T} \frac{D_p}{c_p} e^{r_p(T-p)} + S_T\left(1 - \frac{c_t}{c_T}\right)$	$F_{t+1}{}^* = S_t e^{r_{t+1}(T-t)} - \sum_{p=t}^{T} \frac{D_p}{c_{p+1}} e^{r_{p+1}(T-p)} + S_T\left(1 - \frac{c_{t+1}}{c_T}\right)$

Notes: This table compares the cost of carry model in different views as to variable selection and model modifications for the CME futures contracts. The original view ignores the time lag between the stock closing price in the TSE and the futures settlement price in the CME. From the perspective of the CME investors, the past view assumes that the historical rates released prior to arbitrage, yet on the same day, are used in arbitrage; the future view assumes that rates on the next day can be known precisely and used in arbitrage today. The first row shows the variables that are required in the cost of carry model in each view. The variables are stock closing price (*S*), futures settlement price (*F*), exchange rate (*c*) and risk-free interest rate (*r*). Their subscripts *t* and *t*+1 indicate the timing difference. Since COC1 uses the continuous dividend rate d_t, while COC2 and COC3 use the aggregate dividend term D_p paid on day *p*, D_p is followed by d_t which is in brackets, as they both are dividend-related variables. The following rows list the modifications to the three versions of cost of carry model using the variables. [a] d_t has been converted to its dollar equivalent using c_t. [b] d_t has been converted to its dollar equivalent using c_{t+1}.

The effect of the different trading hours is examined by performing paired *t*-tests and Wilcoxon signed rank tests for differences in CME theoretical futures price and mispricing generated from the modified versions of COC1, COC2 and COC3 in each view, with the null hypothesis of zero mean (median) differences. The results are presented in Panel A of Table 4.1. It is found that these results are qualitatively the same as those of the CME data in the original view, which suggests that the difference in trading hours may not be important. Panel B gives the test results for the past view and the future view when positive and negative exchange rate effects are separated. Again they are very close to the results generated in the original view. More directly, the three views are compared pairwise by each cost of carry model. The null hypothesis is that the means (medians) of the differences between any two views in theoretical futures price and mispricing are zero. As indicated in Panel C of Table 4.1, the differences are all very small in magnitude, with the means (medians) close to zero; paired *t*-tests and Wilcoxon signed rank tests suggest that none of the mean (median) differences is significant at any conventional level. This is probably due to the short period of the time lag, as it only lasts for 1 trading day. The exchange rate is relatively stable in the sample period, and it further smoothes the effect of the 1-day time lag. Since the impact of the different trading hours is negligible, index arbitrageurs in the CME Nikkei futures market could ignore the 1-day time lag between the stock closing price and the futures settlement price. Moreover, as the differences among the past view, the future view and the original view are trivial, the timing of the rates is less important, as long as they are on day t or t+1, in association with trading on day t. By contrast, more attention should be paid to the dividend risk and currency risk embodied in the CME Nikkei futures contracts. Therefore, for simplicity, COC3 in the original view will be adopted to form the CME mispricing series from now on.

4.2.5 Transaction costs

The effect of transaction costs on the pricing of the Nikkei futures contracts is considered here. The assumption 3) at the beginning of section 4.2, i.e. no transaction costs, is replaced with the assumption that transaction costs are one-off payment made at the start of each trade. In general, transaction costs invite lower and upper limits around the fair futures price, within which arbitrage activities are not profitable. Denote TC_t^U as the transaction costs at time t of a long arbitrage, and TC_t^L as the transaction costs at time t of a short arbitrage, both of which include the costs of dividend and currency risk adjustments. The transaction costs are measured in relative terms as percentages of the index value. Based on Brenner et al. (1989a), the lower limit, F_t^L, and the upper limit, F_t^U, can be formulated for the OSE and SGX Nikkei futures contracts:

$$F_t^L = S_t(1-TC_t^L)e^{r_t(T-t)} - \sum_{p=t}^{T} D_p e^{r_p(T-p)} \tag{4.5a}$$

$$F_t^U = S_t(1+TC_t^U)e^{r_t(T-t)} - \sum_{p=t}^{T} D_p e^{r_p(T-p)} \tag{4.5b}$$

Similarly, the lower and upper limits for the CME Nikkei futures contracts:

$$F_t^L = S_t(1-TC_t^L)e^{r_t(T-t)} - \sum_{p=t}^{T} \frac{D_p}{c_p} e^{r_p(T-p)} + S_T\left(1-\frac{c_t}{c_T}\right) \tag{4.6a}$$

$$F_t^U = S_t(1+TC_t^U)e^{r_t(T-t)} - \sum_{p=t}^{T} \frac{D_p}{c_p} e^{r_p(T-p)} + S_T\left(1-\frac{c_t}{c_T}\right) \tag{4.6b}$$

With transaction costs, the mispricing formula, equation (2.4), is modified as below (Fung and Draper, 1999):

$$Mis_t = \begin{cases} \dfrac{F_t - F_t^U}{S_t} & \text{if} \quad F_t^U < F_t \\ 0 & \text{if} \quad F_t^L \le F_t \le F_t^U \\ \dfrac{F_t - F_t^L}{S_t} & \text{if} \quad F_t < F_t^L \end{cases} \tag{4.7}$$

Equation (4.7) clearly shows that mispricing opportunities (and profitable arbitrage activities) only appear when actual futures price F_t move away from the lower and upper transaction cost bounds. Equations (4.5a)-(4.7) will be used to compile the mispricing series of the Nikkei futures contracts in the presence of transaction costs.

4.3 Data

4.3.1 Data description

Daily closing prices of Nikkei 225 index and daily settlement prices of the corresponding futures are collected from Datastream, OSE, SGX and CME, during the whole sample period 20/06/1996-31/12/2014 (OSE and SGX); 01/01/1997-31/12/2014 (CME).[39] The starting date is the earliest possible date I can find with dividend data (OSE and SGX), or with sufficient trading volume (CME). Although higher-frequency intraday data have been used in some literature, daily data are used in this study due to the daily re-settlement procedure in futures markets. Futures contracts are marked to market on a daily basis, and the gains or losses on a particular contract are realised at the end of a trading session each trading day, with reference to the daily settlement price. It follows that the daily settlement price reflects the arbitrage activities and the supply-demand relation in the futures market each trading day. In nature, mispricing is a measure of the deviation from the theoretical futures price. The daily settlement price as a benchmark of everyday trading activities makes it more meaningful to quantify such deviations on a daily basis. Statistically, the power of many tests will not improve by increasing the number of observations without extending the data range (Shiller and Perron, 1985). In other words, given the sample period, intraday data will not necessarily produce better statistical power than daily data. Instead of using intraday data, therefore, I make my sample as long as possible, and the 19 years under consideration should be sufficient to generate reasonable power. Non-trading days such as weekends and public holidays are excluded from the sample according to Japanese holiday observances for the TSE and OSE, and US holiday observances for the CME. The SGX used the same holiday schedule as the OSE until March 2011, and thus Japanese holiday observances are applied for the SGX data until March 2011. Since April 2011, the SGX has been using a different trading calendar for the Nikkei futures contracts; and from then on, only trading days with zero volume and unchanged open interest are deleted for the SGX. The futures, spot prices are matched with other rates each trading day in each market; dates when these series do not match each other are removed. The total observations are 4554 (OSE), 4603 (SGX), 4539 (CME).

The contract months of the OSE and CME futures contracts follow the usual quarterly cycle - March, June, September and December, while the SGX futures contracts mature in the quarterly months plus a few serial months. Compared with contracts that expire in serial months, contracts

[39] In the process of modelling, this sample is split into a pre-crisis period (sample A) and a post-crisis period (sample B). See Table 4.15.

that expire in the quarterly months in the SGX are more actively traded, probably because of cross-hedging, so that their prices contain more information. As such, only the contracts that mature in the quarterly months are considered in each market. Since there are several futures contracts with different maturities at a specific time point in each market, a single continuous series of futures price does not exist. Following convention, a continuous, synthetic futures price series is compiled using the prices of the nearest contracts and moving onto the next nearest contract at the start of the expiration month.[40] This is because the nearest contracts are the most actively traded, and thus their prices contain more information. Besides, futures prices in the expiration month usually exhibit excessive volatility due to final settlement, known as the expiration effect, which has been reported in the Nikkei markets by Daal et al. (2006). The common practice has been adopted in many studies on the Nikkei markets (e.g. Iihara et al., 1996; Booth et al., 1996; Watanabe, 2001; Covrig et al., 2004).

The gensaki treasury bill overnight (middle) rate is selected as a proxy for the risk-free interest rate in the OSE and SGX, because it is a repo rate with treasury bills as collateral, and it is an open market rate, free from the price control of Ministry of Finance, Japan. In the literature, various kinds of gensaki rates have been widely used, as they represent the longest continuous time series of short-term interest rates in Japan (Flath, 2014), which may facilitate the comparison of the results of this study with those of the existing literature. In addition, foreign investors, whose trading volume takes up 70.5% of the total volume of the OSE Nikkei futures contracts in 2014,[41] are exempted from transaction tax in the gensaki market and from withholding tax and corporation tax in trading treasury bills, which is consistent with the general assumption 4) at the beginning of section 4.2, i.e. no taxes. In the CME, the proxy for the risk-free interest rate is the daily effective federal funds (middle) rate, because the CME Nikkei futures contracts are denominated in dollars, and assumption e) in section 4.2.3 argues that

[40] The SGX Nikkei contracts shifted from open outcry to electronic trading on 01/11/2004. Apart from the roll-over, the SGX futures price series is compiled as the settlement prices on the floor before the date, and the settlement prices traded electronically after the date. It is deemed that the shift is smooth and does not introduce jumps to the series. This is because investors in the SGX were given a period to adapt to the electronic trading system (ETS) in overnight sessions and there was a period when both systems were available for trading. In fact, the ETS started to rival open outcry in volume from 1/11/2004, and shortly afterwards the ETS dominated and became the only trading mechanism. Visual inspection and Quandt-Andrews unknown breakpoint test find that there are no discernible breaks in the compiled series around the date. Results are available upon request.

[41] Data are from the OSE.

American investors will tend to use financial markets in the US. The effective federal funds rate is a weighted average of the rates of inter-bank borrowing or lending overnight without collateral through brokers at the Federal Reserve. Compared with other alternatives, the effective federal funds rate has a longer history sufficient to cover the chosen sample period. The gensaki rate and the federal funds rate are obtained from Datastream.

The daily dividend yield of Nikkei 225 index is collected from Thomson Reuters Eikon. For missing values in the dividend yield series, values on the previous trading days are filled in, assuming that the dividend yield remains constant on the missing day.[42] Given that the index is price weighted, the implied dividend series is computed as the product of the dividend yield and the corresponding index closing price on the previous trading day. The daily exchange rate is downloaded from Datastream. Expressed as the yen price of one dollar, it is the middle rate employed in cable transfers in New York, sampled and certified by the Federal Reserve Bank of New York. It is selected because the fixing-time rates would more precisely represent the actual rates at which investors convert currencies in the midst of their arbitrage activities, compared with averaged rates. The selected exchange rate is fixed at noon in New York, or approximately 11.00am in the CME; as there are nine time zones in the US, the fixing time should be an appropriate hour when investors around the US have started trading.

The transaction costs of two types of investors, brokers and institutional investors, are estimated for the Nikkei futures markets.[43] Here brokers are differentiated from institutional investors in the sense that brokers trade on behalf of customers while institutional investors trade for their own sake. Apart from that, I do not separate the transaction costs of domestic brokers (institutional investors) from those of foreign brokers (institutional investors). In general,

---

[42] There are altogether 22 trading days with missing values. Considering the length of the sample period, and the stability of Japanese dividend payments, it is deemed that the assumption would not lead to important errors in the results.

[43] Individual investors are not taken into account in this study, because (a) they are barred from trading gensaki and/or treasury bills in Japan, meaning that the cost of carry relationship cannot model their theoretical futures prices if the gensaki treasury bill rate is used to proxy for the risk-free interest rate required in the cost of carry model; (b) the trading volume of individual investors accounts for 10.1% of the total volume of the OSE Nikkei futures contracts in 2014; the counterpart is 70.5% (foreign investors), 18.7% (institutional investors). Instead, individual investors are more likely to trade Nikkei 225 E-mini futures, occupying 19.9% of its total volume in 2014 (data from the OSE); (c) individual investors typically face higher transaction costs than institutional investors, who in turn face higher transaction costs than brokers. In practice, the width of the no-arbitrage band is determined by investors with the lowest transaction costs (MacKinlay and Ramaswamy, 1988; Gay and Jung, 1999).

brokers enjoy a lower level of transaction costs than institutional investors; and market participants in the OSE and SGX enjoy a lower level of transaction costs than those in the CME due to costs associated with the currency risk adjustment in the CME. Hence, I simplify a multitude of transaction costs incurred in index arbitrage by using a two-tier transaction cost system: 0.5% for brokers, 1.0% for institutional investors in the OSE and SGX; 1.5% for brokers, 2.0% for institutional investors in the CME.[44] These transaction costs are inclusive of the major costs involved in a typical long or short arbitrage, such as the adjustment costs of dividends (OSE, SGX and CME) and exchange rate (CME). It is recognised that the estimated transaction costs might differ from real transaction costs - ideally, a market survey should be conducted to a group of brokers and institutional investors in these markets. However, the 19-year sample period has seen a set of reforms take place in Japan, Singapore and the US, with frequent changes of fee schedules in their financial markets. A survey of such size and depth in these markets is costly, especially when an increasing number of trading activities employ negotiable costs. More importantly, the purpose of this study is to look into the mispricing or profitable arbitrage opportunities of the Nikkei futures contracts, through finding out the most suitable cost of carry model for each contract. Transaction costs act as filters to help to examine the existence and behaviour of mispricing net of market frictions; the exact amount of the costs themselves is less vital. The estimated transaction costs at both high and low levels should provide a reasonable approximation of the hindrance that different investors face in different markets.

The OSE Nikkei futures contracts have an electronic system launched from the inception of the contracts, and their trading volume is measured as the number of the contracts transacted on that system. The SGX Nikkei contracts shifted from open outcry to electronic trading on 01/11/2004, and their volume is the number of the contracts traded on the floor before the date, and the number of the contracts traded electronically after the date. The CME adopts both open outcry and Globex during the sample period, and thus the volume of the CME Nikkei futures is the total number of the contracts traded on both systems. The futures volume data are obtained from

[44] The estimation is based on the literature: Brenner et al. (1989a;1989b;1990) estimate the transaction costs in the OSE and SGX to be 0.5%, 1.0% and 2.0%; Board and Sutcliffe (1996) estimate the transaction costs of spread arbitrage in the CME to be 1.0%.

Datastream, OSE, SGX and CME.

4.3.2 Behaviour of Nikkei 225 futures and spot returns

The logarithmic returns of Nikkei 225 spot and futures are denoted as Δs_t and Δf_t, respectively: $\Delta s_t=\ln(S_{t+1}/S_t)$, $\Delta f_t=\ln(F_{t+1}/F_t)$. Table 4.5 presents the descriptive statistics of Nikkei spot and futures returns during the sample period. Over the years, the means of the spot returns in the TSE, and the futures returns in the OSE, SGX and CME have similar values with the same signs, which suggests that the four markets may be potentially linked. The standard deviations of the spot and futures returns in the four markets are relatively stable, with the lowest values in 2005 and the highest values in 2008. But they are all higher than the standard deviations reported by Brenner et al. (1990) and Lim (1992),[45] implying that the Nikkei markets may be more volatile in recent years, probably due to heavier trading volume than that at the early stage of the markets. Inter-market comparison indicates that the standard deviations of the futures returns in the OSE and CME tend to be higher in 16 out of 19 years, and this is also true for the overall sample period, suggesting that futures returns are likely to be more volatile in the OSE and CME than in the SGX, although Bacha and Vila (1994) report no significant differences between the OSE and the SGX in volatility.[46] It is noted that the spot market displays higher volatility than the futures markets in 1996, 2006 and 2011; further analysis on the relative volatility of the spot and futures returns is provided later. In contrast to Booth et al. (1996) who found slightly positive skewness, I report slightly negative skewness for most spot and futures returns over the years and over the whole period. Not surprisingly, the daily returns display moderate kurtosis; however, the returns are relatively leptokurtic in 2008 and 2011, and in the overall sample period. This again suggests that the four markets may be intrinsically connected, as the Nikkei returns in the four markets exhibit higher kurtosis simultaneously. Jarque-Bera (1980) statistics show that the null hypothesis of normality can be rejected for the Nikkei returns in most years under consideration.

[45] For reference, the standard deviations of Nikkei spot and futures returns in Brenner et al. (1990) range from 0.441% to 0.615%, and the counterpart values in Lim (1992) range from 0.050% to 0.085%.

[46] Strictly speaking, Bacha and Vila (1994) report no significant differences between Osaka and Singapore in standard deviations, a measure of interday volatility; but they find that Singapore is significantly more volatile than Osaka in Parkinson's extreme value variance estimator, a measure of intraday volatility.

Table 4.5 Descriptive statistics of Nikkei 225 spot and futures returns

Year	Assets	Mean (%)	SD (%)	Skewness	Kurtosis	JB	Autocorrelations (Lag) 1	2	8	No. of obs
1996	S	-0.1117	1.0318	-0.2455	3.2616	1.7020	-0.2130**	0.1180**	-0.0600	132
	OSE	-0.1152	1.0055	-0.2495	3.5231	2.8751	-0.2010**	0.1430**	-0.0530	132
	SGX	-0.1150	0.9869	-0.2649	3.5745	3.3593	-0.2000**	0.1560**	-0.0560	132
1997	S	-0.0972	1.7591	0.0374	4.7102	29.9140**	-0.1390**	-0.1770**	0.0530**	245
	OSE	-0.0964	1.8856	-0.0914	4.1399	13.6058**	-0.2060**	-0.1250**	0.0790**	245
	SGX	-0.0992	1.8695	0.2285	5.6825	75.5874**	-0.1820**	-0.1400**	0.0690**	245
	CME	-0.0937	1.7563	-0.2908	3.7724	9.8164**	-0.2290**	0.0530**	0.0130**	252
1998	S	-0.0394	1.7094	0.3046	4.4274	24.7893**	-0.0070	-0.1350	-0.0030*	247
	OSE	-0.0431	1.7872	0.3380	4.7120	34.8686**	-0.0630	-0.1160	-0.0130**	247
	SGX	-0.0370	1.7770	0.4525	5.0151	50.0184**	-0.0120	-0.1540*	-0.0060*	246
	CME	-0.0419	1.8177	0.2209	4.6683	31.2749**	0.0170	-0.1670**	-0.0100	252
1999	S	0.1279	1.2909	0.1267	4.0178	11.2314**	-0.0900	-0.0520	0.0410	245
	OSE	0.1298	1.3219	0.2301	3.5675	5.4493*	-0.1000	-0.0470	0.0300	245
	SGX	0.1259	1.3152	0.1266	3.4876	3.0690	-0.0710	-0.0460	0.0440	244
	CME	0.1272	1.1905	0.1028	3.9237	9.4393**	-0.0310	-0.0070	-0.0040	253
2000	S	-0.1280	1.4304	-0.4727	5.2118	59.7859**	0.0320	0.0290	0.0090	248
	OSE	-0.1265	1.5272	-0.6385	5.2332	68.3889**	-0.0040	0.0080	0.0220	248
	SGX	-0.1262	1.4726	-0.7583	5.8668	108.6916**	0.0260	0.0160	0.0190	248
	CME	-0.1270	1.4209	-0.1585	2.8609	1.2584	0.0000	-0.0660	-0.0630	252
2001	S	-0.1090	1.8472	0.2061	4.3391	20.1210**	-0.1010	-0.0490	0.0590	246
	OSE	-0.1115	1.9757	-0.0570	6.2409	107.7916**	-0.1710**	-0.0350**	0.0530**	246
	SGX	-0.1134	1.8337	-0.3003	6.2888	114.1008**	-0.1000	-0.0520	0.0560	245
	CME	-0.1103	1.9296	0.3637	4.5760	31.6345**	-0.1050*	-0.0900*	0.1480	252
2002	S	-0.0838	1.6293	0.2804	3.1497	3.4525	0.0000	-0.0310	-0.0790	246
	OSE	-0.0834	1.5648	0.3087	2.9533	3.9282	0.0290	-0.0020	-0.0930	246
	SGX	-0.0849	1.5830	0.2853	3.0811	3.4040	-0.0090	0.0150	-0.0970	246
	CME	-0.0787	1.7587	-0.0416	3.4927	2.6220	-0.1060*	0.0600	-0.0760	252

Table 4.5 continued

							Autocorrelations (Lag)			
Year	Assets	Mean (%)	SD (%)	Skewness	Kurtosis	JB	1	2	8	No. of obs
2003	S	0.0893	1.4509	-0.5229	3.5132	13.8522**	0.0300	-0.0040	-0.1710**	245
	OSE	0.0934	1.5485	-0.6676	3.7551	24.0179**	-0.0640	0.0500	-0.1550**	245
	SGX	0.0964	1.5102	-0.6934	3.9600	29.0386**	-0.0320	0.0310	-0.1520**	245
	CME	0.0920	1.4473	-0.0472	3.7711	6.3364**	0.0340	0.0520	-0.1450	252
2004	S	0.0298	1.1351	-0.3578	3.9792	15.0771**	-0.0100	-0.0170	0.0160	246
	OSE	0.0282	1.1492	-0.5843	5.4160	73.8264**	-0.0370	0.0090	0.0380	246
	SGX	0.0282	1.1276	-0.6501	5.9143	104.3835**	-0.0100	-0.0080	0.0470	246
	CME	0.0271	1.2160	-0.4027	3.6983	11.9314**	-0.0780	0.0130	-0.0380	252
2005	S	0.1380	0.8545	-0.2619	4.7895	35.4900**	0.0510	-0.0990	-0.0220	245
	OSE	0.1368	0.8664	-0.3949	5.0400	48.8492**	0.0780	-0.1250*	0.0040	245
	SGX	0.1362	0.8791	-0.3836	5.1091	51.2098**	0.0610	-0.1290*	-0.0200	244
	CME	0.1339	0.9385	-0.2004	3.9049	10.2839**	-0.0150	-0.0460	0.0180	252
2006	S	0.0270	1.2532	-0.1530	3.3938	2.5707	-0.0520	-0.0240	-0.1210	248
	OSE	0.0295	1.2278	-0.1728	3.3107	2.2320	-0.0250	-0.0290	-0.1210	248
	SGX	0.0302	1.1973	-0.1629	3.2796	1.9043	-0.0120	-0.0190	-0.1220	248
	CME	0.0271	1.2347	-0.1789	3.4111	3.1063	-0.0350	-0.0300	-0.0530	251
2007	S	-0.0482	1.1666	-0.5165	5.0178	52.4566**	0.0090	0.0040	0.0550*	245
	OSE	-0.0508	1.2254	-0.3036	4.0284	14.5609**	-0.0020	-0.0200	0.0150**	245
	SGX	-0.0509	1.2165	-0.3804	4.2151	20.9792**	0.0060	-0.0140	0.0030**	245
	CME	-0.0506	1.2861	-0.3543	3.3408	6.4671**	-0.1640**	0.1170**	0.0020	251
2008	S	-0.2232	2.9292	-0.2335	6.7208	143.5566**	-0.0690	-0.0680	-0.0120	245
	OSE	-0.2230	3.2192	-0.0109	10.3813	556.1879**	-0.1580**	-0.0710**	-0.0190	245
	SGX	-0.2269	3.1529	-0.0266	9.3109	404.9374**	-0.1400**	-0.0760**	-0.0110	244
	CME	-0.2012	3.1491	0.0137	6.1366	103.7187**	-0.0750	-0.1900**	0.0440**	253
2009	S	0.0717	1.7561	-0.0554	3.5056	2.7128	-0.0730	0.1170*	0.0660**	243
	OSE	0.0728	1.7737	0.0178	4.1084	12.4510**	-0.0540	0.1090	0.0720**	243
	SGX	0.0755	1.7659	0.0101	3.9256	8.6789**	-0.0340	0.0940	0.0840**	243
	CME	0.0612	1.8086	0.2930	4.7841	37.0287**	-0.0280	-0.0850	-0.0040	252

Table 4.5 continued

Year	Assets	Mean (%)	SD (%)	Skewness	Kurtosis	JB	Autocorrelations (Lag) 1	2	8	No. of obs
2010	S	-0.0125	1.3202	-0.2161	3.0405	1.9245	-0.0090	-0.1130	-0.0940**	245
	OSE	-0.0130	1.3228	-0.2340	3.2430	2.8383	0.0020	-0.1130	-0.0840*	245
	SGX	-0.0124	1.3188	-0.2427	3.1875	2.7635	0.0080	-0.1240	-0.1030**	245
	CME	-0.0165	1.3765	-0.1593	4.5315	25.7955**	-0.0750	-0.0230	-0.0980	253
2011	S	-0.0777	1.4988	-1.6571	15.6539	1746.6870**	0.0120	-0.0070	-0.0110*	245
	OSE	-0.0772	1.4188	-1.3692	11.2703	774.7770**	0.0830	-0.0300	-0.0050*	245
	SGX	-0.0734	1.3784	-1.2783	10.9811	749.1620**	0.0910	0.0040	-0.0040**	256
	CME	-0.0775	1.4625	-0.6464	6.1385	120.9758**	0.0080	0.1760**	0.0650**	252
2012	S	0.0833	1.0237	-0.1086	2.8483	0.7250	0.0480	0.1120	0.0540	248
	OSE	0.0833	1.0306	-0.0985	2.7638	0.9772	0.0480	0.1110	0.0280	248
	SGX	0.0785	1.0076	0.0374	2.7118	0.9603	0.0440	0.1040	0.0310	260
	CME	0.0901	1.0485	-0.0350	2.9794	0.0562	0.0980	0.0680	0.0260	253
2013	S	0.1834	1.7040	-0.7485	5.1968	72.1407**	-0.1330**	0.0550*	0.0390	245
	OSE	0.1836	1.7517	-0.5385	5.2875	65.2547**	-0.1470**	0.0720**	0.0410*	245
	SGX	0.1727	1.6792	-0.5287	5.8250	98.5652**	-0.1170*	0.0600	0.0330**	260
	CME	0.1746	1.7172	-0.0721	3.7501	6.1266**	-0.0650	-0.0730	0.0660	252
2014	S	0.0282	1.2838	-0.0537	4.2111	15.0303**	-0.0110	0.0810	-0.0020	244
	OSE	0.0282	1.3033	-0.0540	4.3132	17.6519**	-0.0340	0.0930	-0.0540	244
	SGX	0.0257	1.2268	0.1088	4.3814	21.1842**	0.0100	0.0850	-0.0570	260
	CME	0.0232	1.2949	0.5364	7.4101	216.3001**	0.0640	0.0060	0.0050	252
Overall	S	-0.0055	1.5524	-0.3149	8.4193	5646.8630**	-0.0430**	-0.0240**	-0.0010**	4553
	OSE	-0.0056	1.6139	-0.2398	12.4884	17123.0600**	-0.0800**	-0.0180**	-0.0020**	4553
	SGX	-0.0056	1.5760	-0.2319	11.7503	14723.1400**	-0.0570**	-0.0240**	-0.0020**	4602
	CME	-0.0023	1.6202	-0.0786	8.0865	4896.7430**	-0.0530**	-0.0470**	0.0110**	4538

Notes: This table gives the descriptive statistics of Nikkei 225 spot (S) and futures returns by market (OSE, SGX, CME) and by year over the sample period. Returns are calculated as logarithmic changes of spot (futures) prices. The statistics include mean, standard deviation (SD), skewness, kurtosis, Jarque-Bera (1980) statistics (JB) and autocorrelation coefficients. Mean, SD are in percentage. Autocorrelation coefficients are reported at lags 1, 2 and 8. ** denotes significance at the 5% level. * denotes significance at the 10% level.

As to autocorrelation coefficients, Table 4.5 shows that negative first-order autocorrelations are more common than positive first-order autocorrelations in the Nikkei markets. The negative first-order autocorrelations are more likely to be significant at the 5% (or 10%) level, while none of the positive first-order autocorrelations is significant. For comparison, Iihara et al. (1996) find significantly positive first-order autocorrelations for Nikkei spot and futures returns using five-minute data. Since the nonsynchronous trading problem should not be serious for daily returns, the significantly negative first-order autocorrelations may result from the bid-ask bounce of the Nikkei prices. First-order autocorrelations in the spot market are smaller in magnitude than those in the futures markets in most years, and like the evidence in MacKinlay and Ramaswamy (1988), the first-order autocorrelations in spot and futures markets tend to be high or low at the same time, confirming that the effect of nonsynchronous trading is not important. Higher-order autocorrelation coefficients exhibit a slight tendency to die down, but in many years they are indistinguishable from white noise in that the autocorrelations are all small in magnitude and insignificant. Significant autocorrelation coefficients in each market tend to cluster during 1996-1998 and 2007-2011, when the Nikkei markets experienced turmoil due to the Japanese "Big Bang" and the global financial crisis, respectively. For the overall sample, the autocorrelations are small but significant, which indicates weak linear dependence in the daily Nikkei returns.

The relative variability of Nikkei spot and futures returns is shown in Table 4.6. Provided that the risk-free interest rate r and dividend d are non-stochastic or constant, an inference from the cost of carry model is that spot return and futures return should have equal volatility under the no-arbitrage condition. In other words, the variance ratio, computed as the variance of futures return divided by that of spot return, should equal unity to maintain the arbitrage link. To test this null hypothesis, the variance ratios are calculated for the Nikkei returns, and their significance is checked by conventional F-test, with the assumption of independent variance ratios across the years.[47] Panel A of Table 4.6 shows that the OSE futures return has higher variability than the spot return in 15 out of 19 years, and the SGX futures return has higher

[47] In itself, variance ratios that exceed unity are the usual F-statistics; variance ratios less than unity are the inverses of the usual F-statistics, as the F-statistics are usually calculated with the higher variance in the numerator.

Table 4.6 Relative volatility of Nikkei 225 futures and spot returns

Year	OSE	*p*-value	SGX	*p*-value	CME	*p*-value
Panel A: *F*-test						
Year	OSE	*p*-value	SGX	*p*-value	CME	*p*-value
1996	0.9495	0.7673	0.9147	0.6107	NA	NA
1997	1.1490	0.2786	1.1294	0.3424	1.0497	0.7010
1998	1.0930	0.4859	1.0762	0.5658	1.1411	0.2963
1999	1.0487	0.7105	1.0325	0.8036	0.8765	0.2962
2000	1.1399	0.3041	1.0599	0.6481	1.0204	0.8730
2001	1.1440	0.2929	0.9873	0.9206	1.1429	0.2907
2002	0.9224	0.5277	0.9441	0.6527	1.1919	0.1650
2003	1.1390	0.3099	1.0834	0.5322	1.0432	0.7377
2004	1.0249	0.8473	0.9869	0.9180	1.1732	0.2065
2005	1.0280	0.8294	1.0532	0.6865	1.2549	0.0726*
2006	0.9598	0.7476	0.9128	0.4737	0.9891	0.9308
2007	1.1034	0.4427	1.0875	0.5128	1.2332	0.0982*
2008	1.2078	0.1411	1.1470	0.2858	1.1631	0.2311
2009	1.0202	0.8763	1.0112	0.9308	1.0935	0.4794
2010	1.0040	0.9752	0.9979	0.9871	1.1284	0.3383
2011	0.8961	0.3921	0.8839	0.3249	0.9676	0.7943
2012	1.0136	0.9154	1.0156	0.9010	1.0670	0.6073
2013	1.0568	0.6666	1.0301	0.8116	1.0489	0.7053
2014	1.0306	0.8142	0.9733	0.8283	1.0479	0.7110
Overall	1.0809	0.0087**	1.0409	0.1736	1.0981	0.0016**
Panel B: Brown-Forsythe test						
Year	OSE	*p*-value	SGX	*p*-value	CME	*p*-value
1996	0.1709	0.6796	0.4947	0.4825	NA	NA
1997	0.9014	0.3429	0.4274	0.5136	1.3353	0.2484
1998	0.2547	0.6140	0.0340	0.8538	0.8862	0.3470
1999	0.4457	0.5047	0.3628	0.5472	0.1717	0.6788
2000	0.6440	0.4226	0.0316	0.8590	0.9800	0.3227
2001	0.3295	0.5662	0.1604	0.6890	1.7197	0.1903
2002	0.1236	0.7253	0.1148	0.7349	1.7068	0.1920
2003	0.6943	0.4051	0.0887	0.7659	0.8359	0.3610
2004	0.0288	0.8654	0.2302	0.6316	2.4153	0.1208
2005	0.0038	0.9507	0.0050	0.9436	4.0904	0.0437**
2006	0.0406	0.8403	0.2975	0.5857	0.0330	0.8559
2007	0.6525	0.4196	0.3058	0.5805	3.6185	0.0577*
2008	0.1971	0.6572	0.0508	0.8218	0.7566	0.3848
2009	0.0106	0.9179	0.0029	0.9569	0.3223	0.5705
2010	0.0002	0.9902	0.0003	0.9851	0.1646	0.6851
2011	0.2229	0.6370	0.1566	0.6924	0.2167	0.6418
2012	0.0071	0.9328	0.3182	0.5729	0.7534	0.3858
2013	0.0861	0.7694	0.1881	0.6647	1.1685	0.2802
2014	0.0811	0.7760	0.0378	0.8460	0.7536	0.3857
Overall	1.2172	0.2699	0.1049	0.7460	14.5246	0.0001**

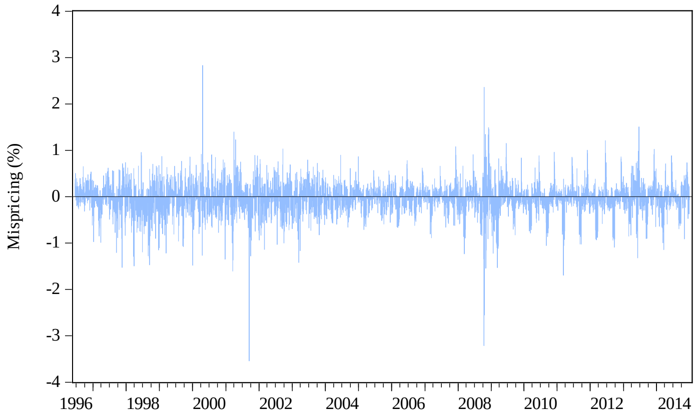
Notes: This table provides the results of *F*-test and Brown-Forsythe test of the relative volatility of Nikkei 225 futures and spot returns by market and year. Panel A shows the variance ratios computed as the ratio of the variance of futures returns to that of spot returns, followed by *p*-values. The *F*-tests are based on the null hypothesis of equal variances between each of the futures market and the spot market. Panel B shows the non-parametric Brown-Forsythe *F*-statistics and their associated *p*-values, with the null hypothesis of equal variances between each of the futures market and the spot market. ** denotes significance at the 5% level. * denotes significance at the 10% level.

variability than the spot return in 11 out of 19 years; yet none of them is significant. The CME futures return is more volatile than the spot return in 15 out of 18 years, and significant variance ratios at the 10% level are found in 2005 and 2007. As to the whole sample, the OSE and CME generate significant variance ratios greater than 1 at the 5% level, which indicates the rejection of the null hypothesis against the alternative that the futures volatilities therein are significantly higher than the spot volatility.

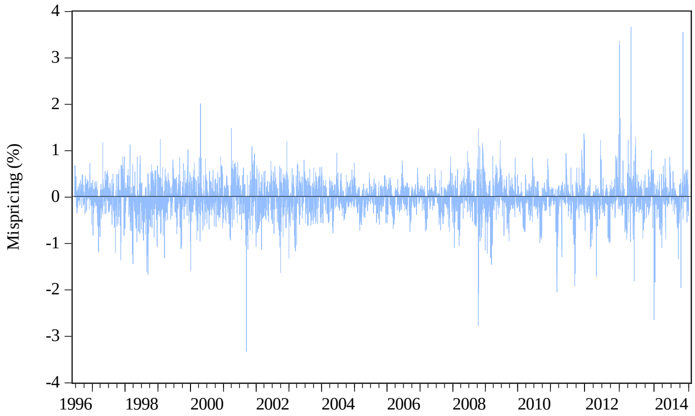
Given that the *F*-test is sensitive to departures from normality, and Jarque-Bera (1980) statistics of the Nikkei returns reject the null hypothesis of normal distribution in most years (Table 4.5), the non-parametric Brown-Forsythe test is run to test the equality of futures variances and stock variance, again with the assumption of independent Brown-Forsythe *F*-statistics across the years. The outcomes are provided in Panel B of Table 4.6. Significant Brown-Forsythe *F*-statistics are present in the CME in 2005 and 2007, which is consistent with the results in Panel A by parametric tests. The CME also shows significant Brown-Forsythe *F*-statistics greater than 1 in the overall sample. On balance, there is evidence supporting more volatile Nikkei futures markets - in particular, the OSE and CME - than the underlying spot market, although the evidence is not very strong in individual years.

4.3.3 Behaviour of Nikkei 225 futures mispricing

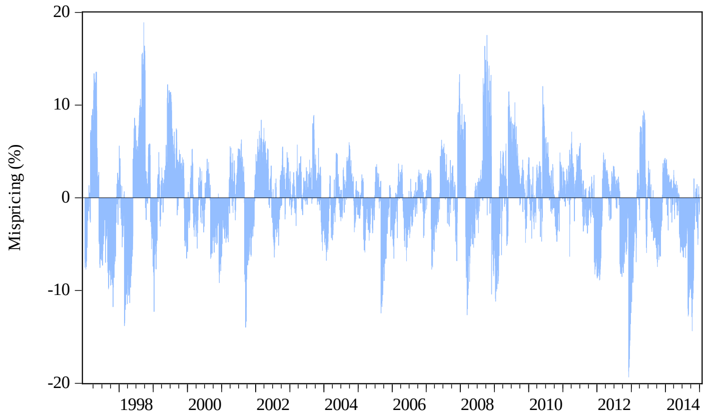
Figure 4.3 plots the mispricing patterns in the three Nikkei exchanges over the sample period without transaction costs. Graphically, the mispricing in the OSE and SGX look similar, and both exhibit moderate persistence with a few spikes. However, the CME mispricing suggests a different pattern which is largely attributable to the currency risk adjustment in the CME futures contracts. The CME mispricing shows strong persistence and is generally larger in magnitude than the OSE and SGX mispricing, which is consistent with the higher risk embodied in the CME futures price. But there seems to be a relatively tranquil period during 2003-2007 with mispricing much smaller in magnitude in the three markets.



(a) OSE



(b) SGX



(c) CME

Figure 4.3 Nikkei 225 futures mispricing without transaction costs

Notes: (a) (b) (c) represent Nikkei 225 futures mispricing in the OSE, SGX and CME, respectively. The OSE and SGX mispricing are calculated from COC2; the CME mispricing is calculated from COC3 in the original view. The mispricing series are in percentage. Transaction costs are not taken into account.

Table 4.7 Descriptive statistics of Nikkei 225 futures mispricing without transaction costs

Year	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	Mean (%)	SD (%)	No. of obs
Panel A: OSE							
1996	91	42	0.20	-0.14	0.09	0.21	133
1997	105	140	0.23	-0.27	-0.06	0.34	245
1998	89	158	0.27	-0.40	-0.16	0.43	247
1999	118	127	0.26	-0.31	-0.04	0.36	245
2000	103	145	0.31	-0.29	-0.04	0.42	248
2001	112	134	0.28	-0.34	-0.06	0.46	246
2002	122	124	0.24	-0.35	-0.06	0.37	246
2003	109	136	0.24	-0.28	-0.05	0.34	245
2004	111	135	0.19	-0.21	-0.03	0.25	246
2005	116	129	0.15	-0.20	-0.04	0.23	245
2006	127	121	0.17	-0.23	-0.02	0.26	248
2007	133	112	0.16	-0.22	-0.01	0.26	245
2008	102	143	0.34	-0.34	-0.06	0.52	245
2009	109	134	0.23	-0.31	-0.07	0.39	243
2010	90	155	0.19	-0.26	-0.09	0.32	245
2011	103	142	0.19	-0.27	-0.08	0.36	245
2012	99	149	0.19	-0.28	-0.09	0.36	248
2013	132	113	0.25	-0.29	0.00	0.37	245
2014	122	122	0.19	-0.27	-0.04	0.31	244
Overall	2093	2461	0.22	-0.28	-0.05	0.36	4554
Panel B: SGX							
Year	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	Mean (%)	SD (%)	No. of obs
1996	93	40	0.19	-0.14	0.09	0.21	133
1997	119	126	0.24	-0.30	-0.04	0.36	245
1998	93	153	0.29	-0.39	-0.13	0.44	246
1999	121	123	0.28	-0.29	-0.01	0.37	244
2000	106	142	0.30	-0.27	-0.03	0.38	248
2001	122	123	0.29	-0.34	-0.03	0.45	245
2002	124	122	0.26	-0.34	-0.04	0.39	246
2003	118	127	0.25	-0.29	-0.03	0.34	245
2004	113	133	0.20	-0.21	-0.02	0.26	246
2005	105	139	0.16	-0.21	-0.05	0.23	244
2006	128	120	0.16	-0.22	-0.02	0.24	248
2007	131	114	0.16	-0.24	-0.03	0.26	245
2008	104	140	0.33	-0.35	-0.06	0.48	244
2009	112	131	0.25	-0.32	-0.06	0.40	243
2010	92	153	0.20	-0.29	-0.11	0.33	245
2011	101	155	0.23	-0.32	-0.11	0.45	256
2012	99	161	0.25	-0.31	-0.10	0.41	260
2013	139	121	0.35	-0.32	0.04	0.55	260
2014	117	143	0.25	-0.31	-0.06	0.46	260
Overall	2137	2466	0.24	-0.29	-0.04	0.39	4603

Table 4.7 continued

Panel C: CME

Year	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	Mean (%)	SD (%)	No. of obs
1997	83	170	6.35	-5.13	-1.36	6.36	253
1998	138	114	6.44	-6.10	0.77	7.50	252
1999	179	74	4.37	-4.04	1.91	4.94	253
2000	81	171	1.83	-3.12	-1.53	2.96	252
2001	109	143	2.72	-3.79	-0.97	3.90	252
2002	179	73	3.22	-2.23	1.64	3.06	252
2003	178	74	2.19	-1.46	1.12	2.42	252
2004	127	125	2.11	-2.32	-0.09	2.74	252
2005	69	183	1.26	-3.46	-2.17	3.36	252
2006	93	158	1.40	-2.10	-0.80	2.15	251
2007	154	97	3.29	-2.70	0.98	3.86	251
2008	137	116	6.06	-4.03	1.44	6.23	253
2009	165	87	3.98	-3.84	1.28	4.67	252
2010	155	98	3.00	-1.68	1.19	3.09	253
2011	155	97	2.21	-2.54	0.38	3.03	252
2012	109	144	1.82	-6.37	-2.84	5.36	253
2013	108	144	3.44	-3.80	-0.70	4.32	252
2014	84	168	1.29	-4.82	-2.79	4.14	252
Overall	2303	2236	3.29	-3.67	-0.14	4.61	4539

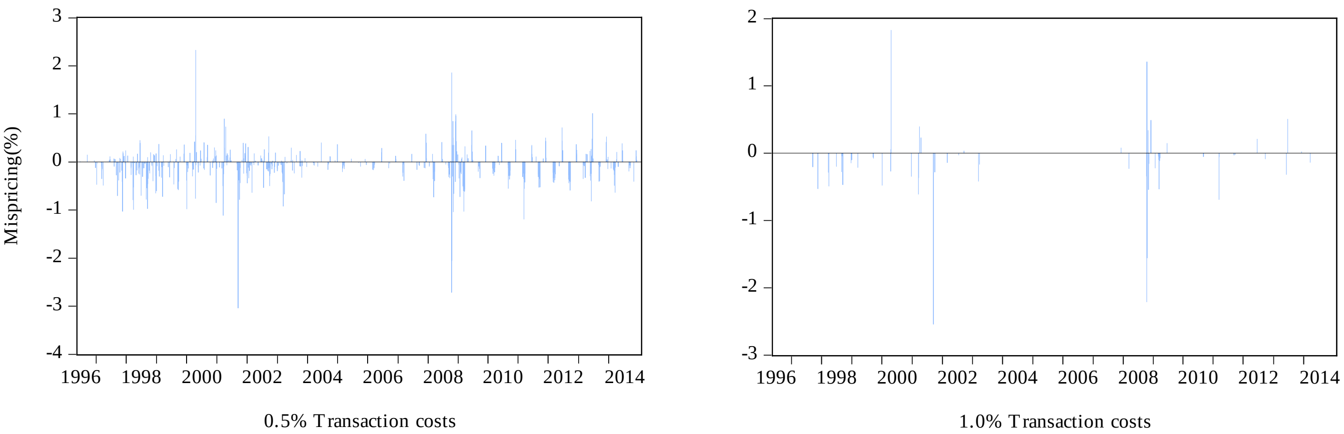
Notes: This table presents descriptive statistics of Nikkei 225 futures mispricing in the absence of transaction costs by market and by year over the sample period. Mispricing is calculated using equations (2.4), (4.1) and (4.4). Panel A, B and C display the mispricing in the OSE, SGX and CME, respectively. The signed mispricing is categorised into the number of overpricing (No. of pos), the number of underpricing (No. of neg), and their respective means, in percentage. The mean, standard deviation (SD) of the mispricing without regard to sign are in percentage.

Table 4.7 reports the descriptive statistics for the Nikkei futures mispricing without transaction costs. The mean and standard deviation of mispricing in the OSE and SGX are also similar, suggesting that the two markets may be more closely linked with each other than any one of them with CME. The standard deviation of the CME mispricing is higher due to currency fluctuations. Following Brenner et al. (1989a; 1989b; 1990), I distinguish overpricing ($Mis_t>0$) from underpricing ($Mis_t<0$) and summarise statistics for each category. Overall, the OSE and SGX are dominated by underpricing, while the CME is dominated by overpricing. This implies that different arbitrage strategies are required in the Nikkei futures markets: short arbitrage seems to be more suitable in the OSE and SGX, and long arbitrage in the CME. However, as

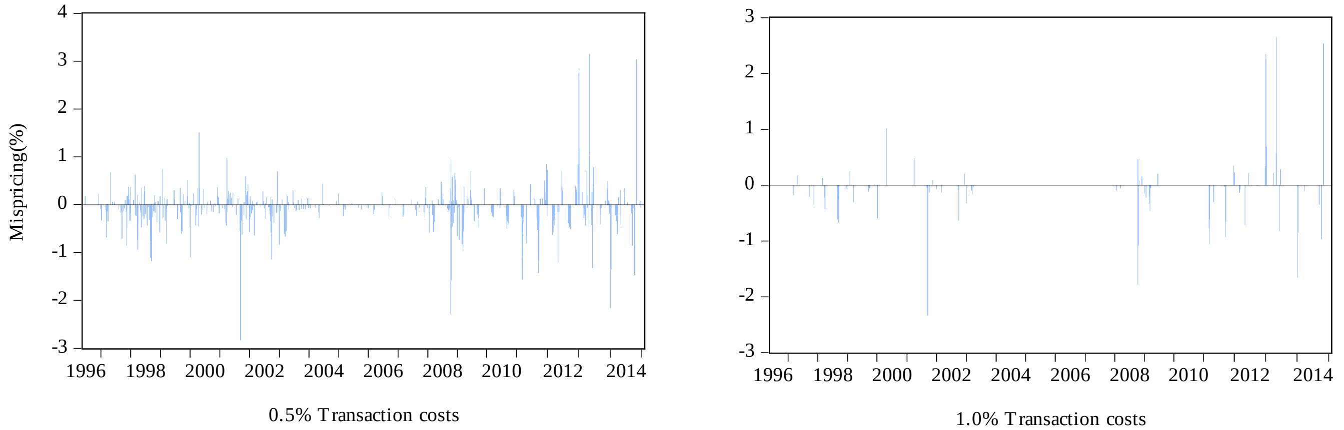
Brenner et al. (1989b) notice, the dominant underpricing in the OSE and SGX may be partly explained by the higher costs related to short sale, e.g. the uptick rule in the stock exchange.[48] As such, underpricings may not necessarily indicate short arbitrage opportunities in the two markets, especially when they are moderately persistent; even if they do, it depends on transaction costs whether the underpricing can be profitably exploited. As mentioned in section 4.2.3, the preponderance of overpricing in the CME is consistent with the general tendency of the appreciation of yen relative to dollar in the sample period. Yet there are a few years when yen decreases in value against dollar, and thus underpricing dominates the CME. The dominant underpricing in the CME might suggest arbitrage opportunities subject to currency risk, in that the dominance only appears in the periods of yen depreciation. At those times, investors may want to engage in a short arbitrage, or replace the stock position by the relatively cheaper futures contracts in their portfolio. But such strategies cannot be completely free from the currency fluctuations. The difference between average overpricing and absolute average underpricing is small in the OSE and SGX, with maxima -0.13% and -0.10%, respectively, in 1998. The counterpart in the CME is much larger, with the maximum -4.55% in 2012. This results from the dramatic trend of yen depreciation starting from September 2012 and lasting until the end of the sample.

With transaction costs, Table 4.8 and Figure 4.4 indicate that the dominance of underpricing remains in the OSE and SGX. However, the OSE underpricing reduces sharply from 2,461 to 432 under 0.5% transaction costs, and to 50 under 1.0% transaction costs over the sample. The same happens in the SGX: only 64 underpricings survive under 1.0% transaction costs. Overpricing becomes even less in the two markets. MacKinlay and Ramaswamy (1988) posit that persistent mispricings are more likely to suggest arbitrage opportunities. Hence, it seems that only brokers with a lower level of transaction costs may have been able to profit from the short arbitrage in the OSE and SGX; it is, however, relatively difficult for institutional investors

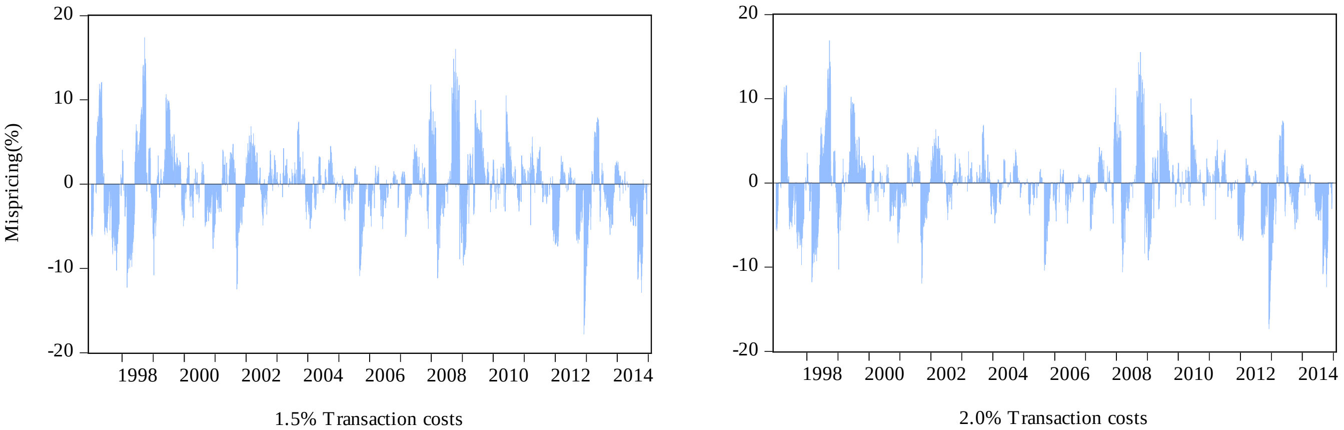
[48] The TSE uptick rule, in effect since the 1940s, stipulates that the price of short sale must be above the last traded price of a stock if the last traded price is lower than the price in the previous trade, or at the last traded price if the last traded price is higher than the price in the previous trade. During the 2008 global financial crisis, all the stocks listed on Japanese stock exchanges were banned from short sale, and higher costs related to short sale lasted until November 2013. From November 2013, the uptick rule applies only when the stock price falls by 10% of a triggered price which is published daily by the TSE, and once active the uptick rule lasts until the end of the next trading day (Data from TSE).



(a) OSE



(b) SGX



(c) CME

Figure 4.4 Nikkei 225 futures mispricing with transaction costs

Notes: (a) (b) (c) represent Nikkei 225 futures mispricing in the OSE, SGX and CME, respectively. The OSE and SGX mispricing are calculated from COC2; the CME mispricing is calculated from COC3 in the original view. 0.5% and 1.0% transaction costs are applied for the OSE and SGX; 1.5% and 2.0% transaction costs are applied for the CME. The mispricing series are in percentage.

Table 4.8 Descriptive statistics of Nikkei 225 futures mispricing with transaction costs

Panel A: OSE

With transaction costs of 0.5%

Year	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	Mean (%)	SD (%)	No. of obs
1996	3	1	0.06	-0.12	0.00	0.02	4
1997	15	20	0.10	-0.28	-0.02	0.11	35
1998	11	48	0.18	-0.29	-0.05	0.18	59
1999	13	20	0.13	-0.26	-0.01	0.10	33
2000	19	26	0.31	-0.21	0.00	0.20	45
2001	20	24	0.23	-0.41	-0.02	0.25	44
2002	16	34	0.15	-0.17	-0.01	0.10	50
2003	10	21	0.10	-0.22	-0.02	0.09	31
2004	4	7	0.23	-0.07	0.00	0.04	11
2005	2	10	0.07	-0.08	0.00	0.02	12
2006	6	9	0.14	-0.10	0.00	0.03	15
2007	6	10	0.24	-0.15	0.00	0.06	16
2008	21	25	0.41	-0.49	-0.01	0.31	46
2009	11	28	0.22	-0.36	-0.03	0.16	39
2010	9	37	0.19	-0.15	-0.02	0.09	46
2011	9	31	0.24	-0.32	-0.03	0.14	40
2012	10	34	0.31	-0.28	-0.03	0.13	44
2013	19	25	0.23	-0.17	0.00	0.12	44
2014	11	22	0.15	-0.17	-0.01	0.08	33
Overall	215	432	0.22	-0.25	-0.01	0.14	647

With transaction costs of 1.0%

Year	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	Mean (%)	SD (%)	No. of obs
1996	0	0	0.00	0.00	0.00	0.00	0
1997	0	2	0.00	-0.37	0.00	0.04	2
1998	0	11	0.00	-0.22	-0.01	0.06	11
1999	0	3	0.00	-0.12	0.00	0.02	3
2000	2	3	0.95	-0.37	0.00	0.12	5
2001	2	4	0.32	-0.95	-0.01	0.17	6
2002	1	2	0.03	-0.09	0.00	0.01	3
2003	0	2	0.00	-0.30	0.00	0.03	2
2004	0	0	0.00	0.00	0.00	0.00	0
2005	0	0	0.00	0.00	0.00	0.00	0
2006	0	0	0.00	0.00	0.00	0.00	0
2007	1	0	0.08	0.00	0.00	0.01	1
2008	6	6	0.50	-0.84	-0.01	0.21	12
2009	1	9	0.15	-0.13	0.00	0.04	10
2010	0	1	0.00	-0.05	0.00	0.00	1
2011	1	4	0.00	-0.20	0.00	0.04	5
2012	1	1	0.21	-0.09	0.00	0.01	2
2013	2	1	0.27	-0.32	0.00	0.04	3
2014	0	1	0.00	-0.14	0.00	0.01	1
Overall	17	50	0.38	-0.34	0.00	0.07	67

Table 4.8 continued

Panel B: SGX

With transaction costs of 0.5%

Year	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	Mean (%)	SD (%)	No. of obs
1996	3	1	0.14	-0.09	0.00	0.03	4
1997	14	23	0.17	-0.25	-0.01	0.12	37
1998	18	42	0.16	-0.34	-0.05	0.18	60
1999	14	16	0.21	-0.29	-0.01	0.12	30
2000	16	19	0.27	-0.22	0.00	0.14	35
2001	18	21	0.27	-0.39	-0.01	0.22	39
2002	15	28	0.14	-0.24	-0.02	0.13	43
2003	10	21	0.13	-0.17	-0.01	0.08	31
2004	6	7	0.16	-0.09	0.00	0.04	13
2005	1	12	0.03	-0.08	0.00	0.02	13
2006	5	6	0.15	-0.11	0.00	0.03	11
2007	6	12	0.13	-0.12	0.00	0.04	18
2008	24	39	0.27	-0.29	-0.02	0.24	63
2009	12	26	0.22	-0.39	-0.03	0.16	38
2010	9	36	0.15	-0.19	-0.02	0.09	45
2011	15	37	0.26	-0.44	-0.05	0.23	52
2012	13	38	0.39	-0.31	-0.03	0.17	51
2013	23	30	0.68	-0.19	0.04	0.36	53
2014	12	29	0.36	-0.34	-0.02	0.28	41
Overall	234	443	0.27	-0.28	-0.01	0.17	677

With transaction costs of 1.0%

Year	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	Mean (%)	SD (%)	No. of obs
1996	0	0	0.00	0.00	0.00	0.00	0
1997	1	3	0.18	-0.25	0.00	0.03	4
1998	1	9	0.13	-0.28	-0.01	0.07	10
1999	2	4	0.13	-0.13	0.00	0.03	6
2000	1	1	1.01	-0.59	0.00	0.07	2
2001	2	4	0.28	-0.64	-0.01	0.15	6
2002	1	4	0.20	-0.30	0.00	0.05	5
2003	0	3	0.00	-0.10	0.00	0.01	3
2004	0	0	0.00	0.00	0.00	0.00	0
2005	0	0	0.00	0.00	0.00	0.00	0
2006	0	0	0.00	0.00	0.00	0.00	0
2007	0	0	0.00	0.00	0.00	0.00	0
2008	5	6	0.16	-0.53	-0.01	0.14	11
2009	1	10	0.20	-0.17	-0.01	0.05	11
2010	0	0	0.00	0.00	0.00	0.00	0
2011	2	10	0.17	-0.46	-0.02	0.12	12
2012	3	4	0.26	-0.23	0.00	0.05	7
2013	8	1	1.14	-0.82	0.03	0.27	9
2014	1	5	2.53	-0.79	-0.01	0.21	6
Overall	28	64	0.58	-0.37	0.00	0.10	92

Table 4.8 continued

Panel C: CME

With transaction costs of 1.5%

Year	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	Mean (%)	SD (%)	No. of obs
1997	64	151	6.54	-4.17	-0.83	5.19	215
1998	123	98	5.63	-5.46	0.62	6.29	221
1999	146	57	3.66	-3.51	1.32	3.93	203
2000	47	123	1.04	-2.49	-1.02	1.98	170
2001	84	118	1.77	-2.93	-0.78	2.76	202
2002	146	43	2.30	-1.74	1.04	2.05	189
2003	100	26	1.80	-1.37	0.57	1.64	126
2004	73	76	1.70	-1.87	-0.07	1.66	149
2005	26	123	0.70	-3.25	-1.51	2.65	149
2006	43	92	0.72	-1.57	-0.45	1.17	135
2007	110	68	2.82	-2.07	0.68	2.85	178
2008	114	90	5.61	-3.47	1.30	5.09	204
2009	131	58	3.29	-3.87	0.82	3.61	189
2010	104	50	2.59	-1.11	0.85	2.17	154
2011	96	50	1.61	-2.82	0.05	2.04	146
2012	62	121	1.11	-5.95	-2.58	4.35	183
2013	74	122	3.18	-2.85	-0.45	3.17	196
2014	32	131	0.86	-4.51	-2.23	3.29	163
Overall	1575	1597	2.96	-3.35	-0.15	3.57	3172

With transaction costs of 2.0%

Year	No. of pos	No. of neg	Mean pos (%)	Mean neg (%)	Mean (%)	SD (%)	No. of obs
1997	61	143	6.34	-3.88	-0.67	4.82	204
1998	118	92	5.35	-5.30	0.57	5.90	210
1999	126	54	3.69	-3.18	1.16	3.62	180
2000	29	109	1.03	-2.28	-0.87	1.71	138
2001	68	110	1.62	-2.63	-0.71	2.44	178
2002	130	36	2.06	-1.52	0.84	1.76	166
2003	78	19	1.72	-1.29	0.43	1.44	97
2004	59	62	1.54	-1.74	-0.07	1.35	121
2005	14	106	0.58	-3.22	-1.32	2.45	120
2006	27	68	0.53	-1.54	-0.36	0.93	95
2007	90	57	2.88	-1.93	0.59	2.57	147
2008	105	82	5.57	-3.28	1.25	4.73	187
2009	120	53	3.07	-3.72	0.68	3.29	173
2010	88	32	2.52	-1.06	0.74	1.93	120
2011	74	41	1.52	-2.87	-0.02	1.77	115
2012	48	117	0.87	-5.65	-2.45	4.07	165
2013	71	115	2.81	-2.50	-0.35	2.83	186
2014	22	120	0.66	-4.39	-2.03	3.06	142
Overall	1328	1416	2.97	-3.24	-0.14	3.28	2744

Notes: This table presents descriptive statistics of Nikkei 225 futures mispricing in the presence of transaction costs by market and by year. Mispricing is calculated using equations (4.5a)-(4.7). The transaction costs are 0.5% for brokers, 1.0% for institutional investors in the OSE and SGX; 1.5% for brokers, 2.0% for institutional investors in the CME. Panel A, B and C display the mispricing in the OSE, SGX and CME, respectively. The signed mispricing is categorised into the number of overpricing (No. of pos), the number of underpricing (No. of neg), and their respective means, in percentage. The mean, standard deviation (SD) of the mispricing without regard to sign are in percentage.

to make a profit, for a majority of the mispricings disappear and the remaining mispricings scatter around over several years under a higher level of transaction costs. In contrast, the CME Nikkei futures contracts tend to be primarily underpriced in the presence of transaction costs during the sample period. Most of the mispricings survive and cluster even with the stricter 2.0% transaction costs. This implies that mispricings mainly resulting from the currency fluctuations are sufficient to cover transaction costs involved in a typical arbitrage, such that it is possible for investors in the CME to profit from the arbitrage.[49] It is therefore important to grasp the trend of the yen-dollar exchange rates and respond to it accordingly. Nonetheless, as mentioned, since the currency risk cannot be completely eliminated, the profit gained from the arbitrage in the CME is not strictly risk-free.

The persistence of mispricing is measured by its autocorrelation coefficients up to lag 8 in Table 4.9. First-order autocorrelations are significantly positive in the three markets: moderate values are observed in the OSE and SGX in most years under consideration, indicative of mild persistence; while high values up to 0.963 are observed in the CME, indicative of strong persistence, which is probably due to the currency risk adjustment. Beyond first order, the autocorrelations in the three markets diminish gradually but do not disappear, especially in the CME, where even the eighth-order autocorrelation is 0.748 over the sample. Transaction costs may deter investors from removing mispricing (Brenner et al, 1989a; 1989b), and the higher the costs are, the more mispricings are preserved, as in the case of the CME. In terms of first differences in mispricing, the first-order autocorrelations in the three markets are significantly negative, consistent with the notion that mispricing is a mean-reverting process. Given that the nonsynchronous trading problem is not serious with the use of daily data, arbitrage may explain the mean reversion of mispricing in the sense that investors drag the diverged prices back inside the no-arbitrage bounds (MacKinlay and Ramaswamy, 1988). However, this is not the sole reason. Tse (2001), McMillan and Speight (2006) argue that heterogeneous arbitrage activities could be another explanation. I will formally look into this issue in section 4.4.4.

[49] In the real world, as S_T is not known at time t, investors use expectations $E(S_t)$ to form S_T, assuming rational expectations. The CME mispricing could simply result from the expectation biases of the investors. If this is the case, the number of overpricings should equal the number of underpricings in the CME; in other words, the CME mispricing should be symmetrical around zero. However, the CME is found to be dominated by overpricing (without transaction costs) and underpricing (with transaction costs). As such, it is maintained that the CME mispricing is not likely to be a result of the expectation biases.

Table 4.9 Autocorrelation coefficients of Nikkei 225 futures mispricing

Panel A: OSE								
	Autocorrelations (Lag)							
Year	1	2	3	4	5	6	7	8
Level of mispricing								
1996	0.074	0.118	0.092	-0.030	0.112	-0.011	0.029	-0.029
1997	0.221**	0.295**	0.236**	0.194**	0.231**	0.186**	0.145**	0.171**
1998	0.281**	0.059**	0.062**	0.149**	0.221**	0.139**	0.109**	0.096**
1999	0.271**	0.156**	0.206**	0.175**	0.076**	0.093**	0.092**	0.026**
2000	0.247**	-0.035**	-0.043**	0.117**	0.166**	0.094**	-0.035**	0.000**
2001	0.188**	0.254**	0.213**	0.154**	0.110**	0.202**	0.069**	0.016**
2002	0.162**	0.008**	-0.060*	0.077*	-0.063*	0.010	0.004	0.065
2003	0.136**	0.213**	0.183**	0.164**	0.119**	0.024**	0.085**	0.010**
2004	0.241**	0.238**	0.174**	0.173**	0.157**	0.115**	0.112**	0.103**
2005	0.488**	0.356**	0.344**	0.317**	0.207**	0.172**	0.141**	0.069**
2006	0.511**	0.482**	0.267**	0.313**	0.245**	0.314**	0.214**	0.174**
2007	0.494**	0.455**	0.388**	0.307**	0.273**	0.192**	0.238**	0.139**
2008	0.118*	0.185**	0.248**	0.178**	0.047**	0.133**	0.100**	0.007**
2009	0.544**	0.414**	0.496**	0.496**	0.350**	0.337**	0.351**	0.300**
2010	0.674**	0.630**	0.557**	0.502**	0.457**	0.433**	0.335**	0.320**
2011	0.646**	0.595**	0.520**	0.498**	0.431**	0.371**	0.314**	0.300**
2012	0.771**	0.666**	0.613**	0.515**	0.487**	0.426**	0.336**	0.274**
2013	0.434**	0.357**	0.300**	0.322**	0.285**	0.162**	0.199**	0.202**
2014	0.512**	0.488**	0.341**	0.347**	0.311**	0.253**	0.226**	0.216**
Overall	0.357**	0.299**	0.271**	0.270**	0.222**	0.201**	0.163**	0.133**
	Autocorrelations (Lag)							
Year	1	2	3	4	5	6	7	8
First-order difference in mispricing								
1996	-0.517**	0.023**	0.059**	-0.118**	0.100**	-0.039**	0.034**	0.030**
1997	-0.547**	0.087**	-0.008**	-0.058**	0.054**	-0.005**	-0.040**	0.032**
1998	-0.335**	-0.161**	-0.047**	0.007**	0.092**	-0.042**	0.003**	-0.008**
1999	-0.418**	-0.095**	0.046**	0.042**	-0.059**	0.009**	0.038**	-0.080**
2000	-0.319**	-0.188**	-0.097**	0.074**	0.081**	0.035**	-0.111**	0.012**
2001	-0.538**	0.062**	0.011**	-0.006**	-0.077**	0.131**	-0.045**	-0.056**
2002	-0.417**	-0.038**	-0.116**	0.175**	-0.135**	0.055**	-0.044**	0.067**
2003	-0.544**	0.064**	-0.005**	0.015**	0.034**	-0.099**	0.076**	-0.113**
2004	-0.499**	0.047**	-0.049**	0.020**	0.012**	-0.024**	0.004**	0.066**
2005	-0.362**	-0.114**	0.012**	0.079**	-0.075**	-0.008**	0.035**	-0.081**
2006	-0.473**	0.198**	-0.260**	0.110**	-0.141**	0.167**	-0.061**	0.041**
2007	-0.448**	0.028**	0.021**	-0.052**	0.030**	-0.113**	0.127**	-0.074**
2008	-0.538**	0.003**	0.078**	0.034**	-0.122**	0.066**	0.033**	-0.031**
2009	-0.357**	-0.230**	0.088**	0.161**	-0.150**	-0.032**	0.080**	0.085**
2010	-0.430**	0.045**	-0.031**	-0.014**	-0.036**	0.116**	-0.126**	0.040**
2011	-0.427**	0.033**	-0.074**	0.064**	-0.009**	-0.007**	-0.059**	0.001**
2012	-0.271**	-0.114**	0.100**	-0.154**	0.073**	0.062**	-0.061**	-0.043**
2013	-0.432**	-0.017**	-0.070**	0.052**	0.076**	-0.142**	0.030**	0.015**
2014	-0.476**	0.126**	-0.156**	0.042**	0.022**	-0.032**	-0.017**	0.068**
Overall	-0.455**	-0.023**	-0.021**	0.037**	-0.021**	0.013**	-0.006**	-0.011**

Table 4.9 continued

Panel B: SGX

	Autocorrelations (Lag)							
Year	1	2	3	4	5	6	7	8
Level of mispricing								
1996	0.114	0.268**	-0.014**	0.021**	0.051**	0.023*	-0.012*	0.011
1997	0.258**	0.352**	0.151**	0.176**	0.237**	0.189**	0.161**	0.159**
1998	0.313**	0.087**	0.074**	0.222**	0.273**	0.107**	0.080**	0.112**
1999	0.242**	0.156**	0.172**	0.158**	0.082**	0.077**	0.065**	0.057**
2000	0.277**	0.024**	0.005**	0.057**	0.152**	0.076**	-0.052**	-0.003**
2001	0.217**	0.233**	0.239**	0.170**	0.119**	0.254**	0.076**	0.048**
2002	0.132**	0.004	-0.048	0.169**	-0.035**	-0.004*	0.000*	0.013
2003	0.220**	0.154**	0.181**	0.137**	0.081**	0.032**	0.027**	0.021**
2004	0.340**	0.287**	0.247**	0.178**	0.154**	0.149**	0.122**	0.072**
2005	0.448**	0.387**	0.295**	0.318**	0.238**	0.222**	0.162**	0.107**
2006	0.518**	0.487**	0.272**	0.313**	0.255**	0.294**	0.162**	0.142**
2007	0.447**	0.413**	0.332**	0.291**	0.236**	0.166**	0.223**	0.067**
2008	0.203**	0.269**	0.275**	0.185**	0.082**	0.167**	0.072**	0.002**
2009	0.512**	0.411**	0.423**	0.384**	0.293**	0.312**	0.311**	0.259**
2010	0.645**	0.612**	0.527**	0.474**	0.414**	0.415**	0.288**	0.290**
2011	0.593**	0.505**	0.452**	0.477**	0.426**	0.325**	0.272**	0.265**
2012	0.572**	0.509**	0.454**	0.377**	0.345**	0.314**	0.278**	0.219**
2013	0.399**	0.137**	0.117**	0.112**	0.064**	0.058**	0.118**	0.132**
2014	0.220**	0.201**	0.233**	0.180**	0.115**	0.233**	0.099**	0.112**
Overall	0.358**	0.279**	0.248**	0.247**	0.195**	0.197**	0.145**	0.129**

	Autocorrelations (Lag)							
Year	1	2	3	4	5	6	7	8
First-order difference in mispricing								
1996	-0.589**	0.233**	-0.166**	0.019**	0.003**	0.035**	-0.046**	0.044**
1997	-0.562**	0.197**	-0.151**	-0.012**	0.053**	-0.001**	-0.031**	0.024**
1998	-0.336**	-0.155**	-0.116**	0.072**	0.161**	-0.104**	-0.043**	0.008**
1999	-0.443**	-0.067**	0.028**	0.041**	-0.052**	0.006**	-0.008**	0.021**
2000	-0.335**	-0.168**	-0.034**	-0.028**	0.121**	0.036**	-0.128**	0.048**
2001	-0.504**	0.005**	0.044**	-0.005**	-0.113**	0.189**	-0.091**	-0.061**
2002	-0.425**	-0.019**	-0.155**	0.262**	-0.158**	0.028**	-0.010**	-0.010**
2003	-0.449**	-0.057**	0.051**	0.007**	-0.003**	-0.036**	0.001**	-0.045**
2004	-0.467**	0.001**	0.018**	-0.022**	-0.028**	0.026**	0.015**	0.004**
2005	-0.431**	0.041**	-0.118**	0.093**	-0.061**	0.032**	-0.008**	-0.039**
2006	-0.469**	0.200**	-0.256**	0.097**	-0.106**	0.168**	-0.115**	0.016**
2007	-0.456**	0.041**	-0.024**	0.000**	0.009**	-0.109**	0.179**	-0.166**
2008	-0.534**	0.038**	0.069**	0.004**	-0.123**	0.113**	-0.015**	0.014**
2009	-0.377**	-0.130**	0.059**	0.054**	-0.123**	0.020**	0.064**	0.040**
2010	-0.450**	0.070**	-0.045**	0.011**	-0.085**	0.177**	-0.180**	0.061**
2011	-0.391**	-0.045**	-0.095**	0.094**	0.055**	-0.053**	-0.057**	0.016**
2012	-0.424**	-0.009**	0.024**	-0.051**	0.000**	0.004**	0.024**	-0.066**
2013	-0.277**	-0.205**	-0.011**	0.033**	-0.034**	-0.053**	0.035**	0.063**
2014	-0.493**	-0.027**	0.056**	0.005**	-0.116**	0.165**	-0.102**	0.036**
Overall	-0.439**	-0.037**	-0.023**	0.038**	-0.041**	0.041**	-0.027**	0.000**

Table 4.9 continued

Panel C: CME

	Autocorrelations (Lag)							
Year	1	2	3	4	5	6	7	8
Level of mispricing								
1997	0.963**	0.941**	0.928**	0.916**	0.895**	0.878**	0.858**	0.839**
1998	0.959**	0.925**	0.897**	0.877**	0.863**	0.841**	0.827**	0.801**
1999	0.939**	0.891**	0.854**	0.817**	0.783**	0.751**	0.721**	0.700**
2000	0.859**	0.797**	0.767**	0.711**	0.643**	0.603**	0.570**	0.528**
2001	0.888**	0.853**	0.823**	0.805**	0.781**	0.746**	0.748**	0.723**
2002	0.858**	0.834**	0.797**	0.770**	0.747**	0.723**	0.710**	0.683**
2003	0.788**	0.728**	0.664**	0.612**	0.526**	0.462**	0.401**	0.368**
2004	0.898**	0.849**	0.816**	0.777**	0.764**	0.718**	0.670**	0.628**
2005	0.920**	0.863**	0.806**	0.764**	0.729**	0.680**	0.645**	0.598**
2006	0.819**	0.738**	0.686**	0.641**	0.610**	0.551**	0.509**	0.461**
2007	0.898**	0.853**	0.820**	0.759**	0.696**	0.640**	0.596**	0.555**
2008	0.813**	0.767**	0.782**	0.745**	0.708**	0.690**	0.686**	0.660**
2009	0.868**	0.838**	0.810**	0.779**	0.727**	0.688**	0.655**	0.618**
2010	0.833**	0.750**	0.709**	0.676**	0.629**	0.586**	0.543**	0.477**
2011	0.800**	0.769**	0.722**	0.695**	0.646**	0.616**	0.610**	0.561**
2012	0.945**	0.905**	0.870**	0.832**	0.792**	0.748**	0.707**	0.670**
2013	0.897**	0.871**	0.835**	0.810**	0.753**	0.739**	0.699**	0.682**
2014	0.911**	0.881**	0.863**	0.814**	0.791**	0.766**	0.743**	0.727**
Overall	0.916**	0.884**	0.863**	0.839**	0.812**	0.789**	0.771**	0.748**

	Autocorrelations (Lag)							
Year	1	2	3	4	5	6	7	8
First-order difference in mispricing								
1997	-0.200**	-0.131**	-0.028**	0.132**	-0.034**	0.012**	0.000**	-0.032**
1998	-0.073	-0.084	-0.085	-0.082	0.102*	-0.094*	0.140**	-0.033**
1999	-0.145**	-0.062**	-0.043*	-0.029	-0.088	0.028	-0.035	0.024
2000	-0.289**	-0.112**	0.090**	0.073**	-0.113**	-0.050**	0.042**	-0.059**
2001	-0.341**	-0.031**	-0.057**	0.026**	0.064**	-0.174**	0.138**	0.051**
2002	-0.412**	0.039**	-0.033**	-0.009**	0.012**	-0.043**	0.046**	-0.018**
2003	-0.365**	0.009**	-0.035**	0.079**	-0.043**	-0.013**	-0.073**	0.027**
2004	-0.274**	-0.076**	0.022**	-0.124**	0.155**	0.019**	-0.036**	-0.015**
2005	-0.145**	-0.003*	-0.092*	-0.042*	0.084*	-0.084*	0.071*	0.083*
2006	-0.278**	-0.086**	-0.018**	-0.039**	0.080**	-0.049**	0.013**	-0.044**
2007	-0.324**	-0.047**	0.126**	-0.021**	-0.025**	-0.034**	-0.027**	0.094**
2008	-0.380**	-0.164**	0.132**	0.005**	-0.059**	-0.039**	0.060**	0.020**
2009	-0.390**	-0.004**	-0.004**	0.084**	-0.058**	-0.034**	0.026**	-0.048**
2010	-0.250**	-0.126**	-0.032**	0.050**	-0.011**	0.015**	0.059**	-0.132**
2011	-0.438**	0.037**	-0.052**	0.078**	-0.055**	-0.079**	0.129**	-0.053**
2012	-0.180**	-0.036**	0.015**	0.021*	0.030	-0.033	-0.044	0.010
2013	-0.395**	0.028**	-0.061**	0.145**	-0.199**	0.148**	-0.108**	0.131**
2014	-0.338**	-0.082**	0.168**	-0.139**	0.002**	0.002**	-0.018**	0.033**
Overall	-0.310**	-0.069**	0.021**	0.019**	-0.024**	-0.031**	0.034**	0.001**

Notes: This table gives the autocorrelation coefficients of Nikkei 225 futures mispricing by market and by year over the sample period. The autocorrelation coefficients are calculated up to the eighth lag for the level of mispricing and for the first-order difference in mispricing. Panel A, B and C display the autocorrelation coefficients in the OSE, SGX and CME, respectively. ** denotes significance at the 5% level. * denotes significance at the 10% level.

4.3.4 Nikkei 225 futures mispricing and a set of variables

4.3.4.1 Mispricing and time to maturity

Without early unwinding as prescribed in assumption 1) at the beginning of section 4.2, the magnitude of mispricing should increase with time to maturity, as longer dated futures contracts carry more uncertainties. This means that in terms of signed mispricing, underpricing should be more negative for longer time to maturity, and overpricing more positive. A non-parametric method is used to examine the relationship between mispricing and time to maturity.[50] Following Brenner et al. (1989b) and Yadav and Pope (1994), the mispricing data are categorised into 5 groups by time to maturity in descending order, with each group covering roughly 20 trading days, and the means (medians) of the mispricing data are checked for monotonic orderings. As shown in Table 4.10, the mean absolute mispricing in the OSE and CME are found to increase with time to maturity. The mean (median) underpricing in the OSE, and the mean underpricing in the SGX and CME become more negative for longer time to maturity, which is consistent with the positive relationship between absolute mispricing and time to maturity. The mean (median) overpricing in the CME also increases monotonically with time to maturity. The null hypothesis of equal means across the groups is tested by running an OLS regression on dummy variables that represent the groups; the mean relationships are significant if the *F*-statistics of the regression are significant. The null hypothesis of equal medians across the groups is tested by the Jonckheere trend test (Jonckheere, 1954; Terpstra, 1952), which is a non-parametric test for suspicious median ordering among groups, complemented with Kendall's tau-b coefficient (Kendall, 1938), which helps to identify the direction of the ordering. The test statistics show that the observed positive relationships are all significant at the 5% level, leading to the rejection of the null hypotheses. Thus, I support the literature by holding that mispricings tend to be greater in magnitude for longer dated contracts. This can be particularly attributed to the riskier adjustments for dividends and exchange rate fluctuations for the Nikkei futures contracts with longer time to maturity, among other

[50] Throughout section 4.3.4, I examine the Nikkei mispricing without transaction costs to have sufficient observations.

uncertainties. The significantly positive relationships are largely located in the underpricing of the OSE and SGX, and in the overpricing of the CME, in agreement with the dominant signs of mispricing in these markets.

4.3.4.2 Mispricing and stock volatility

To examine the relationship between mispricing and stock volatility, the fitted value of the conditional variance of a GARCH (1, 1) model of Bollerslev (1986) with constant mean is used to estimate the time-varying volatility in the TSE. Likewise, following Yadav and Pope (1994), the mispricing data are divided into 5 groups of roughly equal size based on the stock volatility estimate in descending order, and the means (medians) of the mispricing data are checked for monotonic orderings. Table 4.11 presents the results. Monotonically positive relationships between the magnitude of mispricing and stock volatility are mainly in the OSE and SGX, yet the evidence is less in the CME, where only median overpricing increases with stock volatility. The null hypothesis of equal means across the groups is tested by *F*-statistics of a regression on dummy variables that represent the groups, and the null hypothesis of equal medians across the groups is tested by the Jonckheere trend test (Jonckheere, 1954; Terpstra, 1952), complemented with Kendall's tau-b coefficient (Kendall, 1938). The observed positive relationships between the magnitude of mispricing and stock volatility are all significant at the 5% level, which indicates rejection of the null hypotheses against the alternative that mispricing in magnitude increases when the stock market is more volatile. Given the positive relationship between the magnitude of mispricing and time to maturity, the effect of stock volatility on mispricing is likely to be larger for longer dated contracts.

4.3.4.3 Mispricing and futures volume

The relationship between mispricing and futures volume is investigated by sorting the mispricing data into 5 groups of roughly equal size by futures volume in descending order and

Table 4.10 Nikkei 225 futures mispricing and time to expiration

	Mispricing (%)		Absolute mispricing (%)		Underpricing (%)		Overpricing (%)		
Time to expiration	Mean	Median	Mean	Median	Mean	Median	Mean	Median	No. of obs
Panel A: OSE									
(80, 105]	-0.1361	-0.1514	0.3976	0.3506	-0.4259	-0.3879	0.3501	0.2825	1071
(60, 80]	-0.0518	-0.0109	0.2615	0.1946	-0.3022	-0.2109	0.2177	0.1742	955
(40, 60]	-0.0248	-0.0106	0.2008	0.1444	-0.2136	-0.1551	0.1866	0.1296	1047
(20, 40]	-0.0036	0.0034	0.1952	0.1502	-0.2015	-0.1522	0.1891	0.1479	1032
[8, 20]	-0.0099	-0.0047	0.1833	0.1443	-0.1861	-0.1348	0.1802	0.1564	449
Test statistics			132.0443**[a]		80.6546**[a]	-16.2661**[b]			
						-0.2410**[c]			
Panel B: SGX									
(80, 105]	-0.1411	-0.1464	0.4043	0.3442	-0.4323	-0.3846	0.3564	0.3078	1078
(60, 80]	-0.0352	-0.0166	0.2827	0.2039	-0.3062	-0.2190	0.2573	0.1941	967
(40, 60]	-0.0219	-0.0130	0.2145	0.1490	-0.2282	-0.1622	0.1998	0.1407	1060
(20, 40]	0.0096	0.0171	0.2157	0.1654	-0.2191	-0.1641	0.2127	0.1662	1048
[8, 20]	-0.0150	-0.0150	0.1847	0.1332	-0.1856	-0.1303	0.1836	0.1445	450
Test statistics					69.3707**[a]				
Panel C: CME									
(80, 105]	-0.3509	-0.1287	4.2746	3.2544	-4.4934	-3.7474	4.0425	2.9710	1055
(60, 80]	-0.0796	0.2133	4.0243	3.2705	-4.2241	-3.8294	3.8356	2.9169	949
(40, 60]	-0.2386	0.2841	3.4716	2.6425	-3.9061	-3.3511	3.0786	2.3496	1057
(20, 40]	0.0137	0.2164	2.7914	2.1636	-2.8971	-2.5648	2.6941	1.9219	1068
[8, 20]	0.1005	-0.1444	1.9750	1.5074	-1.7628	-1.4761	2.2161	1.6406	410
Test statistics			68.9583**[a]		48.6807**[a]		25.1099**[a]	9.5344**[b]	
								0.1461**[c]	

Notes: This table provides non-parametric results of the relationship between Nikkei futures mispricing and time to expiration. Mispricing, absolute mispricing, underpricing and overpricing are each categorised into 5 groups by time to expiration in descending order, with each group covering roughly 20 trading days. The means (medians) of the mispricing data are checked for monotonic orderings. The mispricing data are in percentage. Shaded columns indicate the location of the monotonic relationships observed. With the null hypothesis of equal means across the groups, significance of the means is tested by F-statistics of an OLS regression on dummy variables that represent the groups. With the null hypothesis of equal medians across the groups, significance of the medians is tested by the Jonckheere trend test (Jonckheere, 1954; Terpstra, 1952); Kendall's (1938) tau-b coefficients are calculated additionally to help identify the direction of median orderings. [a] F-statistics. [b] Standardised Jonckheere-Terpstra statistics. [c] Kendall's tau-b coefficients (one-tailed). **denotes significance at the 5% level.

Table 4.11 Nikkei 225 futures mispricing and stock volatility

	Mispricing (%)		Absolute mispricing (%)		Underpricing (%)		Overpricing (%)		
Stock volatility (%)	Mean	Median	Mean	Median	Mean	Median	Mean	Median	No. of obs [d]
Panel A: OSE									
(0.0289, 0.1926]	-0.0812	-0.0489	0.3342	0.2431	-0.3741	-0.2822	0.2843	0.2057	908
(0.0205, 0.0289]	-0.0680	-0.0356	0.2728	0.2076	-0.3028	-0.2425	0.2342	0.1884	901
(0.0158, 0.0205]	-0.0665	-0.0439	0.2527	0.1892	-0.2758	-0.2003	0.2210	0.1692	921
(0.0120, 0.0158]	-0.0208	-0.0025	0.2259	0.1665	-0.2443	-0.1819	0.2072	0.1553	895
[0.0019, 0.0120]	-0.0149	0.0015	0.1861	0.1272	-0.2024	-0.1300	0.1701	0.1251	900
Test statistics	6.6462**[a]		46.0638**[a]	12.7057**[b]	27.9851**[a]	-10.0536**[b]	16.6563**[a]	7.3849**[b]	
				0.1380**[c]		-0.1487**[c]		0.1183**[c]	
Panel B: SGX									
(0.0283, 0.1908]	-0.0636	-0.0436	0.3391	0.2591	-0.3726	-0.2841	0.2997	0.2290	918
(0.0202, 0.0283]	-0.0631	-0.0477	0.2807	0.2146	-0.3016	-0.2333	0.2530	0.1952	921
(0.0156, 0.0202]	-0.0635	-0.0516	0.2666	0.1986	-0.2959	-0.2159	0.2296	0.1866	909
(0.0119, 0.0156]	-0.0071	-0.0008	0.2483	0.1740	-0.2546	-0.1845	0.2420	0.1601	919
[0.0019, 0.0119]	-0.0247	-0.0037	0.2087	0.1402	-0.2291	-0.1539	0.1875	0.1248	907
Test statistics			27.9282**[a]	11.8805**[b]	17.8626**[a]	-8.6795**[b]		7.8965**[b]	
				0.1283**[c]		-0.1281**[c]		0.1252**[c]	
Panel C: CME									
(0.0286, 0.1988]	-0.0016	-0.0871	3.9398	2.9723	-3.8772	-3.1705	4.0046	2.8735	905
(0.0205, 0.0286]	0.4844	0.4814	3.2888	2.6094	-3.1638	-2.5576	3.3883	2.6747	898
(0.0158, 0.0205]	0.2068	0.1967	3.6085	2.6679	-3.5434	-2.6417	3.6686	2.6722	900
(0.0122, 0.0158]	-0.3709	-0.0698	3.2195	2.4342	-3.5317	-3.0999	2.8967	2.0164	903
[0.0057, 0.0122]	-1.2189	-0.2921	3.2269	2.3225	-4.1604	-3.4714	2.1559	1.8587	904
Test statistics								8.4513**[b]	
								0.1294**[c]	

Notes: This table provides the non-parametric results of the relationship between Nikkei futures mispricing and stock volatility. Stock volatility is estimated by the fitted value of the conditional variance of a GARCH (1, 1) model of Bollerslev (1986) with a constant mean equation. Mispricing, absolute mispricing, underpricing and overpricing are each divided into 5 groups of roughly equal size by the volatility estimate in descending order. The means (medians) of the mispricing data are checked for monotonic orderings. The stock volatility and mispricing data are in percentage. Shaded columns indicate the location of the monotonic relationships observed. With the null hypothesis of equal means across the groups, significance of the means is tested by F-statistics of an OLS regression on dummy variables that represent the groups. With the null hypothesis of equal medians across the groups, significance of the medians is tested by the Jonckheere trend test (Jonckheere, 1954; Terpstra, 1952); Kendall's (1938) tau-b coefficients are calculated additionally to help to identify the direction of median orderings. [a] F-statistics. [b] Standardised Jonckheere-Terpstra statistics. [c] Kendall's tau-b coefficients (one-tailed). [d] A period of 28 trading days during 14/10/2008-21/11/2008 (OSE, SGX), 15/10/2008-21/11/2008 (CME) are excluded from the data because of extreme volatility. ** denotes significance at the 5% level.

Table 4.12 Nikkei 225 futures mispricing and trading volume

	Mispricing (%)		Absolute mispricing (%)		Underpricing (%)		Overpricing (%)		
Futures volume	Mean	Median	Mean	Median	Mean	Median	Mean	Median	No. of obs
Panel A: OSE									
(82555.2, 393139]	-0.0495	-0.0198	0.2472	0.1752	-0.2758	-0.2024	0.2139	0.1564	911
(53987, 82555.2]	-0.0438	-0.0204	0.2139	0.1500	-0.2395	-0.1640	0.1841	0.1408	911
(37155.2, 53987]	-0.0551	-0.0185	0.2437	0.1708	-0.2774	-0.1966	0.2043	0.1406	910
(24576.8, 37155.2]	-0.0490	-0.0291	0.2627	0.1978	-0.2868	-0.2145	0.2340	0.1884	911
[65, 24576.8]	-0.0545	-0.0307	0.3167	0.2472	-0.3409	-0.2709	0.2878	0.2206	911
Panel B: SGX									
(94467.4, 568962]	-0.0721	-0.0528	0.2675	0.1860	-0.2896	-0.1953	0.2362	0.1757	921
(58340.2, 94467.4]	-0.0333	-0.0115	0.2133	0.1500	-0.2363	-0.1654	0.1881	0.1381	920
(21217, 58340.2]	-0.0610	-0.0326	0.2824	0.1872	-0.3150	-0.2205	0.2433	0.1615	921
(13891.6, 21217]	-0.0122	0.0044	0.2725	0.2126	-0.2878	-0.2269	0.2576	0.1890	920
[0, 13891.6]	-0.0451	-0.0211	0.3174	0.2539	-0.3413	-0.2747	0.2902	0.2426	921
Panel C: CME									
(11226.2, 59428]	-0.3853	-0.2179	3.6314	2.5787	-3.7522	-2.9399	3.4923	2.3012	908
(6783, 11226.2]	0.0914	0.2895	3.1119	2.4851	-3.1708	-2.5595	3.0583	2.4315	907
(2767, 6783]	-0.5277	0.0198	2.8437	2.0378	-3.3789	-2.4077	2.3109	1.7901	906
(1253, 2767]	0.2409	0.3154	3.4770	2.7324	-3.5534	-2.9596	3.4131	2.5324	907
[3, 1253]	-0.1268	0.0569	4.3244	3.4656	-4.4757	-4.0185	4.1746	3.1127	911

Notes: This table provides the non-parametric results of the relationship between Nikkei 225 futures mispricing and futures trading volume. Mispricing, absolute mispricing, underpricing and overpricing are each sorted into 5 groups of roughly equal size by futures trading volume in descending order. The means (medians) of the mispricing data are checked for monotonic orderings. The mispricing data are in percentage.

checking for monotonic orderings in the means (medians) of the mispricing data. Table 4.12 reports the results. However, there does not seem to be any monotonic relationship between mispricing and trading volume in the Nikkei futures markets. Rather, the futures volume appears to exhibit a U-shaped pattern, with the lowest mispricing in magnitude associated with modest volume. It seems that more mispricings attract heavier futures volume, yet more mispricings might also be related to relatively thin trading. Empirical studies using multivariate regressions (e.g. Brailsford and Cusack, 1997; Wang, 2011; Cummings and Frino, 2011) generally document an insignificant effect of futures volume on mispricing. With the non-parametric method, I still cannot clearly conclude the relationship between mispricing and futures volume.

4.3.5 Path dependence in Nikkei 225 futures mispricing

The practice of early unwinding has been ignored so far. Here I look at its potential effect on the Nikkei mispricing series in terms of path dependence. Specifically, I address the following question: what is the probability that the Nikkei futures mispricing crosses a lower/upper transaction cost bound on day t+1, given that it crosses a lower/upper bound on day t-1 and returns to zero on day t? If the stochastic behaviour of mispricing does not depend on its past, the probability of hitting a lower/upper bound on day t+1 should be equal, or 0.5. But if early unwinding protects mispricing from reversing its direction, the future behaviour of mispricing becomes conditional on its historical behaviour, and thus the probability of hitting a lower/upper bound on day t+1 becomes conditional as well. Based on MacKinlay and Ramaswamy (1988) and Kempf (1998), I calculate the conditional probability of each of the four scenarios: “lower, lower”, “lower, upper”, “upper, upper” and “upper, lower”. A “lower, lower” scenario describes the case that mispricing hits a lower bound on day t+1, given that it hits a lower bound on day t-1 and returns to zero on day t; similarly, a “lower, upper” scenario describes the case that mispricing hits an upper bound on day t+1, given that it hits a lower bound on day t-1 and returns to zero on day t; and so forth. The narrower transaction cost bounds, i.e. 0.5% for the OSE, SGX and 1.5% for the CME, are adopted to calculate the conditional probabilities as there are more observations to enable valid significance tests. Table 4.13 shows that the “lower, lower”, “upper,

upper" scenarios have much larger conditional probabilities in each of the Nikkei futures markets. χ^2 tests are performed to test the null hypothesis that there is no association between hitting a lower/upper bound on day t+1 and hitting a lower/upper bound on day t-1, given that mispricing returns to zero on day t. Since the χ^2 statistics are highly significant, the null hypothesis can be rejected, and thus I support path dependence in the Nikkei futures markets, with the argument that the Nikkei futures mispricings are more likely to cross the same transaction cost bound as the bound they crossed in the past. The daily measure makes the argument stronger compared with studies using higher-frequency data (e.g. MacKinlay and Ramaswamy, 1988; Kempf, 1998).

Table 4.13 Path dependence in Nikkei 225 futures mispricing

Scenario	Conditional probability	No. of obs
Panel A: OSE		
0.5% Transaction costs		
Lower, lower	0.8750	56
Lower, upper	0.1250	8
Upper, upper	0.7407	20
Upper, lower	0.2593	7
χ^2 statistic	42.2593**	
Panel B: SGX		
0.5% Transaction costs		
Lower, lower	0.8302	44
Lower, upper	0.1698	9
Upper, upper	0.6316	12
Upper, lower	0.3684	7
χ^2 statistic	24.4290**	
Panel C: CME		
1.5% Transaction costs		
Lower, lower	0.9000	81
Lower, upper	0.1000	9
Upper, upper	0.8714	122
Upper, lower	0.1286	18
χ^2 statistic	134.8571**	

Notes: This table gives the evidence of path dependence in the Nikkei futures mispricing. The conditional probabilities are calculated for each of the four scenarios: "lower, lower", "lower, upper", "upper, upper" and "upper, lower". A "lower, upper" scenario describes the case that mispricing hits an upper bound on day t+1, given that it hits a lower bound on day t-1 and returns to zero on day t; other scenarios can be analogously defined. The transaction costs are 0.5% for the OSE and SGX, 1.5% for the CME. The χ^2 tests are based on the null hypothesis that there is no association between hitting a lower/upper bound on day t+1 and hitting a lower/upper bound on day t-1, given that mispricing returns to zero on day t. ** denotes significance at the 5% level.

4.4 Index arbitrage activities in the Nikkei 225 futures markets

4.4.1 The ESTAR model

An interesting dynamic issue is to measure the reaction of a market to a given mispricing. The speed of the reaction can be interpreted as the propensity-to-arbitrage of the market, a gauge of how quickly index arbitrage activities take place to pull deviated prices back to equilibrium. A parametric estimate of such propensity is the smoothness parameter in an ESTAR model. Besides, different trading objectives, capital constraints, transaction costs and perceived risks contribute to heterogeneous investors (Tse, 2001), such that in the aggregate a market is more likely to adjust price discrepancies in a smooth, gradual fashion than in an discontinuous, abrupt way. Taking market participants as a whole, the ESTAR model has an exponential transition function that is able to depict such adjustments in the sense that the transition between regimes is continuous and smooth, and that large mispricings are removed more rapidly than small mispricings. Econometrically, the ESTAR model belongs to the family of regime-switching models for returns, and it is often proved to outperform other regime-switching models for returns, in terms of better explanation of the nonlinear adjustment process of futures mispricing.

Here it is assumed that the Nikkei futures mispricing follows an ESTAR model; the linear alternative is an autoregressive (AR) model, as Table 4.9 suggests linear dependence in the mispricing. Following Teräsvirta (1994) and Michael et al. (1997), I formulate a STAR model as below:

$$y_t = k + \sum_{j=1}^{p} \pi_j y_{t-j} + (k^* + \sum_{j=1}^{p} \pi_j^* y_{t-j}) \times T(y_{t-d}) + u_t \tag{4.8}$$

where $\{y_t\}$ is a stationary, ergodic series; k, k^* are constants; π_j, π_j^* are adjustment coefficients, j=1, 2, …, p, with p as a positive integer; $u_t \sim \text{iid}(0, \sigma_t^2)$; y_{t-d} is the transition variable with the delay parameter d, d>0; $T(\cdot)$ is a continuous smooth transition function, bounded between 0, the middle regime where no investors will trade, and 1, the outer regime where all investors will trade. An exponential STAR (ESTAR) model has an exponential $T(\cdot)$ as:

$$T(y_{t-d}) = 1 - \exp[-\gamma(y_{t-d} - c^*)^2] \tag{4.9}$$

The location parameter c^* gives the centre of $T(\cdot)$. With the restriction $k^*=c^*=0$, equations (4.8)-(4.9) form the exponential autoregressive (EAR) model of Haggan and Ozaki (1981). The smoothness parameter γ, an estimate of the propensity-to-arbitrage, measures the rate of transition from one regime to the other, or how quickly investors respond to mispricing in a market. The higher the value of γ, the greater is the speed that deviated prices are adjusted towards equilibrium, and hence more arbitrage activities. γ should be positive in value. If $\gamma=0$, or $T(\cdot)=0$, the ESTAR model (4.8)-(4.9) reduces to a linear AR(p) model:

$$y_t = k + \sum_{j=1}^{p} \pi_j y_{t-j} + u_t \tag{4.10}$$

Thus, π_j's are the adjustment coefficients in the middle regime; equation (4.10) constitutes an ESTAR model under the null hypothesis H_0: $\gamma=0$.

If $\gamma=\infty$, or $T(\cdot)=1$, the ESTAR model (4.8)-(4.9) also becomes a linear AR(p) model but with a different representation:

$$y_t = k + k^* + \sum_{j=1}^{p} (\pi_j + \pi_j^*) y_{t-j} + u_t \tag{4.11}$$

As such, $(\pi_j+\pi_j^*)$ measure the adjustments towards equilibrium in the outer regime. The adjustment coefficients are analysed more deeply in section 4.4.4.

Alternatively, a logistic STAR (LSTAR) model has a logistic transition function as:

$$T(y_{t-d}) = \{1 + \exp[-\gamma(y_{t-d} - c^*)]\}^{-1} \tag{4.12}$$

The effect of transaction costs on the cost of carry model justifies an exponential rather than a logistic transition function. With the restriction $k^*=c^*=0$, equation (4.9) is a U-shaped curve with quicker (slower) reversion for larger (smaller) mispricings, which is in agreement with the expectation that arbitrage rises with the magnitude of mispricing. Nonetheless, under the restriction, equation (4.12) is monotonically increasing, suggesting that arbitrage increases over time without any relevance to mispricing, and hence LSTAR models are not able to capture the mean-reverting behaviour of mispricing. The superiority of the ESTAR models is confirmed by a formal selection procedure of Teräsvirta (1994), which will be provided later. Therefore, I only model the nonlinear adjustment process of the Nikkei futures mispricing with an ESTAR specification.

4.4.2 Methodology

4.4.2.1 Unit root tests

Given the positive relationship between mispricing and time to maturity (section 4.3.4.1), I run an OLS regression of the Nikkei futures mispricing on a constant *c* and time to maturity (*T*-*t*):[51]

$$Mis_t = c + \beta_t (T - t) + Mis_t^*$$

The error term Mis_t^* is the demeaned mispricing series free from the effect of time to maturity.[52] To check the suitability of Mis_t^* as the transition variable in equation (4.8), a set of unit root tests are performed to examine whether the series is stationary. These tests include Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Zivot-Andrews (ZA). Appendix 4.3 provides methodological details of these tests.

4.4.2.2 Linearity tests

Assume that the demeaned mispricing series is the transition variable, it is at first modelled as a linear AR(*p*) process as equation (4.10) in each market; the model order *p* is selected by Box-Jenkins (1976) approach. It is necessary to consider whether the linear AR is able to adequately describe the dynamics of the mispricing. This is examined by taking the linear AR model as the null model and the ESTAR model as the alternative. The null hypothesis of linearity

---

[51] The regression is run to remove the time to maturity from the Nikkei futures mispricing. As the mispricing is unobservable and has to be estimated, the regression could suffer from measurement errors in the mispricing. However, based on the analysis in section 4.2, errors in the mispricing estimated from COC2 (OSE, SGX) and COC3 in the original view (CME) should not be important, and errors in the mispricing as a dependent variable will not cause serious problems.

[52] The ESTAR-GARCH model is sensitive to outliers (Chan and McAleer, 2002). 7 trading days with outliers are later found to lead to excessive ARCH in the SGX residual. These trading days are 21/04/2000, 12/09/2001, 02/01/2013, 03/01/2013, 06/05/2013, 03/01/2014, and 03/11/2014. As such, for the mispricing in the SGX, the OLS regression is modified as:

$$Mis_t = c + \beta_t (T - t) + \sum_{i=1}^{7} dum_i + Mis_t^*$$

where dum_1=1 if the day is 21/04/2000, 0 otherwise; the other dummy variables are defined analogously. The regression error Mis_t^* is without the influence of the outliers and thus will be used in the following procedures. For consistency, it is still called the demeaned mispricing series.

can be expressed as H_0: γ=0, in which case an ESTAR model collapses to a linear AR model. However, under the hypothesis, the ESTAR model suffers from the problem of unidentified nuisance parameters, which means that with γ=0, the parameters k^*, π_j^* and c^* are not restricted in equations (4.8)-(4.9) and hence the model is not identified (Teräsvirta, 1994; Franses and van Dijk, 2000). The problem can be circumvented using the Lagrange multiplier (LM)-type linearity test proposed by Saikkonen and Luukkonen (1988) and Teräsvirta (1994). To be more specific, given the value of d, run the following auxiliary regression by OLS:

$$\hat{u}_t = \beta_{00} + \sum_{j=1}^{p} (\beta_{0j} y_{t-j} + \beta_{1j} y_{t-j} y_{t-d} + \beta_{2j} y_{t-j} y_{t-d}^2) + v_t \tag{4.13}$$

where the dependent variable is the residual estimated from equation (4.10); v_t is the residual from the auxiliary regression. The null hypothesis of linearity H_0: γ=0 corresponds to H_{01}: $\beta_{1j}=\beta_{2j}=0$, under which a LM-type statistic asymptotically follows a χ^2 distribution with $2p$ degrees of freedom. The alternative hypothesis is an ESTAR(p) model. To specify d, the linearity test is repeated for different candidates of d, and d is selected as the one that generates the smallest p-value of the test, because a correct d should have the highest power in the test (Tsay, 1989; Teräsvirta, 1994). With the restriction $k^*=c^*=0$, it is useful to test two additional hypotheses, H_{02}: $\beta_{1j}=0$ against the alternative hypothesis of an ESTAR(p) model, and provided that H_{02} is not rejected, H_{03}: $\beta_{2j}=0 \mid \beta_{1j}=0$ against the alternative hypothesis of an EAR(p) model (Michael et al., 1997). Ordinary F-statistics approximate the LM-type statistics, and for data with relatively large p and small sample, the F-statistics are more powerful and without size distortions (Teräsvirta, 1994).

4.4.2.3 Selection between ESTAR and LSTAR models

If linearity is rejected, the alternative hypothesis, an ESTAR(p) specification as equation (4.8), will be used to model the Nikkei futures mispricing. But prior to the modelling, I formally demonstrate the incompatibility of the LSTAR model with the data using the selection approach of Teräsvirta (1994). Consider a similar auxiliary regression by OLS:

$$\hat{u}_t = \beta_{00} + \sum_{j=1}^{p} (\beta_{0j} y_{t-j} + \beta_{1j} y_{t-j} y_{t-d} + \beta_{2j} y_{t-j} y_{t-d}^2 + \beta_{3j} y_{t-j} y_{t-d}^3) + v_t \tag{4.14}$$

and test three null hypotheses as the following:

H_{04}: β_{3j}=0

H_{05}: β_{2j}=0 | β_{3j}=0

H_{06}: β_{1j}=0 | β_{2j}=β_{3j}=0

The hypotheses H_{04}, H_{05} and H_{06} are tested consecutively by F-tests. The relative strengths of rejecting these hypotheses shed light on the suitability of a model. Provided that the p-value of the test of H_{05} is the smallest, the ESTAR(p) model is favoured by the data; otherwise the LSTAR(p) model is more desirable.

4.4.2.4 Estimation and evaluation

If the ESTAR(p) model is selected as the mean equation, the exponential transition function, equation (4.9), is standardised by dividing its exponent by the sample variance of the transition variable to make the smoothness parameter γ scale-free and to facilitate searching for initial values (Teräsvirta, 1994; van Dijk et al., 2002). The model order p is determined by the method of Haggan and Ozaki (1981): keep γ fixed at one of a grid of values such that the ESTAR model becomes linear, and estimate the resultant model with different values of p; and p is selected as the order with which the model has the smallest Akaike Information Criterion (AIC).

The estimation of an ESTAR model is by nonlinear least squares (NLS). This is equivalent to maximum likelihood if the model residual u_t is normal; otherwise NLS estimates can be interpreted as quasi-maximum likelihood estimates (van Dijk et al., 2002). The NLS estimates are consistent and asymptotically normal under certain conditions, which hold provided that $\{y_t\}$ is stationary and ergodic, $u_t \sim \text{iid}(0, \sigma_t^2)$ (Klimko and Nelson, 1978; Tong, 1990; Michael et al., 1997). The starting values are also obtained by a grid search over γ and estimating the resultant linear model (Teräsvirta, 1994; van Dijk et al., 2002). Since there may be several local maxima in the likelihood function, various sets of starting values are used, including the estimates with the lowest residual sum of squares (RSS), the estimates with the highest log likelihood, and the OLS estimates. Among the models whose algorithms converge and parameter estimates look reasonable, the final model is decided as the one that generates the lowest residual variance.

For the variance equation, u_t is allowed to follow a GARCH (1, 1) process of Bollerslev (1986):

$$u_t = \sigma_t \eta_t \tag{4.15}$$

$$\sigma_t^2 = \omega + a u_{t-1}^2 + b \sigma_{t-1}^2 \tag{4.16}$$

where $\eta_t \sim$ iid(0,1); ω>0; a≥0; b≥0; a+b<1; σ_t is a time-varying, positive and measurable function of the information set at time t-1. This model is chosen because a preliminary estimation of equations (4.8)-(4.9) reveals significant ARCH effect in the residual, which could lead to severe problems in the estimation. Besides, the GARCH (1, 1) model is widely used and has fewer parameters than higher order GARCH models.[53] The estimation of equations (4.15)-(4.16) is by maximum likelihood, or quasi-maximum likelihood if η_t is not assumed to be normal.

Equations (4.8)-(4.9), (4.15)-(4.16) form an ESTAR-GARCH model. The stationarity and ergodicity of the model and the existence of moments are proved in Chan and McAleer (2002). Essentially they require that $\{y_t\}$ is stationary and ergodic, $u_t \sim$ iid(0, σ_t^2). However, joint estimation of the mean equation and the variance equation is difficult. I apply the two-step procedure of Chan and McAleer (2002): estimate equations (4.8)-(4.9) by NLS, and then estimate equations (4.15)-(4.16) using the residual computed from equations (4.8)-(4.9). The separate estimation of the mean and the variance does not affect the consistency and the asymptotic normality of the (quasi-)maximum likelihood estimates, nor bias the ESTAR model. See proofs in Chan and McAleer (2002).[54]

The estimated ESTAR-GARCH model is subjected to diagnostic checks, including the LM serial correlation test of Eitrheim and Teräsvirta (1996) for residual autocorrelation, the ARCH-LM test of Engle (1982) for remaining ARCH, the BDS independence test of Brock et al. (1996) for remaining nonlinearity, and the Jarque-Bera (1980) test for residual normality. The RSS of the linear AR model and the RSS of the ESTAR-GARCH model are compared to see whether the latter is smaller.

---

[53] It is found that a GARCH (2, 2) process is necessary to remove the excessive ARCH in the residual of SGX (sample A). Thus, for SGX (sample A) only, equation (4.16) is $\sigma_t^2 = \omega + a_1 u_{t-1}^2 + a_2 u_{t-2}^2 + b_1 \sigma_{t-1}^2 + b_2 \sigma_{t-2}^2$, where the sum of the non-negative (G)ARCH parameters is less than 1.

[54] It is recognised that the separate estimation could lead to a loss of efficiency of the estimates. Due to computational difficulties of the joint estimation, however, the two-step procedure provides a practical way to estimate the ESTAR-GARCH.

4.4.3 Empirical results

Table 4.14 reports the unit root test statistics for the demeaned mispricing series of the three Nikkei markets. The ADF test and the PP test suggest strong rejection of the null hypothesis of a unit root. The KPSS test does not suggest rejection of the stationary null even at the 10% significance level. Allowing for an endogenous one-time structural break, the ZA test again indicates strong rejection of the null hypothesis of a unit root in the series. Overall, the results of these unit root tests are consistent: the demeaned mispricing series is stationary at the level, or I(0). Thus it will act as the transition variable in the modelling.[55] It follows that the restriction $k=k^*=c^*=0$ will be applied to the ESTAR model, for the series $\{y_t\}$ is mean-adjusted ($k=k^*=0$) and the transition functions are usually centred at zero ($c^*=0$); fixing c^* can also improve the accuracy of the remaining estimates (Chan and McAleer, 2002). This is a common restriction to reduce model parameters in ESTAR studies with demeaned data; see Michael et al. (1997), Anderson (1997), Taylor (2007), among others.

The demeaned mispricing series is first modelled as a linear AR(p) process as equation (4.10) in each market during the whole sample period. It seems that p=6 for the OSE and SGX, p=4 for the CME, but the residuals are autocorrelated by Ljung-Box (1978) Q-statistics.[56] The residual autocorrelation may result from the structural break in the data. Hence two stability tests are conducted: the Quandt-Andrews unknown breakpoint test shows the breakpoint on 16/10/2008; the recursive coefficients show the breakpoint during October-November 2008, which are in agreement with the market turbulence characterised by trading halts, Nikkei index plummets and abnormal volatility at that time. For this reason, in the process of modelling, my data range is divided into a pre-crisis period (sample A) and a post-crisis period (sample B), excluding a short turmoil interval in the middle of the crisis, as listed in Table 4.15.

[55] According to Granger and Teräsvirta (1993), it is impossible to test the ergodicity of a finite series in practice; however, for a simplified nonlinear model $y_t=g(y_{t-1})+\varepsilon_t$, the ergodicity of y_t is essentially achieved if $|g(y)/y|<1$ for $|y|$ large. In the ESTAR model equation (4.8), this implies that either $u_t\neq 0$, or $y+[k+\sum\pi_j y+(k^*+\sum\pi_j^* y)\times T(y)]\neq 0$ for $|y|$ large. These are satisfied for the demeaned mispricing series.

[56] Results are available upon request.

Table 4.14 Unit root test statistics for the demeaned mispricing series

	ADF	PP	KPSS	ZA
OSE	-18.8820***	-59.6999***	0.0358	-17.4756***
SGX	-19.2524***	-58.6547***	0.0377	-18.0052***
CME	-8.1904***	-15.4427***	0.1053	-8.0323***

Notes: This table reports the statistics of unit root tests, i.e. Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Zivot-Andrews (ZA), for the mispricing series by market. The mispricing series is demeaned and the time to maturity effect removed by running the following OLS regressions. For the OSE, CME: $Mis_t = c + \beta_t (T-t) + Mis_t^*$; for the SGX: $Mis_t = c + \beta_t (T-t) + \sum_{i=1}^{7} dum_i + Mis_t^*$, where *dum* represents 7 trading days with outliers. The error term Mis_t^* is the series that undergoes the unit root tests. The ADF test is carried out excluding any constant and trend term because Mis_t^* is demeaned and the time to maturity effect removed. The lag length *l* is determined by Schwartz Bayesian Criterion (SBC). The constant and trend are also excluded from the PP test. However, for robustness the KPSS test is carried out with a null of trend stationarity. The test critical values for the ADF test and the PP test are -2.57(1% level), for the KPSS test are 0.12 (10% level), for the ZA test are -4.80 (1% level). They are taken from MacKinnon (1991), Kwiatkowski et al. (1992), and Zivot and Andrews (1992), respectively. *** denotes significance at the 1% level.

Table 4.15 Sample division

	Pre-crisis (sample A)	Post-crisis (sample B)
OSE	28/06/1996-09/10/2008	04/11/2008-30/12/2014
SGX	28/06/1996-09/10/2008	04/11/2008-31/12/2014
CME	09/01/1997-12/09/2008	02/12/2008-31/12/2014

Notes: This table lists the start and end dates of each sample in each Nikkei market. The whole data range is 20/06/1996-31/12/2014 (OSE, SGX); 01/01/1997-31/12/2014 (CME). In the process of modelling, it is split into a pre-crisis period (sample A) and a post-crisis period (sample B), excluding a short turmoil interval in the middle of the crisis.

Table 4.16 Estimation and evaluation results: the linear AR model

	OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
p	6	4	5	6	4	4
k	0.0000	0.0000	0.0001	-0.0001	0.0001	-0.0002
	(0.1898)	(-0.0810)	(0.9167)	(-0.7127)	(0.4880)	(-0.4741)
π_1	0.1958	0.3788	0.2247	0.3346	0.6755	0.5560
	(7.4765)	(9.1015)	(10.3369)	(9.0508)	(23.2624)	(11.9645)
π_2	0.1035	0.1542	0.1010	0.1353	0.1556	0.2216
	(4.6015)	(4.1665)	(4.4093)	(4.4840)	(5.2394)	(5.4275)
π_3	0.0529	0.1328	0.0488	0.1108	0.0742	0.1147
	(2.0718)	(3.5978)	(2.1652)	(3.9022)	(2.9855)	(3.1055)
π_4	0.0942	0.0878	0.1042	0.1036	0.0528	0.0582
	(4.5043)	(2.3424)	(5.0056)	(3.5220)	(2.4860)	(1.9417)
π_5	0.0584		0.0591			
	(2.6903)		(2.7986)			
π_6	0.0377			0.0250		
	(1.7406)			(0.9665)		
R^2	0.1140	0.3913	0.1260	0.3033	0.8789	0.8485
RSS	0.0312	0.0118	0.0293	0.0172	0.7220	0.4734
Q(6)	[1.0000]	[0.9416]	[0.9656]	[0.9849]	[0.9473]	[0.6868]
Q(12)	[0.9983]	[0.7760]	[0.8927]	[0.8815]	[0.1702]	[0.8117]
ARCH(12)	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
JB	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Notes: This table presents the estimation and evaluation results of the linear AR model, equation (4.10):

$$y_t = k + \sum_{j=1}^{p} \pi_j y_{t-j} + u_t$$

The estimation is by OLS with White (1980) heteroskedasticity-consistent standard errors and covariance. The model order p is determined by Box-Jenkins (1976) model selection criteria. Diagnostic checks include the Ljung-Box (1978) portmanteau test (Q), the ARCH-LM test (ARCH) of Engle (1982) and the Jarque-Bera (1980) normality test (JB). Q (m) and ARCH (m) are respective test statistics up to order m. Numbers in parentheses are t-statistics. Numbers in square brackets are p-values.

Table 4.17 Linearity tests

	OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
Panel A: The linearity test H_{01} for different *d*						
d						
1	2.25E-09	1.04E-14	6.01E-04	6.26E-07	3.21E-05	3.51E-07
2	3.61E-07	4.05E-01	1.99E-07	1.95E-02	7.76E-03	5.04E-01
3	6.04E-04	1.40E-01	1.34E-02	2.68E-03	1.93E-03	1.32E-02
4	1.51E-02	7.95E-04	1.93E-01	1.05E-02	9.28E-04	2.26E-01
5	2.35E-01	5.05E-02	1.01E-02	1.04E-03	9.78E-04	7.81E-02
Panel B: The linearity tests H_{01}-H_{03}						
d	1	1	2	1	1	1
H_{01}	2.25E-09	1.04E-14	1.99E-07	6.26E-07	3.21E-05	3.51E-07
H_{02}	2.33E-06	1.05E-12	1.34E-03	3.50E-06	3.93E-01	3.37E-01
H_{03}					3.91E-06	3.25E-08

Notes: This table gives the results of the linearity tests of the residual estimated from the linear AR model, equation (4.10). An auxiliary regression by OLS as equation (4.13) is run:

$$\hat{u}_t = \beta_{00} + \sum_{j=1}^{p} (\beta_{0j} y_{t-j} + \beta_{1j} y_{t-j} y_{t-d} + \beta_{2j} y_{t-j} y_{t-d}^2) + v_t$$

And three hypotheses, H_{01}:$\beta_{1j}=\beta_{2j}=0$, H_{02}: $\beta_{1j}=0$, H_{03}: $\beta_{2j}=0 \mid \beta_{1j}=0$ are tested by *F*-statistics. The *p*-values of the *F*-statistics are reported. Panel A shows the results of testing H_{01} for different *d* selected from {1, 2, 3, 4, 5}. *d* is determined as the candidate that generates the smallest *p*-value of the test. Panel B shows the results of testing the three hypotheses for the determined *d*.

Table 4.18 ESTAR vs LSTAR models

	OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
H_{04}	1.31E-01	7.30E-03	1.53E-03	3.77E-02	1.19E-01	8.30E-01
H_{05}	1.57E-06	7.80E-06	9.12E-05	1.37E-02	1.73E-06	1.48E-07
H_{06}	8.69E-05	4.42E-11	1.56E-04	2.75E-06	6.76E-01	1.05E-01

Notes: This table gives the results of the selection between ESTAR and LSTAR models. An auxiliary regression by OLS as equation (4.14) is run:

$$\hat{u}_t = \beta_{00} + \sum_{j=1}^{p} (\beta_{0j} y_{t-j} + \beta_{1j} y_{t-j} y_{t-d} + \beta_{2j} y_{t-j} y_{t-d}^2 + \beta_{3j} y_{t-j} y_{t-d}^3) + v_t$$

And three hypotheses, H_{04}: $\beta_{3j}=0$, H_{05}: $\beta_{2j}=0 \mid \beta_{3j}=0$, H_{06}:$\beta_{1j}=0 \mid \beta_{2j}=\beta_{3j}=0$ are tested by *F*-statistics. The *p*-values of the *F*-statistics are reported.

Table 4.16 presents the linear estimation results for each market in each sample. The model order *p* indicates that the linear dependence in the demeaned mispricing lasts for approximately a week. While the constants are not significantly different from zero, the AR coefficients are highly significant. The model residuals are not autocorrelated, but are heteroskedastic and non-normal. Based on the linear models, the linearity tests are performed and their results are in Table 4.17. Panel A shows the test results of H_{01} for different delay parameters *d* selected from {1, 2, 3, 4, 5}. The smallest *p*-values of the test occur when d=1 for OSE, SGX (sample B), CME; d=2 for SGX (sample A). Panel B shows the test results of H_{01}-H_{03}. It can be seen that linearity is rejected in each Nikkei market in each sample. Despite that the CME does not reject H_{02}, its strong rejection of H_{03} indeed reveals the presence of nonlinearity. As such, the null linear AR models can be rejected.

The results of the selection between ESTAR and LSTAR models are given in Table 4.18. H_{05} is most strongly rejected in all the data except the OSE, SGX in sample B. This reinforces the superiority of the ESTAR models over the LSTAR models for most mispricings. The relatively weak rejection of H_{05} in sample B of the OSE (SGX) may be because more observations lie above (below) zero, in which case an ESTAR model could be approximated by a LSTAR model. In fact, Teräsvirta (1994) finds that if data are asymmetrically distributed, the ESTAR and LSTAR models are close substitutes. Given that the substitutability disappears when the restriction $k=k^*=c^*=0$ is imposed, and more importantly, a logistic transition function contradicts the common understanding of the arbitrage behaviour, an ESTAR model with the restriction will be applied to each Nikkei market in each sample.

The ESTAR model is estimated by NLS; the GARCH model is estimated by quasi-maximum likelihood, both assuming a student *t*-distribution, with which the NLS estimates can be interpreted as quasi-maximum likelihood estimates and the two estimation methods are consistent in the ESTAR-GARCH framework. The estimation results of the ESTAR-GARCH are provided in Table 4.19. The model orders *p* reduces from 6 or 5 (sample A) to 4 (sample B) in the OSE and SGX, which implies a quicker adjustment of the two markets over time. The (standardised) smoothness parameter γ is quite small in all the markets in sample A, but in sample B, an increase in γ is found in the OSE and SGX, while a slight decrease in γ is found in the CME. The opposite directions of change in γ are clearly illustrated in Figure 4.5 (note the differences in scales of the vertical axes). The U-shaped transition functions reveal the mean-reverting behaviour of the Nikkei futures mispricing, with tails depicting quicker movements to equilibrium for larger mispricings. In the OSE and SGX, steeper transition functions in the post-crisis period suggest higher propensity-to-arbitrage, or more arbitrage activities to remove mispricing. In particular, about 0.02% investors respond to a mispricing of 1%, and about 0.04% investors respond to a mispricing of 1.5%; the counterpart proportions of investors in the pre-crisis sample are much lower. In the CME, as γ decreases slightly in sample B, the transition function becomes flatter, meaning slower market response to a given mispricing. Inter-market comparison indicates that the quickest market response to the Nikkei futures mispricing is in the CME before the crisis, which is consistent with my previous finding about the greater size and risk of the CME mispricing; however, after the crisis, it is the OSE that enjoys the quickest market response.

Table 4.19 also evaluates the estimated ESTAR-GARCH model. It is clear that the model does not suffer from any remaining autocorrelations, ARCH effects, or nonlinearity. Moreover, the RSS of the ESTAR-GARCH model is smaller than the RSS of the linear AR model in each market in each sample (compared with Table 4.16). The two-stage estimates could be inefficient, but the GARCH estimates in the table are generally very significant and efficiency does not appear to be a problem.[57] However, the Jarque-Bera (1980) test of residual normality is not passed because of excess kurtosis in the residual. This suggests that the model may not fully describe the higher moments of my data. Even so, I decide to retain the model as my goal is not to find a model that could explain everything in the data. The fairly satisfactory nature of the model exhibited by other diagnostic tests is more important for my research focus. The rejection of normality is also reported and tolerated by other ESTAR studies such as Michael et al. (1997) and Taylor (2007).

[57] A minor puzzle in Table 4.19 is the significance of most ω's even though they are very small in value. This could be caused by remaining deterministic components in the demeaned mispricing series and would not affect the variance model.

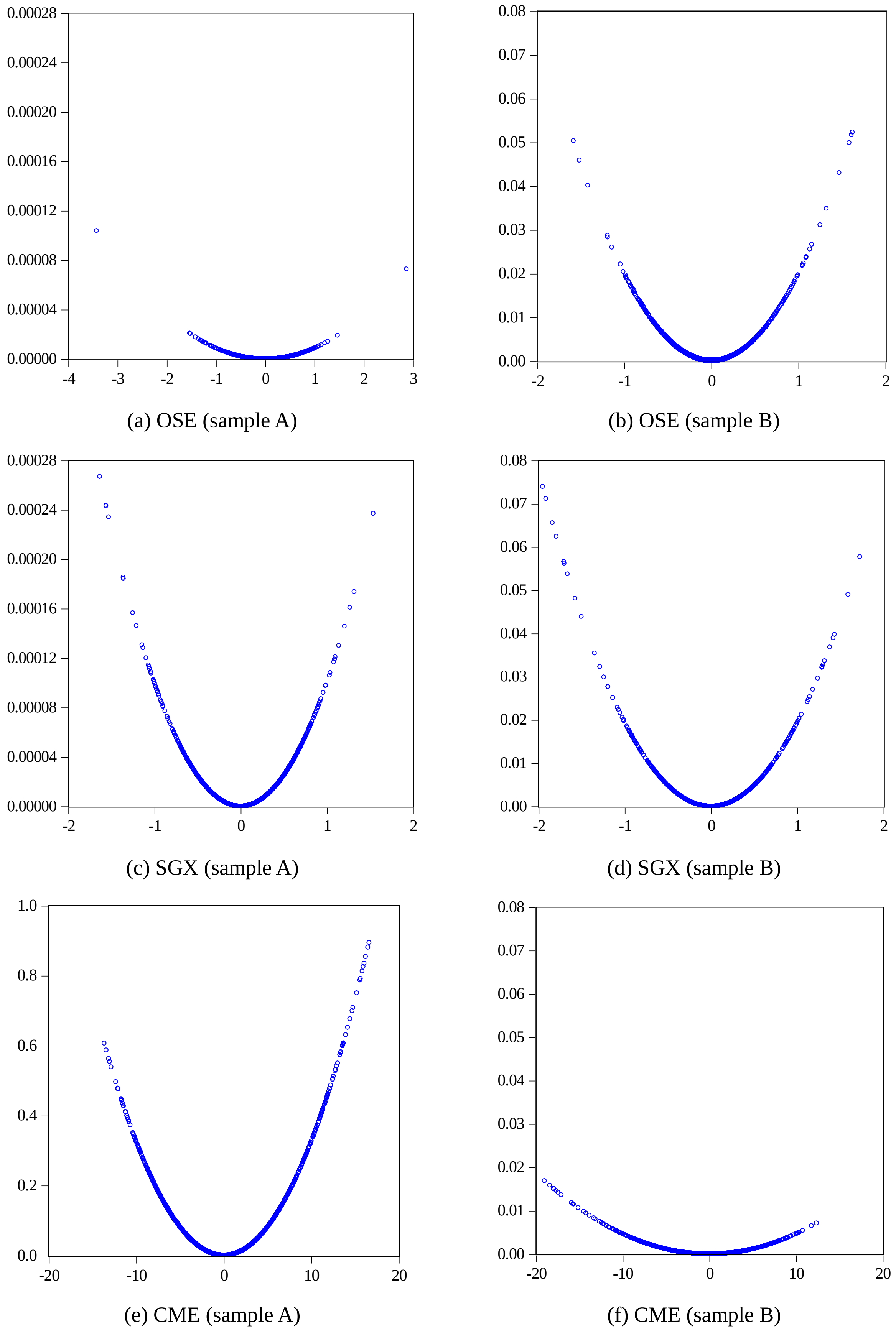


Figure 4.5 Transition functions in Nikkei 225 futures markets

Notes: (a)-(f) represent the transition functions computed from equation (4.9) in each Nikkei market in each sample. $T(y_{t\text{-}d})$ on vertical axis, $y_{t\text{-}d}$ on horizontal axis, have been multiplied by 100.

Table 4.19 The ESTAR-GARCH model

	OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
ESTAR coefficients						
p	6	4	5	4	4	4
d	1	1	2	1	1	1
γ	0.0009	1.9950	0.0100	1.9395	0.3260	0.0047
	(0.0073)	(3.7140)	(0.1426)	(4.0019)	(1.3951)	(0.0150)
π_1	0.2364	-0.0330	0.2165	0.0122	0.5744	0.4723
	(9.4586)	(-0.3350)	(9.8748)	(0.1310)	(18.6496)	(12.9091)
π_2	0.1526	0.0072	0.2015	-0.0169	0.1850	0.2453
	(7.1242)	(0.1524)	(6.8062)	(-0.4110)	(6.3220)	(7.1839)
π_3	0.0566	0.0578	0.0581	0.0364	0.0697	0.1541
	(2.7574)	(1.4238)	(2.7337)	(1.0790)	(2.5348)	(4.7825)
π_4	0.0873	0.0658	0.0684	0.0522	0.1113	0.0783
	(4.1525)	(1.7166)	(3.1657)	(1.7403)	(4.6614)	(2.6632)
π_5	0.0466		0.0453			
	(2.2320)		(2.1857)			
π_6	0.0417					
	(2.0618)					
π_1^*	-3.5581	0.4416	1.8244	0.3073	0.2604	6.6508
	(-0.0075)	(4.0012)	(0.1476)	(2.8330)	(2.8218)	(0.0152)
π_2^*	-8.7582	0.2429	-2.2817	0.2991	-0.1695	-3.5954
	(-0.0074)	(3.2591)	(-0.1540)	(4.6939)	(-1.6091)	(-0.0152)
π_3^*	4.6466	0.0837	-0.2018	0.1161	0.0742	-1.3846
	(0.0074)	(1.1435)	(-0.1117)	(1.8882)	(0.7645)	(-0.0152)
π_4^*	-5.8337	0.0051	1.3754	0.0444	-0.1207	-1.6491
	(-0.0074)	(0.0756)	(0.1470)	(0.8497)	(-1.4831)	(-0.0153)
π_5^*	9.5721		1.6016			
	(0.0074)		(0.1494)			
π_6^*	-4.3488					
	(-0.0074)					
GARCH coefficients [a]						
ω	1.09E-07	9.15E-07	4.76E-09	6.22E-06	2.51E-05	4.55E-05
	(3.1334)	(4.3185)	(1.3183)	(5.9142)	(4.4284)	(4.0407)
a_1	0.0539	0.2275	0.0963	0.4857	0.1097	0.1775
	(6.3732)	(4.9765)	(4.1796)	(4.3766)	(5.3348)	(4.3921)
a_2			-0.0909			
			(-4.1561)			
b_1	0.9371	0.6813	1.6254	0.1353	0.7851	0.6742
	(100.3153)	(14.5597)	(13.1883)	(1.6621)	(20.9452)	(11.4593)
b_2			-0.6311			
			(-5.2261)			
Evaluation						
R^2	0.1183	0.3999	0.1326	0.3075	0.8804	0.8521
RSS	0.0310	0.0116	0.0291	0.0171	0.7131	0.4620
LM(6)	[0.3838]	[0.8176]	[0.8813]	[0.7528]	[0.2468]	[0.3075]
LM(12)	[0.7523]	[0.6074]	[0.7065]	[0.7221]	[0.2181]	[0.5055]
ARCH(12)	[0.9254]	[0.1436]	[0.4823]	[0.8853]	[0.9714]	[0.9999]
BDS	[0.5540]	[0.1140]	[0.5860]	[0.3780]	[0.9660]	[0.9300]
JB	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Notes for Table 4.19: This table shows the estimation and evaluation results of the ESTAR-GARCH model, equations (4.8)-(4.9), (4.15)-(4.16):

$$y_t = k + \sum_{j=1}^{p} \pi_j y_{t-j} + (k^* + \sum_{j=1}^{p} \pi_j^* y_{t-j}) \times T(y_{t-d}) + u_t, \quad T(y_{t-d}) = 1 - \exp[-\gamma(y_{t-d} - c^*)^2];$$

$$u_t = \sigma_t \eta_t, \quad \sigma_t^2 = \omega + a u_{t-1}^2 + b\sigma_{t-1}^2.$$

The model restriction is $k=k^*=c^*=0$. y_t is the demeaned mispricing series. p is determined by the method of Haggan and Ozaki (1981). d is determined by the selection approach in the linearity tests. The estimation of the ESTAR model is by NLS; the estimation of GARCH is by quasi-maximum likelihood, both assuming a student t-distribution, with which the NLS estimates can be interpreted as quasi-maximum likelihood estimates. Diagnostic checks include the LM serial correlation test (LM) of Eitrheim and Teräsvirta (1996), the ARCH-LM test (ARCH) of Engle (1982), the BDS independence test (BDS) of Brock et al. (1996) and the Jarque-Bera (1980) normality test (JB). LM (m) and ARCH (m) are respective test statistics up to order m. Numbers in parentheses are z-statistics. Numbers in square brackets are p-values. [a] For SGX (sample A), a GARCH (2, 2) model, $\sigma_t^2 = \omega + a_1 u_{t-1}^2 + a_2 u_{t-2}^2 + b_1\sigma_{t-1}^2 + b_2\sigma_{t-2}^2$ is used as equation (4.16).

4.4.4 The heterogeneous arbitrage activities

One interpretation of the ESTAR model is the heterogeneity in the arbitrage behaviour. Apart from transaction costs, heterogeneous arbitrage activities may also contribute to the mean reversion of futures mispricing. Nonetheless, with heterogeneous arbitrageurs, small mispricings are argued to be resolved more rapidly than large mispricings. The rationale is that, based on a market composed at least of noise traders who divert prices away and fundamental traders who restore equilibrium, small price deviations with short-term risks and low capital requirements are more likely to be arbitraged. As such, large price deviations are mostly foregone, rather than resolved to pull the prices back to equilibrium (McMillan and Speight, 2006). The heterogeneity in the Nikkei markets is explored through the adjustment coefficients in the ESTAR model. Table 4.20 gives the ESTAR adjustment coefficients in the middle regime and the outer regime. Negative adjustment coefficients, especially in the outer regime, are indicative of mean reversion. In addition, following McMillan and Speight (2006), I test two parameter restrictions, H_{07}: $\pi_j=\pi_j+\pi_j^*=0$ to check the mean-reverting properties of mispricing and the interaction of heterogeneous arbitrageurs, and H_{08}: $\pi_j=\pi_j+\pi_j^*$ to check whether the adjustments in different regimes are symmetric.[58] The hypotheses are considered by Wald tests. *Wald*$_1$, *Wald*$_2$ are used to name the χ^2 statistics under H_{07}, H_{08}, respectively, and they are also reported in Table 4.20.

[58] H_{08} is tested separately for each lag and jointly for all lags.

For the OSE and SGX, negative adjustment coefficients in the outer regime in sample A suggest mean reversion of the mispricing. H_{07} is strongly rejected in the two markets, supporting the mean-reverting behaviour and the existence of heterogeneous arbitrageurs. The slow adjustments from one regime to the other are obvious, as the reversion even takes place 6 trading days after a given mispricing appear. Though slow, the adjustments in different regimes are symmetric, as H_{08} cannot be rejected. In sample B, both hypotheses are strongly rejected, and the reversion is found at low lags in the middle regime. While in the outer regime the reversion is not very apparent and prices seem to be driven further away from equilibrium, it is found that the size of the deviations decays over time. Large mispricings are removed more quickly than small mispricings within 2-3 trading days, after which the adjustments in different regimes become symmetric. The opposite is true for the CME. Before the crisis, the CME mispricing tends to exhibit persistence yet diminishing size of deviations. Large mispricings are arbitraged more quickly, but after 1 trading day, the adjustments in different regimes are symmetric. After the crisis, however, there is evidence of mean reversion, heterogeneity and symmetric adjustments. Therefore, it turns out that in the Nikkei markets, the effect of transaction costs may be stronger than the effect of heterogeneous arbitrageurs, such that large mispricings have quicker market responses than small mispricings, not the reverse.

Table 4.20 ESTAR adjustment coefficients

	OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
Panel A: Testing for mean reversion and heterogeneity (H_{07})						
j						
Middle regime adjustment coefficients						
1	0.2364	-0.0330	0.2165	0.0122	0.5744	0.4723
2	0.1526	0.0072	0.2015	-0.0169	0.1850	0.2453
3	0.0566	0.0578	0.0581	0.0364	0.0697	0.1541
4	0.0873	0.0658	0.0684	0.0522	0.1113	0.0783
5	0.0466		0.0453			
6	0.0417					
Outer regime adjustment coefficients						
1	-3.3217	0.4086	2.0409	0.3195	0.8347	7.1231
2	-8.6056	0.2500	-2.0802	0.2822	0.0155	-3.3502
3	4.7032	0.1415	-0.1437	0.1525	0.1439	-1.2304
4	-5.7465	0.0709	1.4438	0.0966	-0.0094	-1.5708
5	9.6187		1.6468			
6	-4.3070					
$Wald_1$	536.7086	1040.5250	602.6965	986.1742	16157.2793	12177.4101
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Panel B: Testing for symmetric adjustments (H_{08})						
j						
1	0.0001	16.0093	0.0218	8.0261	7.9628	0.0002
	[0.9941]	[0.0001]	[0.8826]	[0.0046]	[0.0048]	[0.9879]
2	0.0001	10.6217	0.0237	22.0329	2.5892	0.0002
	[0.9941]	[0.0011]	[0.8776]	[0.0000]	[0.1076]	[0.9879]
3	0.0001	1.3075	0.0125	3.5653	0.5845	0.0002
	[0.9941]	[0.2528]	[0.9111]	[0.0590]	[0.4446]	[0.9879]
4	0.0001	0.0057	0.0216	0.7220	2.1996	0.0002
	[0.9941]	[0.9397]	[0.8831]	[0.3955]	[0.1380]	[0.9878]
5	0.0001		0.0223			
	[0.9941]		[0.8813]			
6	0.0001					
	[0.9941]					
Joint $Wald_2$	0.0001	49.4841	0.0364	67.5145	12.3675	0.0002
	[1.0000]	[0.0000]	[1.0000]	[0.0000]	[0.0148]	[1.0000]

Notes: This table reports the adjustment coefficients estimated from the ESTAR-GARCH model, equations (4.8)-(4.9), (4.15)-(4.16); and the associated Wald statistics. Panel A shows the adjustment coefficients in the middle regime (π_j) and the outer regime ($\pi_j+\pi_j^*$), j=1, 2, ..., p. $Wald_1$ is a χ^2 statistic to test H_{07}: $\pi_j=\pi_j+\pi_j^*=0$ against $\pi_j\neq\pi_j+\pi_j^*\neq 0$. Rejection of H_{07} indicates the mean-reverting behaviour of mispricing and the heterogeneity in arbitrage activities. $Wald_2$ is a χ^2 statistic to test H_{08}: $\pi_j=\pi_j+\pi_j^*$ against $\pi_j\neq\pi_j+\pi_j^*$. Rejection of H_{08} indicates asymmetric adjustments in different regimes. Panel B shows the results of $Wald_2$ separately for each j and jointly for all j. Numbers in square brackets are p-values.

4.5 Discussion and conclusion

The chapter investigates the pricing of Nikkei 225 stock index futures contracts, the static and dynamic behaviour of the Nikkei futures mispricing and index arbitrage activities in the three Nikkei markets: the OSE, SGX and CME. The specific question it focuses on is whether the Nikkei futures mispricing, if any, represent profitable arbitrage opportunities for investors in the three Nikkei markets. The investigation starts from the cost of carry equilibrium between the Nikkei spot and futures markets. The standard cost of carry model cannot be directly applied to the triple-listed Nikkei futures contracts, as the standard model assumes continuous dividend payment over a year and ignores the effects of currency risk and time zones. Allowing for the unique characteristics of the Nikkei futures contracts, such as dividend lumpiness, currency risk and different trading hours, I find that the dividend payout practices of Japanese firms and the yen-dollar exchange rate fluctuations are essential in influencing theoretical Nikkei futures prices, while the effect of the time differences among the exchanges is negligible. Accordingly, this chapter modifies the standard cost of carry model for each Nikkei contract: the cost of carry model adjusted for dividends (COC2) for the OSE, SGX contracts; the cost of carry model adjusted for dividends and exchange rate fluctuations (COC3) in the original view for the CME contracts. This chapter further modifies the formula of no-arbitrage bounds to allow for the effect of transaction costs to study mispricing net of transaction costs, or profitable arbitrage opportunities in the three Nikkei exchanges.

The comprehensive new 19-year sample period covers a few important events in the Nikkei markets, including the Japanese “Big Bang”, the SGX shift from open outcry to electronic trading, and the 2008 financial crisis. With the sample, the chapter examines the static behaviour of the Nikkei mispricing in a systematic way. The Nikkei markets are found to be intrinsically connected, and the OSE and SGX may be more closely linked with each other than any one of them with the CME. Without transaction costs, the OSE and SGX are dominated by underpricing; the CME by overpricing. While this might imply different arbitrage strategies in the different Nikkei markets, the higher costs related to short sale could impede investors from carrying out short arbitrage in the OSE and SGX. With transaction costs, mispricing reduces considerably in the OSE and SGX, and the short arbitrage strategy could be even more difficult for institutional investors whose transaction costs are higher than those of brokers. By contrast, the large magnitude and strong persistence of the CME mispricing in the presence of transaction costs may suggest profitable arbitrage opportunities for brokers and institutional investors, but it is important to notice that the yen-dollar exchange rate fluctuations make the arbitrage costly and riskier. In fact, since the currency risk cannot be completely eliminated, the profit gained from the arbitrage in the CME is not strictly risk-free. Using non-parametric methods, I report a significantly positive relationship between the Nikkei mispricing and time to maturity, and between the Nikkei mispricing and stock volatility, consistent with mainstream studies. However, the relationship between the Nikkei mispricing and the Nikkei futures volume does not seem to be clear. Furthermore, the Nikkei mispricing shows strong evidence of path dependence and hence the impact of early unwinding.

The dynamic behaviour of the Nikkei mispricing is examined in terms of market responses to a given mispricing, or propensity-to-arbitrage. The whole sample is divided into a pre-crisis period and a post-crisis period at this stage to exclude structural changes. With demeaned mispricing series as the transition variable, a restricted ESTAR-GARCH model is constructed to describe the nonlinear adjustment processes of the Nikkei mispricing. In the post-crisis period, quicker market responses to mispricing are found in the OSE and SGX, but slower responses are found in the CME. This could be because of the increased currency risk in arbitraging the CME futures contracts in more recent years. Regarding the mean reversion of mispricing, the transaction cost argument is that arbitrage pulls deviated prices back inside the transaction cost bounds; as arbitrage increases with the magnitude of mispricing, large mispricings exceeding the transaction cost bounds are more likely to be removed. Heterogeneous arbitrageurs could also prevent prices from diverting away, but only small mispricings with low risks and capital requirements are likely to be exploited. The adjustment coefficients in the ESTAR model indicate the existence of mean reversion and heterogeneous arbitrage activities in the Nikkei markets. However, the effect of transaction costs may be stronger than the effect of heterogeneous arbitrageurs, as evidenced by quicker adjustments for larger mispricings.

Two implications from the chapter are as follows. First, I consider the triple-listing nature of the Nikkei futures contracts and key institutional differences among the Nikkei exchanges in studying the cost of carry, mispricing and index arbitrage in the Nikkei markets. In this respect, I find that the influences of the dividend and currency risks are essential on the theoretical Nikkei futures prices, while the influence of the different trading hours among the Nikkei exchanges is trivial. For this reason, I adjust the standard cost of carry model for dividends and exchange rate fluctuations for the Nikkei futures contracts. In the course of futures market globalisation, an increasing number of futures contracts become listed on more than one trading venue. Though based on the same asset, they can be quite different in specifications, costs and risks. These differences should be taken into consideration when pricing these futures contracts. Second, the Nikkei futures mispricing exhibits mean reversion, explained by transaction costs and heterogeneous arbitrageurs. Given the weaker effect of heterogeneity which may echo the low emphasis on individuals in the Japanese businesses, investors in the Nikkei markets may want to be more concerned about transaction costs in their arbitrage activities.

The index arbitrage behaviour in the Nikkei markets could be studied from another perspective by including the error correction mechanism in the smooth transition model. Besides, the asymmetric responses to positive or negative price deviations may exist in the conditional mean and conditional variance. These will be considered in Chapter 5.

Appendix 4.1 The turn-of-the-month effect

Table 4.2 reveals that the coefficients of D_{10}, the last trading day of June, are negative and insignificant in the OSE and SGX. It is suspected that the insignificance be associated with time-related anomalies such as the turn-of-the-month effect. Thus, 11 dummy variables that represent the last trading day of each calendar month except June are added to the regression model. Table A4.1 shows the results of the regression with the newly added dummy variables.

Table A4.1 The turn-of-the-month effect

	OSE			SGX		
Coefficient	Unrestricted	Restricted		Unrestricted	Restricted	
		Jun dummies	Dec dummies		Jun dummies	Dec dummies
β_0	0.0010**	0.0011**	0.0010**	0.0010**	0.0011**	0.0011**
β_1	0.0027**	0.0026**		0.0029**	0.0028**	
β_2	0.0025**	0.0024**		0.0028**	0.0027**	
β_3	0.0011*	0.0010		0.0012**	0.0011*	
β_4	0.0011*	0.0010*		0.0015**	0.0014**	
β_5	0.0014**	0.0013*		0.0015**	0.0014**	
β_6	0.0006	0.0005		0.0010*	0.0009	
β_7	0.0020**	0.0019**		0.0023**	0.0022**	
β_8	0.0019**	0.0018**		0.0022**	0.0021**	
β_9	0.0018**	0.0017**		0.0016**	0.0015**	
β_{10}	0.0000	-0.0001		-0.0004	-0.0005	
β_{11}	0.0029**		0.0029**	0.0023**		0.0022**
β_{12}	0.0012*		0.0012	0.0014**		0.0013**
β_{13}	0.0029**		0.0028**	0.0029**		0.0028**
β_{14}	0.0019**		0.0019**	0.0014**		0.0014**
β_{15}	0.0024**		0.0023**	0.0028**		0.0027**
β_{16}	0.0022**		0.0022**	0.0022**		0.0021**
β_{17}	0.0029**		0.0028**	0.0025**		0.0025**
β_{18}	0.0012**		0.0011**	0.0014**		0.0013**
β_{19}	0.0022**		0.0021**	0.0022**		0.0021**
β_{20}	0.0025**		0.0024**	0.0022**		0.0021**

Table A4.1 continued

Coefficient	OSE			SGX		
	Unrestricted	Restricted		Unrestricted	Restricted	
		Jun dummies	Dec dummies		Jun dummies	Dec dummies
β_{JAN}	-0.0009	-0.0010	-0.0010	-0.0007	-0.0008	-0.0008
β_{FEB}	-0.0009	-0.0010*	-0.0009	-0.0001	-0.0002	-0.0002
β_{MAR}	-0.0006	-0.0007	-0.0007	-0.0008	-0.0009	-0.0009
β_{APR}	0.0001	0.0000	0.0001	0.0006	0.0005	0.0005
β_{MAY}	-0.0010**	-0.0011**	-0.0011**	-0.0014**	-0.0015**	-0.0015**
β_{JUL}	-0.0003	-0.0004	-0.0004	-0.0001	-0.0002	-0.0002
β_{AUG}	-0.0013**	-0.0014**	-0.0014**	-0.0014**	-0.0015**	-0.0015**
β_{SEP}	0.0000	-0.0001	-0.0001	-0.0004	-0.0005	-0.0004
β_{OCT}	-0.0012	-0.0013	-0.0013	-0.0006	-0.0007	-0.0006
β_{NOV}	-0.0001	-0.0002	-0.0002	-0.0005	-0.0006	-0.0006
β_{DEC}	-0.0014	-0.0015*	-0.0014*	-0.0024**	-0.0025**	-0.0024**
F-statistic (EOM)	1.2808	1.5059	1.4336	1.6154*	1.8047**	1.7608*
F-statistic (total dummies)	5.0711**			4.5009**		
R^2	0.0336			0.0296		
No. of obs	4554			4603		

Notes: This table provides the results of an OLS regression of the mispricing calculated from COC1 on 20 dummy variables that represent the proposed dividend payment dates, plus 11 end-of-month (EOM) dummy variables that represent the last trading day of each calendar month except June, for Nikkei 225 futures contracts traded on the OSE and SGX. The regression model is:

$$Mis_t = \beta_0 + \sum_{p=1}^{20} \beta_p D_p + \beta_{JAN} JAN + \beta_{FEB} FEB + ... + \beta_{DEC} DEC + \varepsilon_t$$

where *JAN*=1 if the day is the last trading day of January, *JAN*=0 if otherwise; β_{JAN} is the coefficient of *JAN*. The other EOM dummy variables and their corresponding coefficients are defined analogously. Other variables are defined as in Table 4.2. ** denotes significance at the 5% level. * denotes significance at the 10% level.

Table A4.1 indicates that the last trading days in most months are negative and insignificant. The significant last trading days are found in May, August and December. However, dividends are seldom paid on the last trading days of the three months. In fact, only 3 out of the 225 constituents of the Nikkei index distributed dividends on those dates in 2014. The significance is more likely to be related to calendar effects. To name a few, the Halloween effect which starts from May, the summer effect which covers August, the turn-of-the-year effect which covers December, and the holiday effect as the end of December is a bank holiday in Japan. The joint marginal contribution of the newly added dummy variables is not significant in the

OSE, but significant at the 10% level in the SGX by *F*-test. Overall, there is some weak evidence of the turn-of-the-month effect. Although the last trading day of June is not significant, it is retained as one of the proposed dividend payment dates because of the concentrated dividend payouts on that day.

Appendix 4.2 Dividend payment dates of Nikkei 225 index

To further check the appropriateness of the proposed dividend payment dates, i.e. the last 10 trading days in June and the first 10 trading days in December, an additional set of 40 dummy variables is added to the regression model as displayed in Table 4.2, for the Nikkei futures contracts traded on the OSE and SGX. The new dummy variables represent the 10 trading days before and the 10 trading days after the proposed dividend payment dates in June and December, respectively. The proposed dividend payment dates are justified if the regression with the newly added dummy variables suggests significance of the proposed dividend payment dates, and a tendency of fade-away in significance of the new dummies around the proposed dividend payment dates. The regression results are shown in Table A4.2.

Table A4.2 The proposed dividend payment dates

	OSE			SGX		
Coefficient	Unrestricted	Restricted		Unrestricted	Restricted	
		Jun dummies	Dec dummies		Jun dummies	Dec dummies
β_0	0.0007**	0.0009**	0.0010**	0.0008**	0.0010**	0.0010**
β_1	0.0029**	0.0028**		0.0031**	0.0029**	
β_2	0.0028**	0.0026**		0.0031**	0.0029**	
β_3	0.0014**	0.0012*		0.0015**	0.0013**	
β_4	0.0014**	0.0012*		0.0018**	0.0016**	
β_5	0.0017**	0.0015**		0.0017**	0.0015**	
β_6	0.0008	0.0006		0.0012**	0.0010*	
β_7	0.0022**	0.0020**		0.0025**	0.0023**	
β_8	0.0022**	0.0020**		0.0025**	0.0023**	
β_9	0.0020**	0.0019**		0.0018**	0.0016**	
β_{10}	0.0002	0.0000		-0.0002	-0.0003	

Table A4.2 continued

Coefficient	OSE			SGX		
	Unrestricted	Restricted		Unrestricted	Restricted	
		Jun dummies	Dec dummies		Jun dummies	Dec dummies
β_{11}	0.0032**		0.0029**	0.0025**		0.0023**
β_{12}	0.0015*		0.0012*	0.0016**		0.0014**
β_{13}	0.0031**		0.0029**	0.0031**		0.0029**
β_{14}	0.0022**		0.0019**	0.0017**		0.0015**
β_{15}	0.0026**		0.0024**	0.0030**		0.0028**
β_{16}	0.0025**		0.0022**	0.0024**		0.0022**
β_{17}	0.0031**		0.0029**	0.0028**		0.0025**
β_{18}	0.0014**		0.0012**	0.0016**		0.0014**
β_{19}	0.0024**		0.0022**	0.0024**		0.0022**
β_{20}	0.0027**		0.0025**	0.0024**		0.0022**
β_{-1}	0.0030**	0.0028**		0.0028**	0.0026**	
β_{-2}	0.0029**	0.0027**		0.0027**	0.0025**	
β_{-3}	0.0018**	0.0016**		0.0020**	0.0018**	
β_{-4}	0.0014**	0.0012**		0.0009*	0.0007	
β_{-5}	0.0018*	0.0016		0.0014	0.0013	
β_{-6}	0.0022**	0.0020**		0.0014**	0.0012**	
β_{-7}	0.0023**	0.0021**		0.0027**	0.0025**	
β_{-8}	0.0016**	0.0014*		0.0013*	0.0011	
β_{-9}	0.0014**	0.0012*		0.0016**	0.0014**	
β_{-10}	0.0025**	0.0023**		0.0018**	0.0016**	
β_{-11}	0.0002		0.0000	0.0007		0.0005
β_{-12}	-0.0006		-0.0008	-0.0001		-0.0004
β_{-13}	0.0003		0.0000	0.0006		0.0004
β_{-14}	0.0005		0.0003	0.0004		0.0001
β_{-15}	-0.0006		-0.0009	-0.0006		-0.0008
β_{-16}	-0.0005		-0.0007	-0.0011*		-0.0013**
β_{-17}	0.0002		-0.0001	-0.0002		-0.0004
β_{-18}	-0.0001		-0.0003	-0.0002		-0.0004
β_{-19}	0.0006		0.0003	0.0003		0.0001
β_{-20}	0.0001		-0.0001	-0.0003		-0.0005

Table A4.2 continued

Coefficient	OSE			SGX		
	Unrestricted	Restricted		Unrestricted	Restricted	
		Jun dummies	Dec dummies		Jun dummies	Dec dummies
β_{21}	0.0010*	0.0008		0.0012**	0.0010*	
β_{22}	0.0021**	0.0019**		0.0024**	0.0022**	
β_{23}	0.0004	0.0003		0.0011*	0.0010	
β_{24}	0.0022**	0.0020**		0.0024**	0.0022**	
β_{25}	0.0018**	0.0017**		0.0018**	0.0017**	
β_{26}	0.0008*	0.0006		0.0009**	0.0007	
β_{27}	0.0011*	0.0009		0.0012*	0.0011	
β_{28}	0.0004	0.0002		0.0000	-0.0002	
β_{29}	0.0006	0.0004		0.0002	0.0001	
β_{30}	0.0004	0.0002		0.0005	0.0003	
β_{31}	0.0007		0.0005	0.0007		0.0005
β_{32}	0.0020**		0.0018**	0.0021**		0.0019**
β_{33}	0.0024**		0.0022**	0.0029**		0.0027**
β_{34}	0.0012*		0.0009	0.0010		0.0007
β_{35}	0.0002		-0.0001	0.0004		0.0001
β_{36}	0.0009		0.0007	0.0015		0.0013
β_{37}	0.0022**		0.0020**	0.0036**		0.0033**
β_{38}	0.0028**		0.0026**	0.0025**		0.0022**
β_{39}	0.0006		0.0004	0.0009		0.0007
β_{40}	0.0006		0.0003	0.0008		0.0005
F-statistic (new dummies)	3.6893**	4.2041**	2.0306**	3.4092**	3.3318**	2.5130**
F-statistic (total dummies)	4.8992**			4.3412**		
R^2	0.0614			0.0542		
No. of obs	4554			4603		

Notes: This table provides the results of an OLS regression of the mispricing calculated from COC1 on 20 dummy variables that represent the proposed dividend payment dates, plus 40 dummy variables that represent the 10 trading days before and the 10 trading days after the proposed dividend payment dates in June and December, respectively, for Nikkei 225 futures contracts traded on the OSE and SGX. The regression model is:

$$Mis_t = \beta_0 + \sum_{p=-20}^{40} \beta_p D_p + \varepsilon_t$$

where D_1 to D_{20} are the proposed dividend payment dates, defined as in Table 4.2. The newly added 40 trading days are in ascending order: D_{-1} to D_{-10} are the 10 trading days before the 1st dividend payment date in June; D_{-11} *to* D_{-20} are the 10 trading days before the 1st dividend payment date in December; D_{21} to D_{30} are the 10 trading days after the 10th dividend payment date in June; D_{31} to D_{40} are the 10 trading days after the 10th dividend payment date in December. Each dummy variable has its corresponding coefficient β. Other variables are defined as in Table 4.2. ** denotes significance at the 5% level. * denotes significance at the 10% level.

Apart from the significance of most dividend payment dates, the significance of the newly added dummy variables displays a general trend of fade-away around the proposed payment dates. The 10 trading days after the proposed payment dates in June clearly show a diminishing trend of significance. For the December payment dates, the prior 10 trading days are insignificant, and the subsequent 10 trading days display a similar trend to die down in significance. The significance of D_{37}, D_{38} is likely to be associated with the holiday effect, as they are 23rd-27th December over the years.

The fade-away trend is not so obvious in the 10-day period before the proposed payment dates in June due to the dividend payouts on these days. The dividend streams received on the Nikkei index are unevenly distributed in a calendar month. For instance, 181 stocks paid out dividends in June 2014, including 150 stocks that paid out dividends in the last 10 trading days of June.[59] Since the dividend payouts tend to cluster in the second of half of June, and similarly, in the first half of December, I stick to assumption c) in section 4.2.2, i.e. dividends are only paid in the last 10 trading days in June and the first 10 trading days in December, and support the superiority of COC2 assuming lumpy dividend payouts over COC1 assuming continuous dividend payments for the OSE and SGX Nikkei futures contracts.

Appendix 4.3 Unit root tests

A set of unit root tests are performed to test the stationarity of the demeaned mispricing series, Mis_t^* in section 4.4.2.1. These tests include Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Zivot-Andrews (ZA). The test results are given in Table 4.14.The methodological details of the tests are provided below.

The ADF test of Dickey and Fuller (1979; 1981) estimates the following regression equation:

$$\Delta Mis_t^* = \psi Mis_{t-1}^* + \sum_{i=1}^{l} \phi_i \Delta Mis_{t-i}^* + e_t$$

[59] Data are from Thomson Reuters Eikon.

where e_t is the residual from the regression. The ADF test is based on the assumption that e_t is iid. The null hypothesis of a unit root is H_0: $\psi=0$, against the alternative stationary hypothesis H_1: $\psi<0$. This form of the regression equation, which does not include a constant or a trend, is considered because Mis_t^* is without mean and its time plot does not show obvious evidence of deterministic elements. The lag length l is determined by SBC. If the ADF test statistic is no larger than the critical value at a given significance level, the null hypothesis of a unit root can be rejected in favour of the stationary alternative.

The PP test of Phillips and Perron (1988) is a non-parametric unit root test. It generalises the ADF test by estimating a similar regression equation:

$$\Delta Mis_t^* = \psi Mis_{t-1}^* + e_t$$

with the same null hypothesis H_0: $\psi=0$ and the alternative H_1: $\psi<0$. However, the residual e_t is allowed to be autocorrelated and heterogeneous, such that a wide class of residual processes can be applicable. This is achieved by modifying the ADF test statistics to asymptotically remove the effects of autocorrelation and heterogeneity, while the limiting distributions and the critical values of the ADF test still hold. For the demeaned mispricing series in question, visual inspection of the data does not suggest including a constant or a trend in the regression equation. The PP test is used as a robustness check of the ADF test, as the (non)stationarity of the demeaned mispricing series is strengthened if both tests show consistent results.

The KPSS test of Kwiatkowski et al. (1992) has a null hypothesis of stationarity rather than a unit root. It interprets a series, say Mis_t^*, as the sum of a deterministic trend, a random walk and a stationary error:

$$Mis_t^* = \xi t + r_t + e_t$$

with r_t as a random walk process $r_t=r_{t-1}+\varsigma_t$, $\varsigma_t \sim$ iid$(0, \sigma_\varsigma^2)$, given an initial level r_0. As e_t is stationary, the trend stationary null is $\sigma_\varsigma^2=0$. Equivalently, the model can be expressed as:

$$\Delta Mis_t^* = \xi + v_t - \theta v_{t-1}$$

where v_t is nid. The null hypothesis of trend stationarity corresponds to H_0: $\theta=1$ against the unit root alternative H_1: θ<1. The KPSS test is based on fairly mild assumptions of the residual processes as in the PP test. Despite that the demeaned mispricing series does not appear to have a deterministic trend in its time plot, the trend stationary hypothesis is tested for security. Moreover, tests with a stationary null complement tests with a unit root null in the sense that the latter tends to have low power against the relevant alternatives.

The presence of structural changes is likely to bias unit root tests such that it is difficult to reject the null hypothesis of a unit root. Breaks as exogenous shocks or simply statistical processes are common for long time series, e.g. my 19-year sample. In the time plot of the demeaned mispricing series Mis_t^*, it is suspected that the 2008 global financial crisis induce jumps in the data; if that is the case, the results of the tests above may not be very useful. The ZA test of Zivot and Andrews (1992) is thus performed to further check the stationarity of Mis_t^*, allowing for a one-time structural break in the trend. The null hypothesis is that the series has a unit root without an exogenous structural break:

$$H_0: \quad Mis_t^* = \mu + Mis_{t-1}^* + e_t$$

where the intercept μ is expected to be zero. The alternative hypothesis is that the series is trend stationary with an unknown one-time break in the trend. With λ as the time of the breakpoint relative to sample size n, the test estimates the following regression equation:

$$Mis_t^* = \hat{\mu} + \hat{\xi}'t + \hat{\kappa}DT_t(\hat{\lambda}) + \hat{\psi}'Mis_{t-1}^* + \sum_{i=1}^{l'} \hat{\phi}_i'\Delta Mis_{t-i}^* + \hat{e}_t$$

where $DT_t(\lambda)=t-n\lambda$ if $t>n\lambda$, 0 otherwise; hats are put to indicate fitted values from estimating λ. The lag length l' is selected using a backward testing procedure. The location of the breakpoint is determined as the λ with which the one-tail t-statistics of testing ψ'=1 is the smallest. Compared with other unit root tests that treat breaks as exogenous, the ZA test is chosen because, for the data under consideration, it is easier to attribute the jumps to a period than to an exact date.

Chapter 5

Price discovery in the Nikkei 225 futures markets

5.1 Introduction

Price discovery is the process whereby market participants impound all available information to reach equilibrium asset prices (Booth et al., 1999; Chen and Gau, 2009), representing the first-moment dynamics of asset prices. The price discovery process is a key function of stock index futures markets. Although all prices ultimately transmit information, the differences in market frictions can give rise to different speeds of information transmission, i.e. prices in one market are quicker in reflecting and disseminating information, such that its prices become an important predictor for the subsequent prices in the other markets. Index futures markets are generally thought to assume the price discovery function in theory as opposed to the underlying spot markets, and the reasons for the futures leadership essentially relate to the more efficient trading conditions in futures, such as lower trading costs, absence of short-selling restrictions, etc. However, the observed price dynamics in reality, which could be more complex than the simplified theoretical prediction, necessitates detailed research into the price discovery process in specific markets.

The Nikkei 225 futures contracts are one of the earliest index futures in the world that boast an international dimension. Based on one common stock index market (Tokyo Stock Exchange, TSE), the Nikkei 225 futures are traded on three equivalent yet different markets: Osaka Exchange (OSE), Singapore Exchange (SGX) and Chicago Mercantile Exchange (CME). Following Board and Sutcliffe (1996), I define the domestic or home futures market as the exchange where the futures contracts are traded in the same country as the stocks underlying the index, i.e. the OSE; the corresponding foreign or offshore futures market as the exchange in whose country the futures contracts are traded but the stocks underlying the index are not, i.e.

the SGX and the CME. The triple-listing nature of the Nikkei futures contracts makes their first-moment price dynamics particularly interesting as the spot-futures lead-lag relationships could be quite different in the different trading venues. Furthermore, the price discovery process across the three Nikkei futures markets remains a key issue in exchange competition and asset management in the course of futures market globalisation. To understand cross-border price discovery, two possible hypotheses are put forward in the literature: the home-bias hypothesis and the international centre hypothesis (e.g. Fung et al., 2001; Covrig et al., 2004). The home-bias hypothesis argues that domestic investors enjoy a battery of advantages such as geographic proximity to the underlying spot market, familiarity with local trading environment and regulation, and fewer trading barriers, and thus the domestic market should dominate the information transmission across borders. By contrast, the international centre hypothesis argues if a foreign market is a global financial centre, we might expect it to dominate transnational price discovery because of the better trading conditions it can provide. Higher efficiency in processing and sharing information, and more opportunities for risk management by trading other financial instruments are also available on the foreign market. The empirical research that contributed to this area is far from sufficient to answer which hypothesis is more relevant in the Nikkei futures markets. Hence, this chapter is motivated to explore the international price discovery process in individual Nikkei markets and across the Nikkei futures markets.

The international price discovery process is studied by looking into the linear and nonlinear price adjustments towards equilibrium. Specifically, the chapter tests the following null hypotheses: a) in individual Nikkei markets, the futures prices lead the spot prices; b) across the Nikkei futures markets, the domestic market (OSE) leads the foreign markets (SGX, CME). The tests are in the spirit of Granger (1969) and Sims (1972): futures prices lead or Granger-cause spot prices if the past futures prices help to predict the current spot prices, relative to using the past spot prices alone. A similar logic can be extended to the futures price interactions. Following most studies on price discovery, I first perform such tests in the framework of a linear error correction model (ECM), which is consistent with the cost of carry relationship and Granger causality. The error correction coefficient in the ECM sheds light on the speed of adjustment and the direction of causality in the long run. The short-run causalities are examined by joint significance tests on the autoregressive coefficients. The resulting linear adjustment process is constant and ever-present, irrelevant to the potential states or regimes where the mean-reverting behaviour is different inside or outside. I next use an exponential smooth transition error correction model (ESTECM) to describe the nonlinear price adjustments towards equilibrium. The smooth transition error correction behaviour in the price adjustments can be attributed to transaction costs, heterogeneity and predictive asymmetry. In particular, profitable arbitrage activities will not be triggered unless the benefits gained from the arbitrage can cover the transaction costs incurred, such that large price deviations should be removed more quickly than small price deviations. Besides, investors differ in trading objectives, transaction costs, capital constraints and perceived risks (Tse, 2001), and thus the aggregate market response to a given price deviation should be gradual and smooth, rather than sharp and abrupt. The often observed phenomenon of the leverage effect, i.e. bad news is associated with larger market reactions, may also exist in the price interaction mechanisms between the markets. As such, the nonlinear adjustment process is analysed in terms of the speed of price adjustments towards equilibrium, the rates of smooth transition[60] and the asymmetric market responses to negative and positive price deviations. Based on the ESTECM and a 19-year data range that distinguishes periods before and after the 2008 global financial crisis, I find that, in individual Nikkei markets, the futures prices dominate the price discovery process in the pre-crisis period, while the spot prices react faster in the adjustments in one regime and between the regimes in the post-crisis period. The null hypothesis a) is therefore rejected in the post-crisis period. Across the futures markets, the foreign exchanges play a leading role in the information transmission across the border; and the robustness of their information advantage is checked by re-estimating the models with an alternative time sequence. The null hypothesis b) is again rejected in the Nikkei markets. The results also show evidence of larger impact of bad news in the Nikkei prices and variances. An increasing trend of transaction costs is noticed in the spot-futures arbitrage after the crisis, while the transaction costs in the spread arbitrage among the futures markets are decreasing.

[60] As will be explained in more detail in section 5.2.2, the rates of smooth transition are between a middle regime of a narrow band around zero indicating small price deviations and few arbitrage, and an outer regime of areas far away from zero indicating large price deviations and active arbitrage.

The contributions of the chapter are fourfold. First, studies on the Nikkei price dynamics tend to focus on the OSE and SGX, and circumvent the CME for its currency and time complexities. The only paper of Booth et al. (1996) on the price dynamics in the three Nikkei markets simply uses a linear ECM and does not allow for the effect of transaction costs. This chapter studies the price dynamics of all of the three Nikkei futures markets, allowing for the effects of transaction costs, heterogeneity and asymmetry. In doing so, it significantly extends the work of Fung et al. (2001), Covrig et al. (2004) and Frino et al. (2013) in understanding the key roles of offshore financial centres in global information revelation and price determination. Second, the smooth transition error correction mechanism has been studied in a few markets but never in the triple-listed Nikkei markets. The chapter shows that smooth transition nonlinearity is present in individual Nikkei markets and across the Nikkei futures markets, and that the smooth transition models are more appropriate for describing the first-moment price dynamics in the Nikkei markets. Third, following from Chapter 4, the chapter continues to consider the effect of heterogeneity, yet in the structure of market transaction costs. In this respect, I find that the Nikkei spot market exhibits a lower level of heterogeneity than the futures, and the OSE exhibits a lower level of heterogeneity than the offshore exchanges. The level of heterogeneity as a futures market property was not emphasised in the literature until the 2000s by Taylor et al. (2000), Tse (2001), and McMillan and Speight (2006), for example; but none of these works consider the heterogeneity in an international setting. The chapter makes a significant contribution by demonstrating that the level of heterogeneity does affect the price adjustments within one regime and between the regimes, and hence the information role of the Nikkei markets. Fourth, with the 19-year sample covering a pre-crisis period and a post-crisis period, the chapter is able to compare and contrast the international price discovery process before and after the 2008 financial crisis, offering a comprehensive picture of the Nikkei price dynamics over the years.

The rest of the chapter is organised as follows. Section 5.2 and section 5.3 focuses on the spot-futures price adjustment process in individual Nikkei markets and the price adjustment process across the Nikkei futures markets, respectively, and introduces the relevant linear and nonlinear error correction mechanisms to be used later in estimation. Section 5.4 describes data and analyses preliminary test results of the data. Section 5.5 contains the methodological details involved in estimation and evaluation. The empirical results are provided in section 5.6. The robustness of the futures price interactions is checked in section 5.7. Section 5.8 discusses the main findings and concludes the chapter.

5.2 Price adjustments to cost of carry: the error correction mechanism

5.2.1 Basis, cointegration and linear ECM

The cost of carry relationship implies that spot and futures prices should not deviate far from each other for long, as arbitrage would quickly pull the deviated prices back inside a no-arbitrage band to maintain equilibrium. This means that the basis, the difference between spot and futures prices which are individually I(1), should be I(0), and the spot and futures prices should be cointegrated with one cointegrating vector. A simple way to formulate the cointegrating relationship between spot and futures prices is the following:

$$f_t = \beta_0 + \beta_1 s_t + b_t \tag{5.1}$$

where s_t, f_t are respectively spot and futures prices in natural logarithms, and b_t is a residual. Numerous empirical studies have demonstrated that the spot and futures prices are cointegrated with the cointegrating vector [1, -1]. This requires that b_t, as a measure of the basis spread between the spot and futures prices, should be I(0), and the regression coefficients β_0=0, β_1=1; in other words, b_t is expected to equal (f_t - s_t).

According to the Granger Representation Theorem (Engle and Granger, 1987), an error correction model (ECM) is justified to examine the linear adjustments of the cointegrated spot and futures prices towards equilibrium, and any causal relationships between the spot and futures prices, or causality-in-mean. Based on Engle and Granger (1987), an ECM can be established as below:[61]

$$\Delta s_t = k_s + \sum_{j=1}^{p} \pi_{ss,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j} \Delta f_{t-j} + \alpha_s z_{t-1} + u_{s,t} \tag{5.2a}$$

[61] The subscripts of the model parameters indicate the market to which they belong: *s* means spot and *f* means futures. For simplicity, I omit these subscripts in the notation explanation hereafter unless otherwise confusions might occur.

$$\Delta f_t = k_f + \sum_{j=1}^{p} \pi_{fs,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j} \Delta f_{t-j} + \alpha_f z_{t-1} + u_{f,t} \tag{5.2b}$$

where $\Delta s_t = s_t - s_{t-1}$, $\Delta f_t = f_t - f_{t-1}$ are spot and futures price returns, respectively; the model lag j=1, 2, …, p, with p as a positive integer; k is a constant; u_t is a white noise. z_{t-1} is the error correction term, usually represented by the residual b_t from the cointegrating relationship (5.1). The error correction coefficient α indicates the speed of adjustment towards equilibrium and the direction of causality in the long run. For the error correction mechanism to function properly, it is generally expected that $\alpha_s>0$, $\alpha_f<0$, as the negative α_f suggests a reverse price movement compared with the previous one.[62] For example, a positive basis at time t (futures price $F_t >$ spot price S_t) should be followed by a decrease in the futures price and an increase in the spot price at time t+1. The higher the magnitude of α, the larger the proportion of the pricing errors are adjusted, and therefore the slower the price reflects information. If futures leads spot in transmitting information or futures Granger-causes spot in the long run, α_f is expected to be insignificant while α_s significant, as the spot price which slowly reflects information makes the adjustment (Tse, 2001). The coefficients π_{sf}, π_{fs} capture short-run adjustments between spot and futures prices, and π_{ss}, π_{ff} short-run dynamics within the respective markets.

For hypothesis testing, as futures is generally thought to play a major part in the price discovery process, I test the null hypothesis of futures-to-spot causality with H_{01}: $\alpha_s=0$ and H_{02}: $\pi_{sf,j}=0$, j=1, …, p. Rejecting H_{01} is evidence supporting the error correction effect, i.e. any pricing errors from the cost of carry relationship in the previous period would be corrected in the current period, mainly by the spot prices in this case. Futures prices Granger-cause spot prices in the short run if H_{02} can be rejected. In a similar way, spot-to-futures causality requires either H_{03}: $\alpha_f=0$ or H_{04}: $\pi_{fs,j}=0$, j=1, …, p to be rejected. Bidirectional causality exists in the long run provided that both H_{01} and H_{03} can be rejected; in the short run provided that both H_{02} and H_{04} can be rejected.

[62] In some markets α_s is not necessarily positive; the sign of α_s depends on the net outcome of the two opposing effects of arbitrage and momentum (Zhong et al., 2004; Bohl et al., 2011).

5.2.2 Nonlinear ESTECM for spot-futures arbitrage

The linear error correction mechanism above implies a mean-reverting tendency wherever pricing errors occur. Taking into account the effect of transaction costs, however, it is more likely the case that investors would only correct the pricing errors when their adjustment costs can be offset by potential gains, and thus large pricing errors tend to be removed more quickly than small pricing errors. As such, the adjustment process towards equilibrium can relate closely to the magnitude of the pricing errors, and the error correction behaviour is in fact dependent on the state or regime that takes place at a certain point in time; in other words, regime-switching (Priestley, 1980; Franses and van Dijk, 2000). Particularly, I consider two possible regimes: a middle regime of a narrow band around zero indicating small pricing errors without substantial price adjustments or arbitrage, and an outer regime of areas far away from zero indicating large pricing errors with rapid adjustments and active arbitrage. A further aspect of the effect is that, as transaction costs are different for different investors, the boundaries of the individual regimes of the error correction may be blurred when aggregating over all investors in a market (Anderson, 1997); hence, with heterogeneous transaction costs, the price adjustment process between the different regimes is likely to be continuous, gradual and smooth for a market as a whole. Moreover, the widely documented leverage effect suggests that the speed of adjustment tends to be associated with the sign of the pricing errors: negative information (bad news) with larger market response, whereas positive information (good news) with smaller market response. It follows that the error correction mechanism is actually nonlinear with variable speed of adjustments.

To allow for the nonlinear adjustment process on account of the effects of transaction costs, heterogeneity and asymmetry, based on Anderson (1997) and Tse (2001), it is assumed that the nonlinear adjustment process follows an exponential smooth transition error correction model (ESTECM):

$$\Delta s_t = k_s + \sum_{j=1}^{p} \pi_{ss,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j} \Delta f_{t-j} + (k_s^* + \sum_{j=1}^{p} \pi_{ss,j}^* \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j}^* \Delta f_{t-j} + \alpha_s z_{t-1}) \times T_s(z_{t-d}) + u_{s,t}$$

$$T_s(z_{t-d}) = 1 - \exp[-\gamma_s (z_{t-d} - c^*)^2 \times g_s(z_{t-d})]$$

$$g_s(z_{t-d}) = 0.5 + 1/\{1+\exp[-\theta_s(z_{t-d} - c^*)]\} \tag{5.3a}$$

$$\Delta f_t = k_f + \sum_{j=1}^{p} \pi_{fs,j}\Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j}\Delta f_{t-j} + (k_f^* + \sum_{j=1}^{p} \pi_{fs,j}^*\Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j}^*\Delta f_{t-j} + \alpha_f z_{t-1}) \times T_f(z_{t-d}) + u_{f,t}$$

$$T_f(z_{t-d}) = 1 - \exp[-\gamma_f(z_{t-d} - c^*)^2 \times g_f(z_{t-d})]$$

$$g_f(z_{t-d}) = 0.5 + 1/\{1+\exp[-\theta_f(z_{t-d} - c^*)]\} \tag{5.3b}$$

where k, k^* are constants; π, π^* are the short-run autoregressive coefficients; the model residual u_t is iid with zero mean and finite variance. As in the linear model, the error correction term is z_{t-1}, and the error correction coefficient α measures the long-run speed of adjustments. Thus, I generally expect $\alpha_s>0$, $\alpha_f<0$, and the market with a slower (quicker) speed of information transmission to have significant (insignificant) and larger (smaller) α in magnitude. Note that this type of price adjustments takes place within a single regime.

$T(\cdot)$ is an exponential smooth transition function bounded between 0, the middle regime where no investor will trade, and 1, the outer regime where all investors will trade. z_{t-d} is the transition variable with the delay parameter d, $d>0$. Consistent with the effect of transaction costs that arbitrage will only be triggered when the pricing errors are large, $T(\cdot)$ is a U-shaped curve with larger values for larger z_{t-d} in magnitude, indicating more arbitrage activities. The rate of the transition between the regimes is governed by the smoothness parameter γ, $\gamma>0$. Graphically, this can be seen as the steepness of the transition function - the higher is γ, the steeper the transition function, and the quicker adjustments between the regimes. If $\gamma\rightarrow 0$ or $\gamma\rightarrow\infty$, $T(\cdot)$ converges to 0 or 1, respectively, and the ESTECM approaches a linear model (van Dijk et al., 2002). For example, in the extreme case $\gamma=0$, equations (5.3a) (5.3b) reduce to a linear error correction framework in the middle regime:[63]

$$\Delta s_t = k_s + \sum_{j=1}^{p} \pi_{ss,j}\Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j}\Delta f_{t-j} + u_{s,t}$$

[63] Note that the error correction term z_{t-1} should be included in both the linear and nonlinear parts of a complete specification of the ESTECM to allow for error corrections in the middle regime and the outer regime. If that is the case, with $\gamma=0$, equations (5.3a) (5.3b) collapse exactly to equations (5.2a) (5.2b), respectively. However, I decide to retain z_{t-1} only in the nonlinear section, or the outer regime of the ESTECM for the following reasons: a) arbitrage would be too costly to exist for small pricing errors z_{t-1} in the middle regime, yet arbitrage is expected to be active for large z_{t-1} in the outer regime, and so the error correction in the outer regime is more interesting and deserves more attention; b) the model is simpler to estimate with one error correction term; c) this is the practice in most studies with the ESTECM. This explains why, with $\gamma=0$, equations (5.3a) (5.3b) merely reduce to a linear ECM that appears without an error correction term.

$$\Delta f_t = k_f + \sum_{j=1}^{p} \pi_{fs,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j} \Delta f_{t-j} + u_{f,t}$$

Clearly, the autoregressive coefficient π's indicate the short-run adjustments in the middle regime. As another example, if $\gamma=\infty$, equations (5.3a) (5.3b) become linear but with a different representation in the outer regime:

$$\Delta s_t = (k_s + k_s^*) + \sum_{j=1}^{p} (\pi_{ss,j} + \pi_{ss,j}^*) \Delta s_{t-j} + \sum_{j=1}^{p} (\pi_{sf,j} + \pi_{sf,j}^*) \Delta f_{t-j} + \alpha_s z_{t-1} + u_{s,t}$$

$$\Delta f_t = (k_f + k_f^*) + \sum_{j=1}^{p} (\pi_{fs,j} + \pi_{fs,j}^*) \Delta s_{t-j} + \sum_{j=1}^{p} (\pi_{ff,j} + \pi_{ff,j}^*) \Delta f_{t-j} + \alpha_f z_{t-1} + u_{f,t}$$

The autoregressive coefficients ($\pi+\pi^*$) indicate the short-run adjustments in the outer regime. The parameter γ also has implications for the degree of heterogeneity in the transaction costs in a market: smaller values of γ indicate more heterogeneous, higher transaction costs, while larger values of γ indicate more homogeneous, lower transaction costs (Taylor et al., 2000). The location parameter c^* gives the centre of $T(\cdot)$.

$g(\cdot)$ is an asymmetry function bounded between 0.5 and 1.5. It increases monotonically with the asymmetry parameter θ, which measures the asymmetric market response to positive and negative pricing deviations. Negative (positive) θ suggests that more investors tend to correct a negative (positive) z_{t-d}, than to correct an equally sized positive (negative) z_{t-d}. When θ=0, $g(\cdot)$=1, $T(\cdot)$ becomes symmetrical around c^* and investors would be indifferent about the sign of z_{t-d}. It follows that, as long as $\theta\neq0$, the shape of $T(\cdot)$ will exhibit some sorts of asymmetry, with the higher tail associated with the signed z_{t-d} that is adjusted more quickly.

Alternatively, a logistic transition function may be used as $T(\cdot)$ which would allow for the asymmetric adjustments of positive and negative pricing errors, making the resultant model a logistic smooth transition error correction model (LSTECM). However, I do not consider the alternative as appropriate, for the logistic transition function is monotonically increasing, meaning that the error correction dynamics are irrelevant to the size of the pricing errors, and thus the LSTECM is unable to capture the effects of transaction costs and the associated heterogeneity.

5.3 Error correction dynamics across futures markets

5.3.1 Futures price parity and linear ECM

Futures contracts listed on domestic and foreign markets but sharing the same underlying index and the same maturity date are equivalent assets. Their prices should move together, and their markets are closely linked by spread arbitrage, which aims to profit from buying and selling across these markets. For such spread arbitrage, Board and Sutcliffe (1996) derive the no-arbitrage condition which states that the current futures prices in index points are identical in domestic and foreign markets. Any departures from the price parity, or spreads, or price differentials between the markets, would be quickly removed - even quicker than in the spot-futures arbitrage, as lower transaction costs and risks are involved in trading the futures. In this way, the price differentials function like the basis, and should be I(0) to maintain equilibrium. It follows that dual- or triple-listed futures prices should be cointegrated with one common stochastic factor. Consider a bilateral pair of logarithmic futures prices (f_1, f_2), where 1, 2 represent any two futures markets based on the same spot market. If the long-run relationship between f_1 and f_2 is expressed as the following:

$$f_{1,t} = \beta_0' + \beta_1' f_{2,t} + \delta_t \tag{5.4}$$

where δ_t is a residual, then by the no-arbitrage condition, the constant and slope coefficients are expected to be 0 and 1, respectively (ignoring any scale differences). That is, δ_t is expected to equal ($f_{1,t}$ - $f_{2,t}$), the difference between the two futures prices.

Based on Chou and Lee (2002) and Hsieh (2004), a bivariate (vector) error correction model can be constructed for the cointegrated futures prices (f_1, f_2) as the following:

$$\Delta f_{1,t} = k_1 + \sum_{j=1}^{p} \pi_{11,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j} \Delta f_{2,t-j} + \alpha_1 z_{t-1} + u_{1,t} \tag{5.5a}$$

$$\Delta f_{2,t} = k_2 + \sum_{j=1}^{p} \pi_{21,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j} \Delta f_{2,t-j} + \alpha_2 z_{t-1} + u_{2,t} \tag{5.5b}$$

The error correction term z_{t-1} reflects the price parity across the equivalent futures markets (Roope and Zurbruegg, 2002); it can be represented by the regression residual δ_t from equation

(5.4). Its coefficient α gauges the long-run speed of adjustment between f_1 and f_2. To restore equilibrium, at least one of α should be negative in the ECM system. The magnitude of α sheds light on the location of information leadership: the smallest α in magnitude emerges in the quickest futures market in revealing information; larger α in magnitude implies slower market adjustments and hence redundant role in the process of price formation. The significance of α also suggests the direction of causality, and bidirectional causality in the long run requires both α_1 and α_2 to be significant. The short-run adjustments are captured by the coefficient π's, within the respective markets ($\pi_{11,j}$ and $\pi_{22,j}$) and between the markets ($\pi_{12,j}$ and $\pi_{21,j}$). Futures market 2 Granger-causes futures market 1 if the joint test on all the $\pi_{12,j}$ is significant, and futures market 1 Granger-causes futures market 2 if all the $\pi_{21,j}$ are jointly significant.

5.3.2 Nonlinear ESTECM for futures price interactions

Following a similar logic as in section 5.2.2, I propose the ESTECM to model the possible nonlinear price adjustments across the futures markets, as the smooth transition error correction behaviour is likely to arise from the effects of transaction costs, heterogeneity and asymmetry in the futures markets. The nonlinear ESTECM for futures prices is established by adding a nonlinear component, i.e. a transition function to each of the equations (5.5a) (5.5b), such that a transition variable is allowed to switch between a middle regime and an outer regime. The following is an ESTECM system for a bilateral pair of futures prices (f_1, f_2):

$$\Delta f_{1,t} = k_1 + \sum_{j=1}^{p} \pi_{11,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j} \Delta f_{2,t-j} + (k_1^* + \sum_{j=1}^{p} \pi_{11,j}^* \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j}^* \Delta f_{2,t-j} + \alpha_1 z_{t-1}) \times T_1(z_{t-d}) + u_{1,t}$$

$$T_1(z_{t-d}) = 1 - \exp[-\gamma_1 (z_{t-d} - c^*)^2 \times g_1(z_{t-d})]$$

$$g_1(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_1 (z_{t-d} - c^*)]\} \tag{5.6a}$$

$$\Delta f_{2,t} = k_2 + \sum_{j=1}^{p} \pi_{21,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j} \Delta f_{2,t-j} + (k_2^* + \sum_{j=1}^{p} \pi_{21,j}^* \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j}^* \Delta f_{2,t-j} + \alpha_2 z_{t-1}) \times T_2(z_{t-d}) + u_{2,t}$$

$$T_2(z_{t-d}) = 1 - \exp[-\gamma_2 (z_{t-d} - c^*)^2 \times g_2(z_{t-d})]$$

$$g_2(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_2 (z_{t-d} - c^*)]\} \tag{5.6b}$$

Most model parameters above are the same as those in equations (5.3a) (5.3b), and thus extensions of their interpretations to the futures markets are straightforward. For example, the smoothness parameter γ controls the rate of the regime switch in each of the futures markets, and the asymmetry parameter θ captures the asymmetric market response to positive and negative futures spreads. Worthy of note, however, is that the error correction term z_{t-1} and the transition variable z_{t-d} are to be represented by the futures price differentials, not the spot-futures basis. The joint significance tests on the coefficient π's can now be performed separately in different regimes, enabling a more accurate description of the short-run causal relationships and the cross-border futures price dynamics.

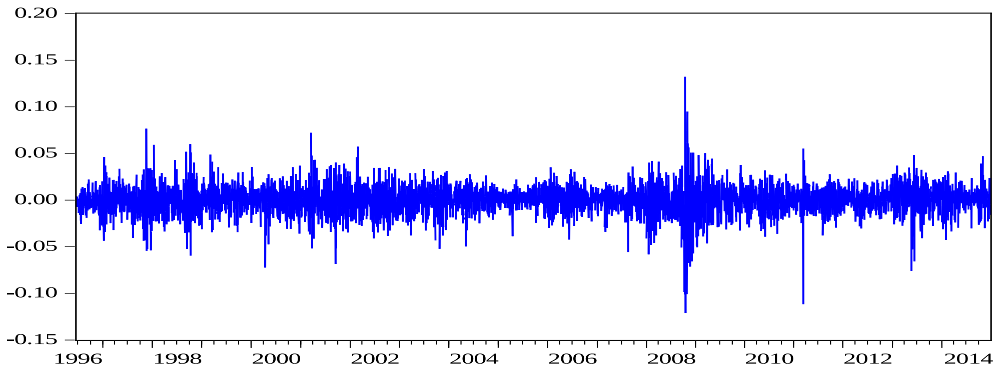
5.4 Data and preliminary analysis

5.4.1 Data and descriptive statistics

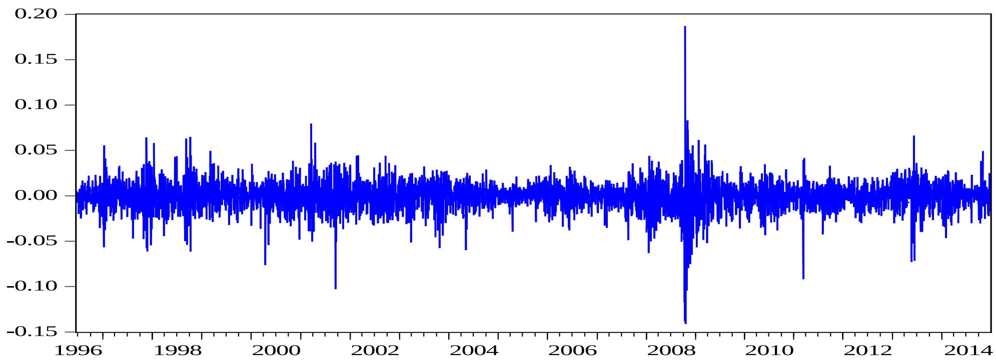
Daily closing prices of Nikkei 225 index and daily settlement prices of the Nikkei 225 index futures on the OSE, SGX and CME are obtained from the respective exchanges and Datastream over the whole sample period 20/06/1996-31/12/2014 (OSE and SGX); 01/01/1997-31/12/2014 (CME). The contract months of the Nikkei futures contracts follow the usual quarterly cycle - March, June, September and December, and the futures price series in each market is compiled using the nearest futures contracts and rolling over to the next nearest contract at the start of the expiration month. For individual spot-futures pairs, the local holiday schedule is applied and holidays are excluded from the data; if the futures market is closed while the spot is open due to the different holiday observances in the different markets, that day is removed as I assume that both markets need to be open to make index arbitrage available. Figure 5.1 displays the time plots of the log-differenced return series in the Nikkei markets. An obvious spike can be found in each series at the time October-November 2008, when Quandt-Andrews breakpoint test suggests structural changes (see Chapter 4, p.136). As such, the overall sample is divided into a pre-crisis period (sample A) and a post-crisis period (sample B), excluding a short turmoil interval in the middle of the crisis.

Pre-crisis period (sample A):

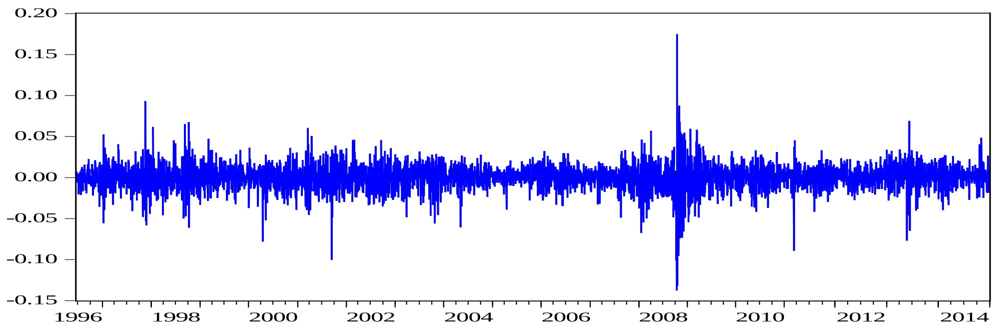
28/06/1996-09/10/2008 (OSE, SGX); 09/01/1997-12/09/2008 (CME)



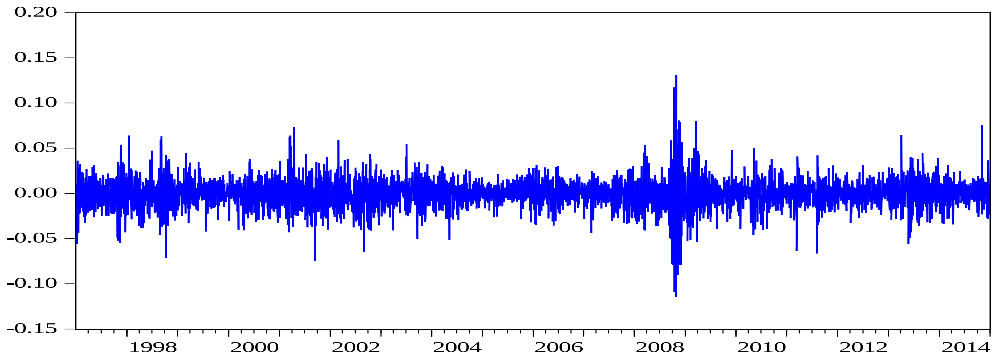
(a) Spot



(b) OSE



(c) SGX



(d) CME

Figure 5.1 Nikkei 225 spot and futures returns

Notes: (a)-(d) plot the log-differenced price returns in the Nikkei spot and futures markets over the whole sample period 20/06/1996-31/12/2014 (OSE and SGX); 01/01/1997-31/12/2014 (CME).

Post-crisis period (sample B):

04/11/2008-31/12/2014 (OSE, SGX); 02/12/2008-31/12/2014 (CME)

For futures price interactions, the three Nikkei futures prices are pooled together but observations are only retained when all of the three markets are open; any date when any one of the markets is closed is removed from the dataset. This is because the three markets adopt different holiday schedules, and for simplicity I do not consider the information transmissions associated with closed markets. Moreover, the starting and ending dates of the sample periods are adjusted such that the three futures series have the same length. As will be explained later, the starting date of sample A is also moved slightly forward to allow for the estimated lags in the linear model. Therefore, a different sample division is employed for the futures price dynamics.

Pre-crisis period (sample A):

17/01/1997-12/09/2008

Post-crisis period (sample B):

02/12/2008-30/12/2014

Table 5.1 presents descriptive statistics for the Nikkei price returns, basis and basis change in each market in each sample. The means of the price returns are negative in sample A and positive in sample B, and the means are very similar in value. This reveals that the Nikkei markets may be potentially linked. The standard deviations of the price returns are also close to each other, with a slight increase in the spot market and the OSE in the post-crisis period. The futures markets tend to have slightly higher standard deviations than the spot market before the crisis, but this is not so obvious after the crisis. As such, one may not draw strong conclusions about the more volatile Nikkei futures markets than the underlying spot. The first-order autocorrelation coefficients of the spot returns are small and significantly negative, suggesting that the nonsynchronous trading problem is not severe. The first-order autocorrelation coefficients of the futures returns are small and negative, and significant in most cases, which may be explained by the effect of bid-ask bounce. The higher-order autocorrelation coefficients generally diminish in magnitude and/or significance.

Table 5.1 Descriptive statistics of Nikkei 225 price returns, basis and basis change

	S		OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
Panel A: Price returns								
Mean	-0.0003	0.0005	-0.0003	0.0005	-0.0003	0.0005	-0.0001	0.0005
SD	0.0147	0.0153	0.0153	0.0154	0.0150	0.0150	0.0149	0.0149
Autocorrelation								
Lag1	-0.0341*	-0.0552**	-0.0712**	-0.0505**	-0.0455**	-0.0371	-0.0729**	-0.0141
Lag2	-0.0300**	0.0110*	-0.0166**	0.0121	-0.0266**	0.0118	-0.0143**	-0.0073
Lag8	-0.0063	0.0241	-0.0032**	0.0183	-0.0062	0.0137	-0.0059**	0.0084
Panel B: Basis								
Mean			-3.5961	-8.4241	-2.1468	-8.9494	10.6465	37.4029
SD			47.3897	34.3022	47.0671	47.6074	129.4377	130.9044
Autocorrelation								
Lag1			0.2540**	0.4357**	0.2620**	0.3176**	0.1288**	0.2023**
Lag2			0.1698**	0.3964**	0.1846**	0.2250**	0.0088**	0.1974**
Lag8			0.0912**	0.2551**	0.0950**	0.1557**	0.0288**	0.1077**
Panel C: Basis change								
Mean			0.0014	0.0836	0.0047	0.0040	0.0240	0.3104
SD			57.8834	36.5534	57.1567	55.6166	170.8389	166.6847
Autocorrelation								
Lag1			-0.4431**	-0.4614**	-0.4471**	-0.4312**	-0.4311**	-0.4891**
Lag2			-0.0342**	0.0065**	-0.0174**	-0.0711**	-0.0962**	0.0284**
Lag8			-0.0187**	0.0475**	-0.0010**	0.0189**	-0.0010**	0.0615**

Notes: The table presents descriptive statistics of the price returns, basis and basis change in the Nikkei spot (S) and futures (OSE, SGX, CME) markets, including mean, standard deviation (SD) and autocorrelation coefficients at the lags 1, 2 and 8. The price returns are calculated as the first-order differences in logarithmic prices. The basis is the difference between actual futures and spot prices. The basis change is the first-order difference in the basis. Panel A shows the descriptive statistics of the price returns in each market. Panel B and Panel C show the descriptive statistics of the basis and basis change, respectively, obtained from each spot-futures pair, and thus the statistics are placed under the relevant futures markets. ** denotes significance at the 5% level. * denotes significance at the 10% level.

Basis is calculated as $Basis_t = F_t - S_t$ (difference between the actual futures and spot prices). The means of the basis are negative in the OSE and SGX, positive in the CME. In other words, on average the futures prices are lower than the spot prices in the OSE and SGX and yet higher than the spot prices in the CME. The standard deviation of the basis provides a measure of basis risk. The higher standard deviations of the CME basis suggest more risks inherent in the spot-futures arbitrage in the CME, probably due to the yen-dollar exchange rate fluctuations. The positive autocorrelation coefficients of the Nikkei basis are moderate and diminishing, indicating a mild persistence of the basis over trading days. I follow Miller et al. (1994) in defining the basis change as the first-order difference in the basis. The Nikkei basis changes exhibit significantly negative first-order autocorrelation coefficients. This indicates a mean-reverting tendency induced by arbitrage[64] and probably error correction in the Nikkei markets.

The cross-correlation coefficients of the Nikkei spot and futures returns are provided in Table 5.2. Not surprisingly, the Nikkei spot and the OSE futures returns are strongly correlated with a coefficient larger than 0.96, suggesting high synchronisation between the two markets. The Nikkei spot and the SGX futures returns show similar high correlations. The OSE and SGX futures returns are even more highly correlated at 0.99. Given that the OSE, SGX contracts based on the same index are denominated in the same currency and traded almost at the same time, daily price information is somewhat homogeneous and shared between the markets through arbitrage activities, resulting in substantial information flows across the spot, OSE and SGX, and their close relationships. However, the correlations of the CME returns with the other returns are relatively low in both samples. For comparison, Booth et al. (1996) report the daily CME correlation coefficients with the OSE, SGX at approximately 0.8 over the period 1990-1994. The low co-movements of the CME with the other Nikkei markets may reflect the relatively small trading volume of the CME futures and/or extra risks associated with the trading. Yet the different trading hours of the CME futures should not be a reason. As an additional check, the CME correlations are computed again between the CME returns on day

[64] According to Miller et al. (1994), the mean reversion in basis change emerges because of arbitrage and/or nonsynchronous trading of the index price. However, the analysis above shows that the nonsynchronous trading is less likely to be a problem in my data.

t-1 and any one of the other returns on day *t*, to allow for a possible time sequence by which the CME is the earliest trading market. The last row of each sample in Table 5.2 still gives low correlations. More discussions on the timing issues are provided in section 5.7.

Table 5.2 Cross-correlations of Nikkei spot and futures returns

	S	OSE	SGX	CME	CME(*t*-1)
Sample A					
S	1				
OSE	0.9646	1			
SGX	0.9637	0.9884	1		
CME	0.6691	0.6718	0.6695	1	
CME(*t*-1)	0.2470	0.2168	0.2367	-0.0654	1
Sample B					
S	1				
OSE	0.9787	1			
SGX	0.9759	0.9922	1		
CME	0.5064	0.5371	0.5327	1	
CME(*t*-1)	0.4241	0.3984	0.4173	-0.0234	1

Notes: The table displays the cross-correlation coefficients of the Nikkei spot (S), futures (OSE, SGX, CME) returns in sample A (17/01/1997-12/09/2008) and sample B (02/12/2008-30/12/2014). The sample division is used to ensure that all the series have the same length. The last row of each sample shows additional evidence of the relatively low correlations of the CME, by matching the CME returns on day *t*-1, denoted as CME(*t*-1), with any one of the other returns on day *t*, which is the default time and thus omitted.

5.4.2 Tests for cointegration

The two-step procedure of Engle and Granger (1987) is adopted to test for cointegration in individual Nikkei markets. Augmented Dickey-Fuller (ADF) tests and Phillips-Perron (PP) tests for unit roots are applied to the log-prices and log-differenced returns in each market.[65] As shown in Panel A of Table 5.3, the spot and futures prices are I(1). The long-run relationship between the spot and futures prices, equation (5.1), is estimated by ordinary least squares (OLS), and Panel B of Table 5.3 indicates the estimated constant close to 0, the estimated slope close to 1. When the coefficient restrictions β_0=0, β_1=1 are tested by Wald statistics, the CME cannot reject these hypotheses, but the OSE and SGX show significant rejections - the significance may arise from the neglected nonlinearity embedded in the asset prices. If the spot

[65] See Appendix 4.3 in Chapter 4 for methodological details of the unit root tests.

and futures prices are indeed cointegrated in the OSE and SGX, the cointegrating vector implied by the cost of carry relationship should be [1, -1]. Therefore I still apply the restrictions β_0=0, β_1=1, and check the stationarity of the regression residual b_t of equation (5.1). The results are given in Panel A of Table 5.3. The ADF tests and PP tests show that b_t is I(0), and hence, the spot and futures prices are cointegrated in each Nikkei market. With the cointegrating vector [1, -1], $b_t = f_t - s_t$, and b_t is to be called the log-basis.

The standard Johansen (1988; 1991) maximum likelihood procedure is followed to test for cointegration across the Nikkei futures markets. From Panel A of Table 5.3, each of the futures prices is I(1). A vector autoregression (VAR) model in levels is built for the three futures series. The optimal lag length of the VAR is determined by the sequential modified likelihood ratio test and Akaike Information Criterion (AIC), as Schwartz Bayesian Criterion (SBC) is found to select too short lags with which the model residuals are not white. The lag selection criteria indicate 8 lags (sample A) and 5 lags (sample B), i.e. 7 lags (sample A) and 4 lags (sample B) in first differences.[66] The results are the same when the VAR model is estimated for each bilateral pair of the futures prices, (OSE_t, SGX_t), (OSE_t, CME_t) and (SGX_t, CME_t). Taking into account an alternative trading sequence (for more details see section 5.7), I also estimate the VAR for the pairs (OSE_t, CME_{t-1}) and (SGX_t, CME_{t-1}), and find 7 lags (sample A) and 5 lags (sample B), i.e. 6 lags (sample A) and 4 lags (sample B) in first differences. The chosen lags will be used in the following linear specifications where relevant.

The Johansen trace and maximal eigenvalue tests are carried out to determine the number of cointegrating relationships. The trace statistic tests the null hypothesis of at most r cointegrating vectors, and is calculated as

$$\lambda_{trace}(r) = -T \sum_{q=r+1}^{n} \ln(1-\hat{\lambda}_q)$$

where T is the sample size, n is the number of endogenous variables, $\hat{\lambda}_q$ is the q-th largest

[66] It is recognised that the pre-crisis lags are longer than what are usually reported in the literature with daily data, but they have to be used to remove the model residual autocorrelations, especially in the CME. The long lags make 17/01/1997 as the starting date of sample A for futures price interactions.

eigenvalue obtained from the **Π** matrix.[67] The maximal eigenvalue statistic tests the null hypothesis of r cointegrating vectors against (r+1) cointegrating vectors, and is calculated as

$$\lambda_{\max}(r, r+1) = -T\ln(1-\hat{\lambda}_{r+1})$$

Panel A of Table 5.4 shows that both tests strongly reject the null hypotheses of r=0 and r≤1 but cannot reject the null hypothesis of r≤2. This means that the three Nikkei futures prices are cointegrated with two cointegrating vectors, or with one common stochastic factor as expected. The result is robust with respect to the number of lags and trend assumptions. It follows that each bilateral pair of the Nikkei futures prices is cointegrated with one cointegrating vector. Panel B of Table 5.4 displays the test results of the restriction imposed on the transposed cointegrating matrix beta

$$\boldsymbol{\beta}' = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & -1 \end{bmatrix}$$

The likelihood ratio tests cannot reject the above restriction at conventional levels. Hence, the long-run equilibrium $\boldsymbol{\beta}'\mathbf{f_t} = \mathbf{0}$, where $\mathbf{f_t}$ is a column vector that contains the three futures prices subscripted by 1, 2 and 3 for brevity, can be written as[68]

$$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & -1 \end{bmatrix} \begin{bmatrix} f_{1,t} \\ f_{2,t} \\ f_{3,t} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

which is equivalent to $f_{1,t} - f_{3,t}=0$, $f_{2,t} - f_{3,t}=0$. Since the order of the futures series is arbitrary, this implies that I cannot reject zero constant and unit slope in equation (5.4); in other words, the cointegrating vector is [1, -1] for any two Nikkei futures prices. Therefore, the price differential (f_1 - f_2) at lag 1 will be used as the error correction term z_{t-1} to study the price dynamics across the futures markets.

[67] $\boldsymbol{\Pi}=\boldsymbol{\alpha\beta}'$, where $\boldsymbol{\alpha}$ is a matrix of speed-of-adjustment parameters, $\boldsymbol{\beta}'$ is a transposed matrix of long-run parameters. For details I refer to the original works.

[68] This is analogous to saying that the error correction term is zero in the long-run equilibrium in a single-equation case (Asteriou and Hall, 2007).

Table 5.3 Tests for (non)stationarity and cointegration in individual Nikkei markets

	OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
Panel A: Unit root tests						
ADF						
s_t	-1.8208	-1.8860	-1.8205	-1.9148	-1.8173	-1.7739
f_t	-1.7740	-1.8810	-1.8641	-1.9030	-1.7527	-1.8133
Δs_t	-56.8693**	-41.4880**	-56.8378**	-42.3184**	-56.9526**	-41.7665**
Δf_t	-59.0176**	-41.5847**	-57.4696**	-41.6747**	-58.3330**	-40.4335**
b_t	-17.4540**	-9.9524**	-17.3997**	-9.5683**	-48.1257**	-14.8581**
b_t^*	-17.5880**	-10.2081**	-17.5705**	-10.2030**	-47.6145**	-14.4661**
PP						
s_t	-1.7379	-1.7552	-1.7315	-1.7881	-1.6766	-1.7076
f_t	-1.7681	-1.7805	-1.7666	-1.8457	-1.6918	-1.7928
Δs_t	-56.9286**	-41.5128**	-56.9140**	-42.3444**	-57.1968**	-41.7198**
Δf_t	-59.0839**	-41.5605**	-57.5571**	-41.6509**	-58.6504**	-40.4262**
b_t	-50.8582**	-30.3514**	-49.1950**	-32.7350**	-49.0954**	-37.5927**
b_t^*	-51.2415**	-32.4737**	-49.5679**	-34.2554**	-49.4651**	-37.5262**
Panel B: The long-run spot-futures relationship [a]						
β_0	-0.0155**	-0.0166**	-0.0129**	-0.0155**	0.0062	-0.0060
β_1	1.0016**	1.0017**	1.0013**	1.0016**	0.9994	1.0010

Notes: The table contains the results of unit root tests and Engle-Granger (1987) cointegration tests for each Nikkei spot-futures pair in each sample. Panel A lists the unit root test results of ADF and PP for the log-prices (s_t, f_t), log-differenced price returns (Δs_t, Δf_t), log-basis (b_t), and the detrended, outlier-free log-basis (b_t^*). For s_t, f_t and b_t, the ADF and PP test statistics are computed with constant and trend; for Δs_t, Δf_t and b_t^*, the ADF and PP test statistics are computed without constant or trend. Lag length is determined by SBC. Panel B lists the OLS regression results of the long-run relationship between the spot and futures prices, equation (5.1): $f_t=\beta_0+\beta_1 s_t+b_t$. [a] The coefficient restrictions, $\beta_0=0$, $\beta_1=1$ are tested by Wald statistics. ** denotes significance at the 5% level.

Table 5.4 Cointegration across the Nikkei futures markets

Panel A: Tests for the number of cointegrating vectors

	Trace test		Maximal eigenvalue test	
H_0	λ_{trace}	Pr(0.01)	λ_{max}	Pr(0.01)
Sample A				
r=0	643.5701	35.6500	343.9272	25.5200
$r\leq1$	299.6429	20.0400	296.9541	18.6300
$r\leq2$	2.6889	6.6500	2.6889	6.6500
Sample B				
r=0	451.1996	35.6500	247.8994	25.5200
$r\leq1$	203.3002	20.0400	202.8050	18.6300
$r\leq2$	0.4952	6.6500	0.4952	6.6500

Panel B: Tests of cointegration restrictions

	No. of cointegrating vectors	LR stat	*p*-value
Sample A	2	1.7245	0.4222
Sample B	2	0.4760	0.7882

Notes: The table contains the results of Johansen (1988; 1991) cointegration tests on the three Nikkei futures returns. Panel A shows the test statistics of the trace test (λ_{trace}) and maximal eigenvalue test (λ_{max}). H_0 is the null hypothesis of at most r cointegrating vectors in the trivariate system. Pr(0.01) is the 1% critical value taken from Osterwald-Lenum (1992). The number of lags used is 7 (sample A) and 4 (sample B) in first differences, determined by the sequential modified likelihood ratio test and AIC. The trend assumption is linear deterministic trend in the level data. However, the test results are robust with respect to the number of lags and trend assumptions. The results indicate 2 cointegrating vectors, shown in Panel B. The following restriction is tested on the transposed cointegrating matrix beta

$$\boldsymbol{\beta}' = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & -1 \end{bmatrix}$$

The likelihood ratio (LR) test statistic is calculated as

$$T\sum_{q=1}^{r} \ln[(1-\hat{\lambda}_q^*)/(1-\hat{\lambda}_q)]$$

where T is the sample size; $\hat{\lambda}_q^*, \hat{\lambda}_q$ are the q-th estimated eigenvalues of the restricted and unrestricted specifications, respectively. The LR statistic is asymptotically distributed as $\chi^2(2)$ in this case. The LR statistics and the associated *p*-values are also shown in Panel B.

5.4.3 Trends and outliers

In effect, the spot-futures log-basis b_t is trended with trends from three possible sources: time to maturity of the futures contracts, rolling over the futures contracts, and the passage of time. From the cost of carry model, b_t equals the net cost of carry of holding a futures contract. As the maturity date draws near, the value of b_t decreases as a result of the decreasing risks contained in the interest rate and dividends; at maturity, the risks are zero, the spot price equals the futures price, and b_t reduces to zero. Low et al. (2002) record that the maturity effect is linear: the average Nikkei log-basis increases linearly and significantly with the time to maturity. To examine whether the maturity effect is significant in my data, b_t is regressed on a constant c and time to maturity (T-t):[69]

$$b_t = c + \beta(T - t) + \tilde{b}_t \tag{5.7}$$

where the last term on the right-hand-side is a residual. Panel A of Table 5.5 shows the regression results in each Nikkei market in each sample. The coefficient of time to maturity is significantly negative (positive) for negative (positive) log-basis on average, except in the CME (sample A) where the coefficient is insignificant; however, an additional regression over the whole sample generates a coefficient of 1.27E-05 with p-value 0.0396 in the CME. Taken together, I support the significantly positive relationship between b_t and time to maturity. The regression residual from equation (5.7) is the log-basis net of the maturity effect.

The practice of rollover introduces jumps into the log-basis series at rollover dates, as the futures contracts of different maturities are spliced together. Switching contracts at the start of the contract month impairs the degree of the basis jumps, for the trading days very near the maturity date, i.e. the second Friday of the contract month in the Nikkei markets, are excluded. The remaining basis jumps can be captured by equation (5.7). This is because when a new futures contract enters the data, the time to maturity jumps as well, so that the series of time to maturity exhibits a similar saw-tooth pattern as in the log-basis series. The above regression of b_t on the time to maturity should allow for the basis jumps caused by the practice of rollover.

[69] Time to maturity is the number of calendar days remaining in a futures contract until expiration. I use calendar days because the cost of carry model uses calendar days and the real world uses calendar days to calculate interest rates and dividends. Replacing time to maturity by the number of trading days remaining in a contract generates qualitatively the same results.

The residual from equation (5.7) is actually the log-basis net of the maturity effect and the rollover effect.

Table 5.5 Possible trends in Nikkei log-basis

	OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
Panel A: Regression of the log-basis on the time to maturity						
Constant	0.0008**	0.0013**	0.0009**	0.0013**	0.0009**	0.0006
Coefficient	-1.99E-05**	-3.74E-05**	-2.05E-05**	-3.88E-05**	-2.50E-06[a]	4.66E-05**
Panel B: Regression of the log-basis on the time intervals						
Constant	-0.0004**	-0.0006**	-0.0002**	-0.0009**	0.0005	0.0036**
Coefficient	8.66E-07	-1.41E-04*[b]	-3.55E-06	1.19E-05	1.42E-04	-2.31E-04
Average log-basis	-0.0004	-0.0009	-0.0002	-0.0009	0.0007	0.0032

Notes: The table shows the possible trends in the log-basis in each Nikkei market in each sample. Panel A reports the regression results of the log-basis on a constant and time to maturity, to allow for the maturity effect and the rollover effect. Panel B reports the regression results of the log-basis on a constant and the time intervals between consecutive data-points, to allow for the calendar effect. Regressions are by OLS with White (1980) heteroskedasticity-consistent standard errors and covariance. The bottom line gives the average of the log-basis in each market in each sample for reference. [a] Regression of the CME log-basis on the time to maturity over the whole sample generates a coefficient of 1.27E-05 with *p*-value 0.0396. [b] Regression of the OSE log-basis on the time intervals over the whole sample generates a coefficient of -2.16E-05 with *p*-value 0.6727. ** denotes significance at the 5% level. * denotes significance at the 10% level.

Time-related patterns, or the calendar effect, are often observed in financial returns but the calendar effect of the (log-)basis is not clear, especially in the Nikkei markets. The passage of time may have significant impacts on the spot and futures prices, and thus their difference. This possibility is checked by regressing b_t on a constant and the time intervals between consecutive data-points; the calendar effect exists if the coefficient of the time interval is significant. In Panel B of Table 5.5, the coefficients of the interval are generally small and insignificant in the Nikkei markets. The only significance is in the OSE (sample B); however, this coefficient becomes insignificant when the regression is re-run for the OSE during the whole sample period. Using s_t, f_t, Δs_t, Δf_t as the dependent variable in turn generates insignificant results in each market in each sample (results available upon request). Since the calendar effect is likely to be consistent in a market, the only significance could be data-specific and thus I decide to ignore the calendar effect in the Nikkei markets.

Nonlinearities in the error correction can be caused by a few outliers in the data (van Dijk and Franses, 1997). To ensure that the nonlinear smooth transition model does describe the "real" adjustment process rather than being the accidental outcome of several anomalies, I remove outliers by dummying out the observations exceeding 6 standard deviations in absolute value of each of the spot, futures and log-basis series. For the log-basis series, equation (5.7) is modified to include the dummy variables that represent the outliers:

$$b_t = c + \beta(T - t) + \sum_l dum_l + b_t^* \tag{5.8}$$

where dum_l=1 if the day has an outlier, 0 otherwise, with l the number of the outliers; b_t^* is a new residual, or the detrended log-basis without the influence of the outliers. Panel A of Table 5.3 indicates that b_t^* is also I(0). This confirms the cointegration between the Nikkei spot and futures, and justifies an ECM representation in studying their first-moment price dynamics. Moreover, b_t^* will act as the error correction term. For the spot and futures returns, each series is regressed on a constant, time to maturity and dummy variables according to equation (5.8). The residuals from the regressions are the demeaned spot and futures returns free from the maturity and rollover effects and outliers; for convenience, they will still be denoted as Δs_t, Δf_t in the following estimation. The outliers are removed in a consistent way for the three series - for example, when day t has an outlier in the futures return, I dummy out this day in the spot, futures and log-basis, to remove any potential effect of the outlier on all the series in a market. The number of the outliers removed is 4(OSE), 8(SGX) and 2(CME), leaving the total amount of observations for estimation to 4533(OSE), 4582(SGX) and 4479(CME).

Across the futures markets, I follow similar steps to check for the possibility of trends and outliers in the futures prices and their differentials. For the maturity and rollover effects, each futures return and price differential is regressed on a constant and the time to maturity; for the calendar effect, each is regressed on a constant and the time intervals between consecutive

Table 5.6 Possible trends in Nikkei futures returns and price differentials

	OSE	SGX	CME	OSE-SGX	OSE-CME	SGX-CME
Panel A: Regressions on the time to maturity [a]						
Sample A						
Constant	0.0001	0.0002	-0.0001	-0.0002**	0.0001	0.0003
Coefficient	-5.34E-06	-5.68E-06	-6.89E-07	1.07E-06	-2.11E-05**	-2.21E-05**
Sample B						
Constant	-0.0009	-0.0009	-0.0014	0.0000	0.0010	0.0010
Coefficient	2.38E-05	2.44E-05	3.36E-05**	9.29E-07	-8.70E-05**	-8.79E-05**
Panel B: Regressions on the time intervals [b]						
Sample A						
Constant	-0.0007	-0.0009	-0.0012**	-0.0001**	-0.0011**	-0.0010**
Coefficient	3.68E-04	4.49E-04	6.65E-04*	7.69E-06	8.36E-06	6.76E-07
Sample B						
Constant	0.0004	0.0004	0.0014*	0.0001	-0.0047**	-0.0048
Coefficient	3.84E-05	5.76E-05	-5.64E-04	1.81E-05	5.26E-04*	5.08E-04*

Notes: The table shows the possible trends in the Nikkei futures returns (OSE, SGX, CME) and price differentials. The price differentials are calculated as the differences between two logarithmic futures prices, presented as OSE-SGX, OSE-CME, and SGX-CME. Given that the order of taking the differences does not affect the results, for consistency, the second price is always subtracted from the first price in each presentation to make the relevant differential series hereafter. Panel A shows the regression results of each series on a constant and time to maturity, to allow for the maturity effect and rollover effect. Panel B shows the regression results of each series on the time intervals between consecutive data-points, to allow for the calendar effect. Regressions are by OLS with White (1980) heteroskedasticity-consistent standard errors and covariance. [a] Regressions on the time to maturity over the whole sample (coefficient followed by *p*-value in parentheses): CME 8.37E-06 (0.3681); OSE-CME -4.36E-05 (0.0000); SGX-CME -4.45E-05 (0.0000). [b] Regressions on the time intervals over the whole sample (coefficient followed by *p*-value in parentheses): CME 0.0003 (0.2734); OSE-CME 0.0002 (0.2091); SGX-CME 0.0002 (0.2623). ** denotes significance at the 5% level. * denotes significance at the 10% level.

data-points. The results are presented in Table 5.6. Panel A shows that the maturity effect is strongly significant mainly in the price differentials between the OSE and the CME, between the SGX and the CME. The strong significance of the time to maturity in the price differentials is confirmed when the regressions are repeated over the whole sample. In contrast, panel B suggests that the calendar effect is only periodical and marginally significant in a few series, and the whole-sample regressions of the time intervals do not indicate significance. As in the case of the individual markets, I therefore decide to ignore the calendar effect. In terms of outliers, I apply the same criterion of 6 standard deviations and dummy out observations exceeding the criterion in absolute value of each of the futures returns and differentials. The number of outliers found is 3 when the timing issues of the CME are ignored; 4 when the timing issues are considered. The complete regression for each of the series is on a constant, the time to maturity and the dummy variables that represent the outliers. The regressions are run consistently throughout all the data - any trends and outliers taken out from one series are also removed from all the other series. The regression residuals, detrended and free from the outliers, are to be used as their dependent variables in estimation. The total number of observations ready for estimation is 2776 (sample A) and 1443 (sample B) in the futures markets.

5.5 Methodology

5.5.1 Linearity tests

To test for the smooth transition nonlinearity in individual Nikkei markets, I employ the specification procedure of Teräsvirta (1994) that takes the linear ECM, equations (5.2a) (5.2b), as the null model, and the ESTECM, equations (5.3a) (5.3b), as the alternative model. The null hypothesis of linearity can be expressed as H_0: γ=0, with which equations (5.3a) (5.3b) become linear. However, when γ=0, the ESTECM is not identified in the sense that the nonlinear model parameters other than γ can each assume more than one value; this is called the problem of unidentified nuisance parameters (Teräsvirta, 1994; Franses and van Dijk, 2000). Yet the problem can be circumvented by performing the LM-type linearity tests of Saikkonen and Luukkonen (1988) and Teräsvirta (1994). Given the value of the delay parameter *d*, this involves running an auxiliary regression in each of the spot and futures markets, and the following is the regression in the spot market (McMillan, 2005):

$$\Delta s_t = \beta_{00} + \sum_{j=1}^{p} (\beta_{0j} x_{t-j} + \beta_{1j} x_{t-j} z_{t-d} + \beta_{2j} x_{t-j} z_{t-d}^2 + \beta_{3j} x_{t-j} z_{t-d}^3) + v_t \tag{5.9}$$

where x_t contains the adjusted price returns Δs_t, Δf_t and the error correction term z_{t-1}; z_{t-d} is the transition variable; v_t is the residual from the auxiliary regression; the model lag p is determined from estimating the linear ECM. Using Δf_t as the dependent variable yields the regression in the futures market. The null hypothesis of linearity H_0: $\gamma=0$ is equivalent to H_0: $\beta_{1j}=\beta_{2j}=\beta_{3j}=0$, $j=1, \ldots, p$, under which a LM-type test statistic asymptotically follows a χ^2 distribution with $3p$ degrees of freedom. The LM-type test statistic is constructed as $LM=T(RSS_L\text{-}RSS_A)/RSS_L$, where T is the sample size, RSS_L is the residual sum of squares from estimating the linear ECM, RSS_A is the residual sum of squares from estimating the auxiliary regression (5.9). F versions of the LM-type statistics can be used for better power and size properties in small samples. H_0 is expected to be rejected, which suggests the smooth transition nonlinearity in the spot-futures adjustment process and thus the ESTECM more appropriate.

The standard selection approach of the delay parameter d is to repeat the LM-type linearity tests for different candidates of d, and determine d as the one that generates the lowest p-value of the test, because the correct d should have the highest power in the test (Teräsvirta, 1994). Alternatively, one can use information criteria and/or other evaluation tests to select the value of d, as it is expected that a suitable d should be accompanied with better model fit (van Dijk et al., 2002; Enders, 2010).

Several modifications are needed when applying the LM-type linearity tests to the bilateral pair of Nikkei futures prices (f_1, f_2). First, the bivariate ECM in the futures markets, equations (5.5a) (5.5b), are the null model and the nonlinear ESTECM in the futures markets, equations (5.6a) (5.6b), are the alternative model. Indeed, with the null hypothesis of linearity H_0: $\gamma=0$, equations (5.6a) (5.6b) become linear, and rejecting H_0: $\gamma=0$ means the presence of smooth transition nonlinearity in the price adjustments between the equivalent futures markets. Second, equation (5.9) should be altered so that both prices f_1 and f_2 enter the auxiliary regression of market 1:

$$\Delta f_{1,t} = \beta_{00} + \sum_{j=1}^{p} (\beta_{0j} x_{t-j} + \beta_{1j} x_{t-j} z_{t-d} + \beta_{2j} x_{t-j} z_{t-d}^2 + \beta_{3j} x_{t-j} z_{t-d}^3) + v_t \tag{5.10}$$

where x_t contains the futures returns $\Delta f_{1,t}$, $\Delta f_{2,t}$ and the error correction term z_{t-1} which is the price differential (f_1 - f_2) at lag 1, all data detrended and free from the influence of outliers. Correspondingly, the transition variable z_{t-d} is the price differential (f_1 - f_2) at a certain lag d. Replacing $\Delta f_{1,t}$ by $\Delta f_{2,t}$ as the dependent variable gives the auxiliary regression of market 2. An additional consideration is about the model lag p, which, in fact, is associated with an alternative trading sequence and also applies in the linear ECM, equations (5.5a) (5.5b). The number of lags in the linearity test should be the same as that in the linear model. Given that the CME market operates in a different time zone, if the CME returns on day t-1 is aligned with the other returns on day t to test for nonlinearity with the alternative trading sequence by which the CME is the earliest trading market, the p lags of the linear ECM should be applied consistently to CME_{t-1}, OSE_t and SGX_t in the test; as a result, the CME maximum lags used in returns would always be 1 lag longer than the maximum lags of the other two markets, even though the lag length is the same p.

5.5.2 Estimation and evaluation

The estimation of the linear ECMs, equations (5.2a) (5.2b) for spot-futures pairs and (5.5a) (5.5b) for bilateral futures pairs, is by OLS. The model lag p is selected by SBC in the individual markets; across the futures markets, p is pre-determined by the sequential modified likelihood ratio test and AIC in the Johansen procedure. The error correction term z_{t-1} is represented by the log-basis b_t^* at lag 1, or by the futures price differentials (f_1 - f_2) at lag 1, detrended and outlier-free. Preliminary estimations show that the model residuals are affected by excessive ARCH effects. For this reason, the conditional variance equation in the Nikkei markets is estimated by a univariate GARCH (1, 1) model of Bollerslev (1986):

$$u_t = \sigma_t \eta_t \tag{5.11}$$

$$\sigma_t^2 = \omega + a u_{t-1}^2 + b \sigma_{t-1}^2 \tag{5.12}$$

where u_t is the ECM residual; η_t ~ iid(0,1); ω>0; a≥0; b≥0; a+b<1; σ_t is a time-varying, positive and measurable function of the information set at time t-1. The GARCH (1, 1) model is chosen because it is widely used and simple enough to provide a benchmark for the conditional variance models at the nonlinear stage.[70] The estimation of equations (5.11) (5.12) is by (quasi-)maximum likelihood. The linear ECM-GARCH forms the base model of the error correction mechanism in individual Nikkei markets and across.

The estimation of the ESTECM, equations (5.3a) (5.3b) and (5.6a) (5.6b), is by nonlinear least squares (NLS). The model restriction $k^*=c^*=0$ is imposed because the adjusted price returns Δs_t, Δf_t and $\Delta f_{1,t}$, $\Delta f_{2,t}$ do not contain constants, and the transition functions are usually centred at zero. The error correction term z_{t-1} is as in the linear ECM. The transition variable z_{t-d} is represented by the detrended and outlier-free log-basis b_t^*, or futures price differential (f_1 - f_2) at a certain lag d, which is to be determined in the linearity tests. To provide a scale-free environment for the nonlinear parameters, I standardise the smoothness parameter γ by dividing it by the sample variance of z_{t-d}, and standardise the asymmetry parameter θ by dividing it by the sample standard deviation of z_{t-d}. The standardisation is a common practice in studies with smooth transition models (e.g. Teräsvirta, 1994; Anderson, 1997).

To find out the model lag p in the ESTECM, I follow Haggan and Ozaki (1981) to grid search for possible combinations of (γ, θ). With fixed (γ, θ), the ESTECM becomes linear, and the resultant linear model is estimated with different lags. The model lag p is determined as the lag that yields the minimal AIC; also, that minimum needs to be stable for different combinations of (γ, θ). The NLS estimation of the ESTECM is equivalent to maximum likelihood if the model residual u_t is assumed to be normally distributed; otherwise the NLS estimates can be interpreted as quasi-maximum likelihood estimates (van Dijk et al., 2002).[71] The NLS estimates are conditional upon starting values. A two-dimensional grid search over γ and θ is performed to obtain different sets of starting values. More specifically, I fix γ first at a given value and then search for θ that generates the lowest residual variance, and then keep θ fixed at that value and search for γ with the lowest residual variance. The selected values of γ and θ,

[70] In some cases, a GARCH (2, 1) process is found necessary to remove the excessive ARCH effects. For example, the OSE, SGX spot residuals in sample B when examining the spot-futures dynamics. If a GARCH (2, 1) model is needed, equation (5.12) is modified to: $\sigma_t^2 = \omega + a_1 u_{t-1}^2 + a_2 u_{t-2}^2 + b\sigma_{t-1}^2$, where the non-negative (G)ARCH parameters have a sum less than 1.

[71] For conditions of consistency and asymptotical normality of the NLS estimates I refer to Klimko and Nelson (1978) and Tong (1990).

together with the OLS estimates of the remaining parameters (the ESTECM is linear with fixed γ and θ), provide a set of starting values with the lowest residual variance for NLS estimation. At the second round, slightly change the given value of γ and repeat the searching process, and obtain another set of starting values with the lowest residual variance. The grid search continues until all the potential values of γ and θ are exhausted (Franses and van Dijk, 2000; Enders, 2010).[72] Among the models whose algorithms converge and parameter estimates look reasonable, the final model is decided as the one with the lowest residual variance.

The ESTECM captures asymmetric market responses through the asymmetry parameter θ; I would expect the corresponding conditional variance model to be able to describe the leverage effect as well. This is because the asymmetric market responses to good news and bad news may also occur in the second moments, and previous studies on a wide range of markets tend to show evidence of more volatile markets in the aftermath of negative shocks than positive shocks of the same magnitude. However, the linear GARCH model is unable to accommodate such asymmetry. As can be seen from equation (5.12), the conditional variance σ_t^2 is parameterised as a function of the magnitude of the lagged squared information shock(s) u_t and the magnitude of the lagged conditional variance σ_t^2 - the signs of the variables play no part in the symmetric framework. In this respect, nonlinear GARCH models with asymmetry are preferable as they allow the conditional variance to depend on both the magnitudes and the signs, and thus capture the asymmetric volatility effect (Bollerslev et al., 1992). Hence, the ESTECM residual u_t is assumed to follow a univariate exponential GARCH (EGARCH) process of Nelson (1991) in the Nikkei markets. The EGARCH model is selected as it takes into account the different impacts of good news and bad news on volatility. Compared with other asymmetric GARCH models, the EGARCH model specifies the conditional variance as an exponential function, consistent with the exponential transition function which contains the asymmetry function in the first moment. Let σ_t^2 be the conditional variance as in equation (5.11). A simple EGARCH (1, 1) model can be formulated as below:[73]

[72] There are two grid searches involved in the estimation procedure. The first is to determine the model lag p and the second is to find starting values. In this context, searching simultaneously over γ and θ would be computationally burdensome and fixing one of the variables and searching the other at a time at each round simplifies the searching process. The risk of missing the global maximum in the likelihood function is deemed to be small. As a robustness check, different sets of starting values are used to estimate the same model, and the model parameter estimates are very similar despite the different starting values.

[73] As in the linear case, sometimes an EGARCH (2, 1) model is found necessary to remove the excessive ARCH effects.

$$\ln\sigma_t^2 = \omega + \lambda(u_{t-1}/\sigma_{t-1}) + a\left|u_{t-1}/\sigma_{t-1}\right| + b\ln\sigma_{t-1}^2 \quad (5.13)$$

where u_t is the residual from the ESTECM; there are no constraints on the non-negativity of the coefficients ω, a and b; the coefficient λ sheds light on the presence of the predictive asymmetry of asset prices. To be more specific, the impact of any price innovations on the logarithmic conditional variance is a linear combination of λ and a. For a positive shock, $u_{t-1}/\sigma_{t-1}>0$, the impact is (λ+a); for a negative shock, $u_{t-1}/\sigma_{t-1}<0$, the impact is (-λ+a) (Enders, 2010). Thus, a negative λ is required for negative shocks to trigger higher volatility, and I expect λ to be significantly negative in the Nikkei spot-futures and futures price adjustments. The estimation of equations (5.11) (5.13) is by (quasi-)maximum likelihood. The joint estimation of the ESTECM as the conditional mean and the EGARCH model as the conditional variance is difficult. A two-step approach in the spirit of Chan and McAleer (2002) is applied that first estimate the ESTECM, and then estimate the EGARCH using the residual obtained from the ESTECM. The ESTECM-EGARCH makes the nonlinear error correction framework alternative to the base model.

The estimated models, linear (ECM-GARCH) and nonlinear (ESTECM-EGARCH), should have reasonable parameters in the conditional mean and conditional variance equations. Besides, the model residuals are subject to diagnostic tests for residual autocorrelation, remaining ARCH effects, remaining leverage effects and normality. The RSS of the linear model is compared with the RSS of the corresponding nonlinear model to see whether the latter is smaller. Model selection criteria, AIC and SBC, are also considered to compare the in-sample fit of the linear and nonlinear models.

5.6 Empirical results

5.6.1 Spot-futures price dynamics

The estimation results of the linear ECM-GARCH in individual Nikkei markets are reported in Table 5.7. The lag length p=1 in the mean model is selected by SBC. The long-run error

---

Accordingly, when needed, equation (5.13) is modified to: $\ln\sigma_t^2 = \omega + \lambda(u_{t-1}/\sigma_{t-1}) + a_1\left|u_{t-1}/\sigma_{t-1}\right| + a_2\left|u_{t-2}/\sigma_{t-2}\right| + b\ln\sigma_{t-1}^2$, where the impact of price innovations is a linear combination of λ, a_1 and a_2. The predictive asymmetry exists if λ<0.

Table 5.7 Estimation and evaluation results in individual Nikkei markets: the linear ECM-GARCH model

	OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
ECM coefficients						
Spot						
k_s	0.0000	0.0007	0.0000	0.0008	0.0006	-0.0002
	(0.1370)	(2.0204)	(-0.0170)	(2.3366)	(3.1755)	(-0.9572)
π_{ss}	-0.1422	-0.4221	-0.2217	-0.2361	-0.0392	-0.0956
	(-1.5292)	(-2.9096)	(-2.4743)	(-2.3913)	(-1.5404)	(-3.2829)
π_{sf}	0.1222	0.4014	0.2126	0.2227	0.0183	0.0723
	(1.3360)	(2.7728)	(2.3791)	(2.2712)	(0.6254)	(2.0604)
α_s	0.3481	0.0109	0.4096	0.2686	0.7631	0.7364
	(3.3224)	(0.0695)	(3.9760)	(2.0821)	(19.9597)	(17.6859)
Futures						
k_f	0.0002	0.0006	0.0002	0.0006	0.0001	0.0006
	(0.9151)	(1.7830)	(0.8421)	(1.6250)	(0.3016)	(1.8947)
π_{fs}	0.0165	-0.1947	-0.0557	-0.0625	-0.0476	0.0402
	(0.1718)	(-1.3335)	(-0.5952)	(-0.6543)	(-1.5514)	(1.0590)
π_{ff}	-0.0460	0.1736	0.0419	0.0532	0.0050	-0.0472
	(-0.4898)	(1.1906)	(0.4507)	(0.5652)	(0.1406)	(-0.9979)
α_f	-0.2665	-0.3488	-0.2090	-0.2342	-0.1049	0.0246
	(-2.4707)	(-2.2769)	(-2.0068)	(-1.8797)	(-2.1596)	(0.4654)
GARCH coefficients						
Spot						
ω_s	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(3.6085)	(2.9298)	(3.6193)	(3.1675)	(2.9284)	(2.0847)
$a_{s,1}$	0.0828	0.0152	0.0825	0.0105	0.0683	0.0546
	(6.6246)	(0.5387)	(6.7476)	(0.4051)	(5.5429)	(2.6988)
$a_{s,2}$		0.0765		0.0766		
		(2.2691)		(2.3325)		
b_s	0.9028	0.8724	0.9035	0.8738	0.9204	0.9140
	(66.3234)	(31.4238)	(67.9445)	(32.7177)	(66.3388)	(29.1230)
Futures						
ω_f	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(3.6093)	(2.9416)	(3.5452)	(3.1563)	(3.2361)	(3.1009)
a_f	0.0840	0.0907	0.0816	0.0926	0.0648	0.0828
	(6.8547)	(4.2444)	(6.4575)	(4.1867)	(6.0745)	(4.0212)
b_f	0.8998	0.8797	0.9022	0.8742	0.9190	0.8740
	(65.7411)	(35.5805)	(64.0633)	(34.1358)	(73.6606)	(31.6330)

Table 5.7 continued

	OSE		SGX		CME	
	Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
Evaluation						
Spot						
RSS	0.6334	0.3382	0.6312	0.3385	0.4606	0.1851
Q(24) for η_t	[0.6953]	[0.9927]	[0.4792]	[0.8925]	[0.9425]	[0.2993]
Q(24) for η_t^2	[0.3413]	[0.3098]	[0.5939]	[0.3240]	[0.2680]	[0.5422]
JB	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Asymmetric tests						
Sign bias test	[0.8058]	[0.6771]	[0.6125]	[0.5761]	[0.5326]	[0.1495]
Neg. size bias test	[0.9723]	[0.5874]	[0.8510]	[0.2475]	[0.9351]	[0.8867]
Pos. size bias test	[0.0002]	[0.4961]	[0.0003]	[0.2318]	[0.3105]	[0.2365]
Joint test	[0.0029]	[0.4079]	[0.0061]	[0.3167]	[0.1846]	[0.6733]
Futures						
RSS	0.6762	0.3468	0.6545	0.3393	0.6515	0.3387
Q(24) for η_t	[0.5667]	[0.9956]	[0.3000]	[0.9421]	[0.9435]	[0.9095]
Q(24) for η_t^2	[0.3057]	[0.2517]	[0.4673]	[0.3789]	[0.9728]	[0.9396]
JB	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Asymmetric tests						
Sign bias test	[0.5975]	[0.6401]	[0.9782]	[0.7278]	[0.0960]	[0.7704]
Neg. size bias test	[0.8283]	[0.9966]	[0.6079]	[0.7804]	[0.2120]	[0.7939]
Pos. size bias test	[0.0004]	[0.0225]	[0.0008]	[0.0901]	[0.4016]	[0.0050]
Joint test	[0.0012]	[0.1190]	[0.0079]	[0.1916]	[0.0307]	[0.1028]

Notes: The table presents the estimation and evaluation results of the linear ECM-GARCH model in individual Nikkei markets. The mean models are equations (5.2a) (5.2b):

$$\Delta s_t = k_s + \sum_{j=1}^{p} \pi_{ss,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j} \Delta f_{t-j} + \alpha_s z_{t-1} + u_{s,t}, \quad \Delta f_t = k_f + \sum_{j=1}^{p} \pi_{fs,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j} \Delta f_{t-j} + \alpha_f z_{t-1} + u_{f,t}$$

The variance models are equations (5.11) (5.12): $u_t = \sigma_t \eta_t$, $\sigma_t^2 = \omega + a u_{t-1}^2 + b\sigma_{t-1}^2$, or a GARCH(2,1) $\sigma_t^2 = \omega + a_1 u_{t-1}^2 + a_2 u_{t-2}^2 + b\sigma_{t-1}^2$ is used instead of (5.12) to remove the excessive ARCH effects in the residuals. The estimation of the ECM is by OLS; the estimation of the GARCH is by quasi-maximum likelihood with Bollerslev-Wooldridge (1992) robust standard errors and covariance. The model lag p=1 is determined by SBC. Δs_t, Δf_t are detrended, outlier-free price returns; z_{t-1} is represented by the detrended, outlier-free log-basis at lag 1. The diagnostic checks include the Ljung-Box (1978) portmanteau test (Q) for standardised residuals and squared standardised residuals up to order 24, the Jarque-Bera (1980) normality test (JB), and the asymmetric test of Engle and Ng (1993) which contains sign bias test, negative (neg.) size bias test, positive (pos.) size bias test, and joint test. Numbers in parentheses are z-statistics. Numbers in square brackets are p-values.

correction coefficient α is positive in the spot and negative in most of the futures, which is consistent with my expectation of the error correction mechanism. The only exception is in the CME (sample B) where the error correction terms are positive in both the spot and futures markets; however, taking the difference (α_f - α_s) gives the net error correction effect in the market and it is negative as expected. The error correction terms are found significant in both the spot and futures markets in the OSE (sample A), SGX and CME (sample A), indicating bidirectional causality between the spot and futures markets. In the OSE (sample B), α_s is insignificant and smaller, but α_f is significant and larger in magnitude: this is evidence of unidirectional causality from spot to futures, implying that the spot market plays a primary role in the information transmission process after the crisis. The reverse causality from futures to spot is found in the CME (sample B) for significant, larger α_s and insignificant, smaller α_f, which supports the predominant function of the futures market in the price discovery. In terms of the speed of information transmission, the Nikkei futures are generally quicker in reflecting information (α_f is smaller in magnitude than α_s), except that, as noted, the spot market shows quicker speed of information transmission than the OSE futures in the post-crisis period.

In the short run, the Nikkei futures lead the spot in the OSE (sample B), SGX and CME (sample B), as indicated by the significant π_{sf} and insignificant π_{fs}. Yet the short-run adjustments may be accomplished within 1 trading day in the rest of the markets, where neither of the lagged returns is significant. Moreover, the spot market needs 1 trading day to adjust to its own equilibrium, as π_{ss} is often significantly negative, while each of the futures markets makes the adjustments within 1 trading day, as π_{ff} is always insignificant. Table 5.7 also provides the results of the diagnostic tests of the linear model. The linear model residuals do not suffer from autocorrelations or remaining ARCH effects, but they show significant leverage effects by the asymmetric tests of Engle and Ng (1993), especially in the futures markets. Clearly, the presence of predictive asymmetry necessitates a nonlinear error correction mechanism with asymmetric considerations.

Table 5.8 Linearity tests in individual Nikkei markets

	OSE				SGX				CME			
	Sample A		Sample B		Sample A		Sample B		Sample A		Sample B	
d	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
1	6.22E-09	1.94E-09	1.85E-09	4.37E-11	8.24E-03	8.38E-03	2.89E-03	4.64E-02	1.70E-04	2.17E-08	2.97E-09	1.56E-09
2	3.95E-03	1.88E-03	4.45E-04	1.93E-05	1.21E-01	6.70E-02	1.49E-02	2.31E-02	3.70E-06	1.12E-01	7.54E-10	2.03E-07
3	5.66E-04	1.70E-04	3.91E-09	2.64E-09	1.38E-06	4.87E-08	7.63E-04	1.98E-02	8.39E-03	1.83E-04	1.46E-04	4.82E-07

Notes: The table displays the results of the LM-type linearity tests in individual Nikkei markets. An auxiliary regression by OLS as equation (5.9) is run in the spot market:

$$\Delta s_t = \beta_{00} + \sum_{j=1}^{p} (\beta_{0j} x_{t-j} + \beta_{1j} x_{t-j} z_{t-d} + \beta_{2j} x_{t-j} z_{t-d}^2 + \beta_{3j} x_{t-j} z_{t-d}^3) + v_t$$

Using Δf_t as the dependent variable yields the regression in the futures market. x_t contains the adjusted price returns Δs_t, Δf_t and the error correction term $z_{t-1.}$ The model lag p=1. Different candidates of the delay parameter d are selected from {1, 2, 3}.The null hypothesis of linearity is equivalent to H_0: $\beta_{1j}=\beta_{2j}=\beta_{3j}=0$, j=1,…, p, under which a LM-type test statistic follows $\chi^2(3p)$ asymptotically. The LM-type test statistic is constructed as $LM=T(RSS_L-RSS_A)/RSS_L$, where T is the sample size, RSS_L is the residual sum of squares from estimating the linear ECM, RSS_A is the residual sum of squares from estimating the auxiliary regression (5.9). The p-values of the LM-type test statistics are reported for different values of d in each market in each sample. Note that d can be determined as the candidate that generates the smallest p-value of the test or by evaluation tests.

Table 5.9 Estimation and evaluation results in individual Nikkei markets: the ESTECM-EGARCH model

	OSE				SGX				CME			
	Sample A		Sample B		Sample A		Sample B		Sample A		Sample B	
	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat
Panel A: ESTECM coefficients												
Spot												
p	2		1		4		2		4		4	
k_s	-0.0001	-0.3939	0.0007	2.0902	-0.0001	-0.5438	0.0006	1.9409	0.0002	0.7660	-0.0003	-1.0955
$\pi_{ss,1}$	-0.6008	-5.9185	-0.4484	-2.9477	-1.0953	-4.8835	-0.1780	-1.3440	-0.2731	-2.7999	0.1764	0.5216
$\pi_{ss,2}$	-0.3050	-3.3769			-0.9696	-4.4204	0.1146	0.9800	-0.1861	-2.1438	0.0727	0.2200
$\pi_{ss,3}$					-0.6463	-3.4864			-0.1598	-2.1835	0.3023	1.2850
$\pi_{ss,4}$					-0.3560	-2.4010			-0.1706	-2.9540	-0.4681	-2.3462
$\pi_{sf,1}$	0.5765	5.7733	0.4474	2.9222	1.1067	4.9270	0.1396	1.0263	0.2220	2.2318	-0.3899	-0.9047
$\pi_{sf,2}$	0.3138	3.5142			0.9632	4.4109	-0.1213	-1.0008	0.2199	2.4459	-0.4410	-1.2840
$\pi_{sf,3}$					0.6421	3.5028			0.2031	2.6240	-0.3504	-1.1271
$\pi_{sf,4}$					0.4103	2.6770			0.1296	2.0532	-0.0894	-0.5128
$\pi_{ss,1}^*$	1.5186	1.7640	0.0975	0.1818	0.9742	3.4631	-0.1627	-0.8335	0.1069	0.7651	-0.4083	-1.1355
$\pi_{ss,2}^*$	0.4753	1.0683			1.0546	4.0967	-0.5705	-2.7705	0.0702	0.5595	-0.1798	-0.5233
$\pi_{ss,3}^*$					0.6421	2.5988			0.1073	1.0176	-0.3363	-1.3776
$\pi_{ss,4}^*$					0.3201	1.5291			0.1825	2.3720	0.4645	2.3041
$\pi_{sf,1}^*$	-1.5768	-1.7406	-0.2703	-0.4700	-1.0370	-3.7486	0.1773	0.9083	-0.0539	-0.3821	0.5802	1.2951
$\pi_{sf,2}^*$	-0.5340	-1.2396			-1.0529	-4.1274	0.6634	3.2381	-0.0881	-0.7003	0.5876	1.6239
$\pi_{sf,3}^*$					-0.6049	-2.4636			-0.1670	-1.4993	0.3927	1.2123
$\pi_{sf,4}^*$					-0.4495	-2.1382			-0.0986	-1.0831	0.0852	0.4666
α_s	1.1559	1.5269	0.1631	0.4695	0.5400	3.3099	0.1831	1.7592	0.6253	7.5587	0.6120	9.9129
γ_s	0.1461	1.0069	0.1478	0.4299	1.9356	1.8197	1.7694	1.1857	4.4606	2.6413	852.7394	1.6061
θ_s	-2.3406	-0.2721	-47.7984	-0.0001	0.4863	0.2775	-1.4902	-0.3643	3.5954	0.6950	1.1110	0.0215

Table 5.9 continued

	OSE				SGX				CME			
	Sample A		Sample B		Sample A		Sample B		Sample A		Sample B	
	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat
Futures												
p	1		1		2		2		1		1	
k_f	0.0001	0.5883	0.0005	1.5775	0.0002	0.8242	0.0003	0.9866	0.0000	0.1376	0.0005	1.3397
$\pi_{fs,1}$	-0.0076	-0.0698	-0.1202	-0.8038	-0.4685	-2.5065	0.0235	0.1759	-0.0926	-1.0127	-0.0068	-0.2084
$\pi_{fs,2}$					-0.3865	-2.4770	0.3036	2.4524				
$\pi_{ff,1}$	0.0065	0.0590	0.1135	0.7492	0.4816	2.5268	-0.0508	-0.3719	0.0451	0.4302	0.0097	0.2483
$\pi_{ff,2}$					0.3853	2.4570	-0.3238	-2.4549				
$\pi_{fs,1}^*$	-0.1067	-0.4799	0.2074	0.3088	0.5647	2.2836	-0.0396	-0.1762	0.0327	0.3252	34.2537	0.0011
$\pi_{fs,2}^*$					0.6064	3.1156	-0.7771	-3.4538				
$\pi_{ff,1}^*$	-0.0125	-0.0576	-0.3307	-0.4960	-0.6414	-2.5938	0.0631	0.2819	-0.0336	-0.2922	-94.3634	-0.0011
$\pi_{ff,2}^*$					-0.6071	-3.1070	0.8945	3.8835				
α_f	-0.3575	-1.9752	-0.2918	-0.7096	-0.0640	-0.4798	-0.2044	-1.5750	-0.1068	-2.4801	-15.3060	-0.0011
γ_f	0.7785	1.0618	0.1051	0.5572	2.3417	1.5282	1.6575	1.4016	20.2189	0.2665	0.0001	0.0011
θ_f	15.0295	0.0101	-16.2092	-0.0011	119.8710	0.0002	-3.0504	-0.5382	30.0258	0.0076	-1.3540	-0.1293
EGARCH coefficients												
Spot												
ω_s	-0.3532	-6.6801	-0.4679	-5.4409	-0.3606	-6.7875	-0.4585	-5.4724	-0.3467	-4.4232	-0.4904	-2.5987
λ_s	-0.0784	-7.1727	-0.0910	-5.5864	-0.0792	-7.0450	-0.0977	-5.7200	-0.0451	-3.0222	-0.0450	-1.6242
$a_{s,1}$	-0.0248	-0.5423	-0.0908	-1.3666	-0.0367	-0.8188	-0.0808	-1.2545	0.1001	1.6899	0.1511	3.6283
$a_{s,2}$	0.1766	3.8254	0.2595	4.0767	0.1952	4.3031	0.2432	3.9369	0.0567	0.9734		
b_s	0.9727	181.9127	0.9612	109.4971	0.9725	179.3767	0.9617	113.3818	0.9747	135.2674	0.9592	52.2453
Futures												
ω_f	-0.3337	-6.4597	-0.5120	-5.5020	-0.3158	-6.4118	-0.4674	-5.5247	-0.2864	-5.5547	-0.5163	-4.2165
λ_f	-0.0821	-7.3079	-0.0986	-6.0936	-0.0796	-7.1750	-0.1043	-6.4223	-0.0603	-5.3048	-0.0882	-4.4347
$a_{f,1}$	0.1364	7.1459	-0.0853	-1.2768	0.1341	7.1199	-0.0758	-1.2059	0.1245	7.0333	0.1733	5.2122
$a_{f,2}$			0.2583	4.0756			0.2371	3.8087				
b_f	0.9734	187.4445	0.9565	100.9841	0.9753	196.8538	0.9609	113.6901	0.9780	187.2128	0.9554	75.0776

Table 5.9 continued

	OSE				SGX				CME			
	Sample A		Sample B		Sample A		Sample B		Sample A		Sample B	
	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Panel B: Evaluation												
RSS	0.6298	0.6738	0.3369	0.3451	0.6228	0.6502	0.3377	0.3381	0.4589	0.6513	0.1803	0.3354
Q(24) for η_t	[0.5645]	[0.4812]	[0.9939]	[0.9915]	[0.2366]	[0.2510]	[0.9082]	[0.9625]	[0.9774]	[0.9307]	[0.4345]	[0.9174]
Q(24) for η_t^2	[0.4959]	[0.4975]	[0.6513]	[0.6092]	[0.8622]	[0.5396]	[0.1932]	[0.9482]	[0.2218]	[0.9683]	[0.6982]	[0.9889]
JB	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Asymmetric tests												
Sign bias test	[0.1673]	[0.2289]	[0.7307]	[0.2921]	[0.8448]	[0.7068]	[0.6884]	[0.4560]	[0.4002]	[0.1630]	[0.4443]	[0.7734]
Neg. size bias test	[0.7356]	[0.3109]	[0.4094]	[0.4463]	[0.3163]	[0.5905]	[0.2956]	[0.3747]	[0.9710]	[0.1784]	[0.5206]	[0.0864]
Pos. size bias test	[0.4694]	[0.2216]	[0.3525]	[0.3495]	[0.9853]	[0.1442]	[0.4729]	[0.3684]	[0.8180]	[0.9151]	[0.4858]	[0.0647]
Joint test	[0.3598]	[0.1098]	[0.5887]	[0.3741]	[0.7266]	[0.3381]	[0.6004]	[0.2642]	[0.4380]	[0.3718]	[0.8764]	[0.2382]

Notes: The table presents the estimation and evaluation results of the nonlinear ESTECM-EGARCH model in individual Nikkei markets. The mean models are equations (5.3a) (5.3b):

$$\Delta s_t = k_s + \sum_{j=1}^{p} \pi_{ss,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j} \Delta f_{t-j} + (k_s^* + \sum_{j=1}^{p} \pi_{ss,j}^* \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j}^* \Delta f_{t-j} + \alpha_s z_{t-1}) \times T_s(z_{t-d}) + u_{s,t},\ T_s(z_{t-d}) = 1 - \exp[-\gamma_s (z_{t-d} - c^*)^2 \times g_s(z_{t-d})],\ g_s(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_s (z_{t-d} - c^*)]\}$$

$$\Delta f_t = k_f + \sum_{j=1}^{p} \pi_{fs,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j} \Delta f_{t-j} + (k_f^* + \sum_{j=1}^{p} \pi_{fs,j}^* \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j}^* \Delta f_{t-j} + \alpha_f z_{t-1}) \times T_f(z_{t-d}) + u_{f,t},\ T_f(z_{t-d}) = 1 - \exp[-\gamma_f (z_{t-d} - c^*)^2 \times g_f(z_{t-d})],\ g_f(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_f (z_{t-d} - c^*)]\}$$

The variance models are equations (5.11) (5.13): $u_t = \sigma_t \eta_t$, $\ln \sigma_t^2 = \omega + \lambda(u_{t-1}/\sigma_{t-1}) + a|u_{t-1}/\sigma_{t-1}| + b \ln \sigma_{t-1}^2$, or $\ln \sigma_t^2 = \omega + \lambda(u_{t-1}/\sigma_{t-1}) + a_1|u_{t-1}/\sigma_{t-1}| + a_2|u_{t-2}/\sigma_{t-2}| + b \ln \sigma_{t-1}^2$ is used instead of (5.13) to remove the excessive ARCH effects in the residuals. The model restriction is $k^*=c^*=0$. The model lag p is determined by the method of Haggan and Ozaki (1981). Δs_t, Δf_t are detrended, outlier-free price returns; z_{t-1} is represented by the detrended, outlier-free log-basis at lag 1.The delay parameter d=1. The estimation of the ESTECM is by NLS; the estimation of the EGARCH is by quasi-maximum likelihood, with Bollerslev-Wooldridge (1992) robust standard errors and covariance in the CME spot due to the excessive ARCH effects in the residuals therein. Panel A presents the coefficient estimates followed by z-statistics in each market in each sample. Panel B presents the model diagnostic checks. The diagnostics include the Ljung-Box (1978) Q-statistics for standardised residuals and squared standardised residuals up to order 24, the Jarque-Bera (1980) normality test (JB), and the asymmetric test of Engle and Ng (1993) which contains sign bias test, negative (neg.) size bias test, positive (pos.) size bias test, and joint test. Numbers in square brackets are p-values.

Table 5.8 displays the results of the LM-type linearity tests based on the linear ECM in individual Nikkei markets. The tests are performed for different delay parameters *d* selected from {1, 2, 3}. The null hypothesis of linearity can be strongly rejected in majority of the cases (except when *d*=2 in the SGX spot and CME futures in sample A), in favour of the nonlinear smooth transition error correction model. The smallest *p*-values of the LM-type test statistics occur when *d*=1 for the OSE, CME futures; *d*=3 for the SGX; and *d*=2 for the CME spot.[74] A value of *d* higher than 1 means that the nonlinear regime switch takes more than 1 trading day to complete. This is not likely the case, however, given the potential arbitrage speed facilitated by the electronic trading systems in the Nikkei markets. As such, I decide to estimate the ESTECM with the *d* whose *p*-value is the smallest and with *d*=1, and defer the final choice of *d* to the evaluation stage.[75] The finding is that the parameter estimates are generally similar despite the use of the different values of *d*, but the AIC of the models with *d*=1 is always smaller than the AIC of the models with *d* higher than 1. This suggests that the models with the unit *d* have a better model fit. Moreover, in the CME (sample A), the spot market shows excessive ARCH in the model residual in high orders of Ljung-Box (1978) Q-statistics of squared standardised residuals (thus heteroscedastic-consistent standard errors are used), yet this is more severe when *d*=2. Hence, I will only report and analyse the estimation results with *d*=1 in the main context. The estimation results with *d* higher than 1 are provided in Table A5.1 in the Appendix.

Table 5.9 presents the estimation results of the nonlinear ESTECM-EGARCH model in individual Nikkei markets. The model lags vary from 1 to 4, but in general, the spot market has longer lags than the futures markets. The SGX, CME show longer lags than the OSE, and in the spot market, the earlier sample (A) shows longer lags than the later sample (B) in the OSE and SGX. In all cases, the error correction terms have the expected signs - positive in the spot and negative in the futures, which supports the error correction adjustments towards equilibrium. However, the common evidence of bidirectional causality in the long run found by the base model remains only in the CME (sample A). With the nonlinear specification, causality is

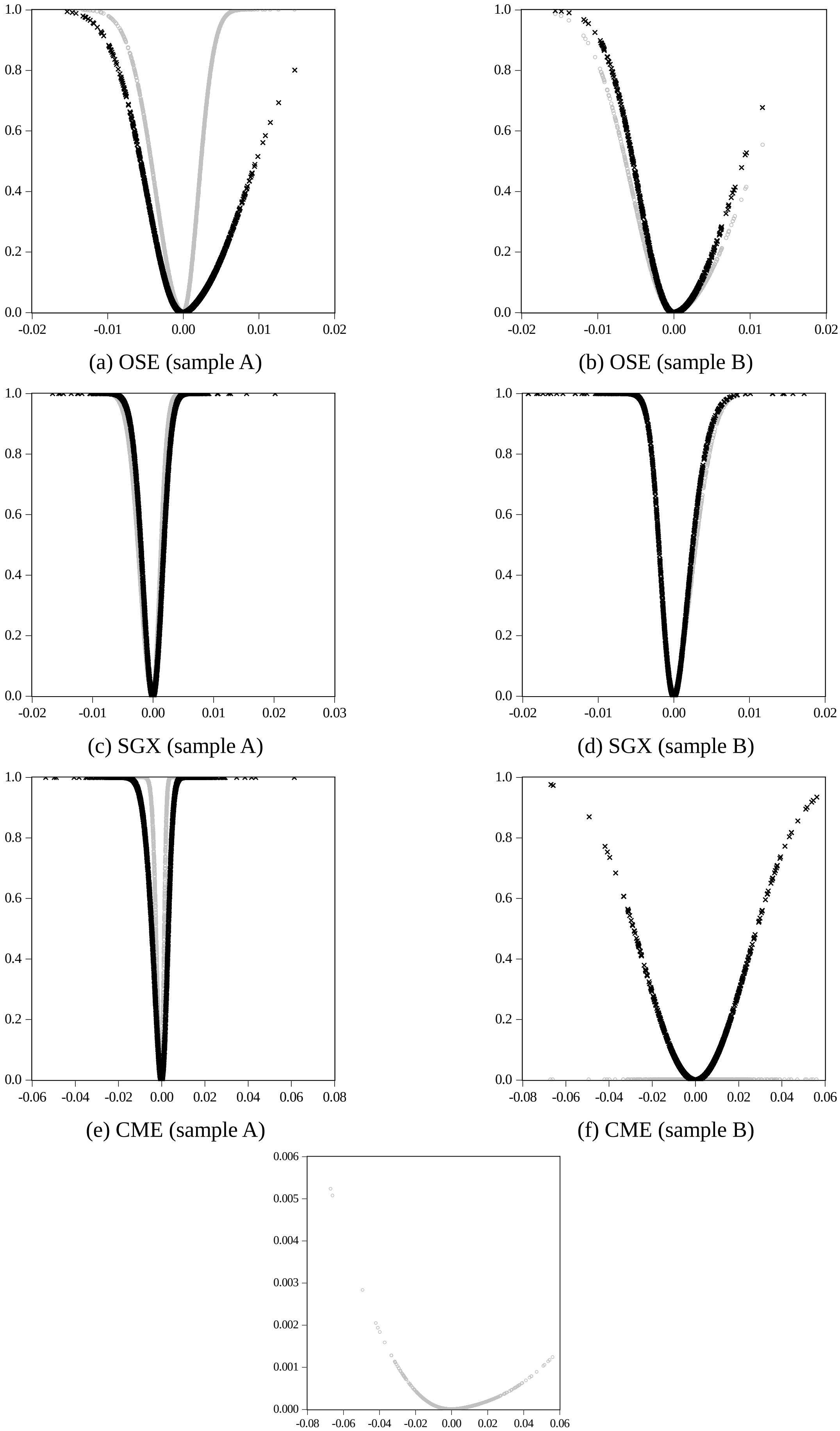
[74] Using *F* versions of the LM-type test statistics generate the same results. Results are available upon request.
[75] van Dijk et al. (2002) defer the final choice of *d* to the evaluation stage and use out-of-sample forecasting to aid the selection of *d*=1 with US unemployment data.

unidirectional in most cases. The Nikkei futures markets show quicker speed of information transmission than the spot in sample A (α_f is smaller than α_s in magnitude); the reverse is true in sample B. This implies that, within a single regime, the futures markets dominate the price discovery process in the pre-crisis period, but the process is dominated by the spot market in the post-crisis period. For short-run adjustments, the evidence of futures leading spot is found in the OSE and CME (sample A). Bidirectional causality in the short run is present in the SGX, but no short-run causality is found in the CME (sample B). Within each market, the futures usually revert to its own equilibrium within 1 trading day, or 2 trading days at most; in contrast, the spot market takes 2-4 trading days to restore its own equilibrium in the SGX and CME.

The estimated exponential transition functions in individual Nikkei markets are plotted in Figure 5.2. The U-shaped curves indicate the effect of transaction costs in the sense that few adjustments will take place when the pricing errors are located in a narrow range in the centre (the middle regime), but rapid regime switch and hence more arbitrage activities are present when the pricing errors are far away from zero (the outer regime). The smoothness parameter γ is found to be larger in the futures markets than in the spot market in sample A. Figure 5.2 illustrates the relatively large γ_f as the transition functions of the futures markets are always above the transition functions of the spot in sample A. This implies that the Nikkei futures prices are not only faster to reflect information within one regime, but also faster to transit between the regimes before the crisis. Compared with the γ in the OSE, the γ's in the SGX and CME are much higher, with steeper functions and even quicker movements between the regimes. By contrast, the Nikkei spot prices exhibit a quicker rate of the smooth transition than the futures prices in sample B, as the transition functions of the spot become steeper. This is most obvious in the CME, where γ_s is considerably large,[76] and yet γ_f is so small that its transition function looks flat in the same diagram.[77] Given that the spot leads the futures in revealing information in sample B, it is the spot market that plays a major part in the nonlinear

[76] The estimate of γ_s in the CME (sample B) appears excessively large compared with the counterpart estimates in the other markets. Different sets of starting values are tried to estimate this parameter in this market but the results are very similar. In fact, an enormous γ is possible to occur in smooth transition models as the precise estimation of γ is difficult. Rescaling the parameters may solve the problem, but at a cost of higher residual variance of the model (Teräsvirta, 1994). Given the invariably large estimates of γ_s in the CME (sample B) despite the use of different sets of starting values, the general message conveyed is the more uniform structure of the spot transaction costs after the crisis.

[77] Figure 5.2(g) shows the transition function of the futures with non-standardised γ in the CME (sample B). It is actually a skewed U-shaped curve.



(a) OSE (sample A)

(b) OSE (sample B)

(c) SGX (sample A)

(d) SGX (sample B)

(e) CME (sample A)

(f) CME (sample B)

(g) CME (sample B) futures (non-standardised)

Figure 5.2 Transition functions in Nikkei 225 spot and futures markets

Notes for Figure 5.2: (a)-(f) represent the transition functions estimated from the ESTECM in each Nikkei spot-futures pair in each sample, with the black crosses for the spot, estimated from equation (5.3a), and the grey dots for the futures, estimated from equation (5.3b). $T(z_{t-d})$ is on vertical axis, and z_{t-d} is on horizontal axis. The parameters γ and θ are non-standardised original values in (a)-(e). Because the parameter estimate γ_s in the CME (sample B) is excessively large, for (f) only, the parameters are standardised: γ is divided by the sample variance of z_{t-d}, and θ is divided by the sample standard deviation of z_{t-d}. (g) shows the transition function of the futures in the CME (sample B) with non-standardised parameters.

dynamics in the post-crisis period. Table 5.9 shows that the value of γ_s stays almost the same from sample A to sample B in the OSE. A decline in the smoothness parameter estimates in sample B is found in the OSE futures and the SGX. Despite the substantial increase in γ_s in the CME market which may suggest less various transaction costs in the spot market after the crisis, the consistently downsized γ_f in sample B, especially in the CME, perhaps suggests higher transaction costs in the Nikkei spot-futures arbitrage in the post-crisis period.

The asymmetric responses of the Nikkei spot and futures prices are examined from the perspectives of the first moment and the second moment. Figure 5.2 also shows that there is some skewness in the transition functions in the mean model; and such skewness indicates the degree of asymmetry. Table 5.9 indicates that most of the asymmetry parameters θ are positive in sample A, negative in sample B. This implies that the aggregated market response to positive (negative) pricing errors is stronger before (after) the crisis, than the response to equally sized negative (positive) pricing errors. The general finding has exceptions in the OSE (sample A), where the spot market has more investors for negative pricing errors than positive pricing errors of the same magnitude, and in the CME (sample B), where the spot market has more investors for positive pricing errors than negative pricing errors of the same magnitude. Note that all the estimates of θ are insignificant by conventional *t*-tests. However, taking θ as zero in the mean model does affect the lag length and estimation of the models. The estimated results of the asymmetry parameter λ in the variance model are more consistent: it is significantly negative in 11 out of 12 cases, which suggests negative shocks associated with greater volatility, or the leverage effect in individual Nikkei markets. Although the literature often reports the larger impact of bad news, and this is also true for most of the Nikkei prices in the post-crisis period and the Nikkei variances, I find that most of the Nikkei prices, especially in the SGX and CME, react to good news more than equally sized bad news in the pre-crisis period.

The diagnostic test results of the nonlinear ESTECM-EGARCH model are also reported in Table 5.9. The model residuals are free from autocorrelations or remaining ARCH effects. There is some evidence of remaining asymmetry in the residual of the CME futures (sample B) by the negative and positive sign bias tests, but the asymmetry effect is insignificant by the joint test. In fact, the asymmetry test results of the nonlinear residuals are much better than the results of the linear residuals in Table 5.7. Besides, in each Nikkei market in each sample, the nonlinear RSS is always smaller than the corresponding linear RSS (compared with Table 5.7). Although the normality tests are not passed as in the linear case, the error correction mechanism represented by the ESTECM-EGARCH specification provides reasonable descriptions for the nonlinear spot-futures price adjustments in the Nikkei markets.

5.6.2 Cross-border futures price dynamics

Following the convention of most studies on the transnational price discovery process, I tabulate the estimation results of the linear and nonlinear models across the Nikkei futures markets in an integrated and interpretable way, with emphases on the long-run speed of adjustments, the rates of the smooth transition, the asymmetric behaviour and the short-run causal relationships. The models are estimated for bilateral pairs of Nikkei futures prices, (OSE_t, SGX_t), (OSE_t, CME_t) and (SGX_t, CME_t), and the results are categorised by the same pairing. For the moment, I ignore the timing issues of the different markets and use all the three futures prices on day *t*, which allows an intuitive understanding of the price adjustment process across the markets and avoids potential modelling difficulties related to matching prices in several time zones. The timing issues and the associated price dynamics are analysed in section 5.7. In terms of the causal relationships, I test the significance of the lagged autoregressive coefficients jointly rather than individually, because the joint influence of one market on the other is much more important, and the cross-border information flows are often considered on an aggregated basis. The individual coefficients and their significance are reported in Table A5.2 and A5.3 in the Appendix for reference. In the linear framework, Wald tests for Granger causality are carried out by the augmented lag method of Toda and Yamamoto (1995), Dolado and Lütkepohl (1996), which involves estimating a VAR (p) in levels with one extra lag and performing the usual Wald tests on the original p variables, to ensure that the Wald statistics follow a standard asymptotic χ^2 distribution with p degrees of freedom.

Table 5.10 shows the estimation results of the linear ECM-GARCH for bilateral pairs of Nikkei futures prices. Panel A presents the estimated error correction coefficients. As expected, at least one α is negative in each pair, implying the presence of price adjustments or error corrections towards the price parity condition across the futures markets. Between the OSE and the SGX, the magnitude of the OSE coefficients is larger than the magnitude of the SGX coefficients, which suggests that the OSE mainly makes the price adjustments and is slow in reflecting information. This is also true for the pair of the OSE and the CME. Between the foreign markets, the SGX coefficients are found larger in magnitude than the CME coefficients, and hence the speed of adjustment is faster in the SGX than in the CME. Moreover, in the pairs concerning the CME, its coefficients are always insignificant while the coefficients in the other market show significance, implying that the long-run causality runs from the CME to the other markets. It turns out that the CME is the quickest market in the price discovery process, followed by the SGX and then the OSE. The foreign markets tend to lead the domestic market.

Panel B of Table 5.10 provides the pair-wise Granger causality test results. The common null hypothesis is that the past prices in one market do not Granger-cause the current prices in the other market in the short run (Covrig et al., 2004). It is found that the non-causality from the OSE to the SGX cannot be rejected at conventional levels, but the reverse non-causality can be easily rejected. The significant Wald statistics in the other pairs indicate bidirectional causality, with the causality from the CME to the other markets much stronger. Consistent with the magnitudes and significance of the error correction coefficients, the CME plays a leading role in the cross-border price determination, and the information flows from the foreign markets to the domestic market are stronger than the other way round.

Table 5.10 Estimation results across the Nikkei futures markets: the linear ECM-GARCH model

Panel A: Parameter estimates

	(OSE, SGX)		(OSE, CME)		(SGX, CME)	
Dependent variable	OSE	SGX	OSE	CME	SGX	CME
Sample A						
α	-1.0946	-0.1595	-0.9659	0.0039	-0.9721	0.0406
	(-1.9044)	(-0.2909)	(-10.8556)	(0.0518)	(-10.8722)	(0.5257)
Sample B						
α	-0.8340	0.0598	-0.8477	-0.0761	-0.8133	-0.0731
	(-1.3173)	(0.0958)	(-11.8565)	(-0.7847)	(-11.4988)	(-0.7472)

Panel B: Granger causality tests

	Wald stat	p-value
Sample A		
OSE does not cause SGX	7.4347	0.4905
SGX does not cause OSE	36.3391	0.0000
OSE does not cause CME	14.9148	0.0608
CME does not cause OSE	909.6269	0.0000
SGX does not cause CME	19.0258	0.0147
CME does not cause SGX	930.2693	0.0000
Sample B		
OSE does not cause SGX	3.0781	0.6880
SGX does not cause OSE	10.7331	0.0569
OSE does not cause CME	20.9322	0.0008
CME does not cause OSE	955.4050	0.0000
SGX does not cause CME	20.2243	0.0011
CME does not cause SGX	975.8948	0.0000

Notes: The table presents the estimation results of the linear ECM-GARCH model for bilateral Nikkei futures pairs (OSE, SGX), (OSE, CME) and (SGX, CME). The mean models are equations (5.5a) (5.5b):

$$\Delta f_{1,t} = k_1 + \sum_{j=1}^{p} \pi_{11,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j} \Delta f_{2,t-j} + \alpha_1 z_{t-1} + u_{1,t}, \quad \Delta f_{2,t} = k_2 + \sum_{j=1}^{p} \pi_{21,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j} \Delta f_{2,t-j} + \alpha_2 z_{t-1} + u_{2,t}$$

The variance models are equations (5.11) (5.12): $u_t = \sigma_t \eta_t$, $\sigma_t^2 = \omega + a u_{t-1}^2 + b \sigma_{t-1}^2$, or a GARCH (2,1) model $\sigma_t^2 = \omega + a_1 u_{t-1}^2 + a_2 u_{t-2}^2 + b \sigma_{t-1}^2$ is used instead of (5.12) to remove the excessive ARCH effects in the residuals. The estimation of the ECM is by OLS; the estimation of the GARCH is by quasi-maximum likelihood with Bollerslev-Wooldridge (1992) robust standard errors and covariance. The model lag p=7 (sample A) or 4 (sample B) in first differences is determined by the sequential modified likelihood ratio test and AIC. The futures returns $\Delta f_{1,t}$, $\Delta f_{2,t}$ are detrended and outlier-free. The error correction term z_{t-1} is represented by the detrended, outlier-free price differentials (f_1 - f_2) at lag 1. Panel A presents the estimated error correction coefficients (α) in each market in each pair. Panel B presents the results of Wald tests for Granger causality, by the augmented lag method of Toda and Yamamoto (1995), Dolado and Lütkepohl (1996), with the null hypothesis that the past prices in one market do not Granger-cause the current prices in the other market in the short run (Covrig et al., 2004). The Wald statistics are asymptotically distributed as $\chi^2(8)$ in sample A, $\chi^2(5)$ in sample B, reported with the associated p-values. Numbers in parentheses are z-statistics. More results such as the individual significant tests on the short-run autoregressive coefficients are reported in Table A5.2 in the Appendix.

Table 5.11 Linearity tests in Nikkei futures markets

	(OSE, SGX)		(OSE, CME)		(SGX, CME)	
Dependent variable	OSE	SGX	OSE	CME	SGX	CME
Panel A: CME with OSE, SGX						
Sample A	1.19E-09	5.10E-09	2.53E-16	1.16E-15	9.11E-16	1.44E-15
Sample B	1.06E-16	2.55E-17	1.81E-15	1.86E-11	3.08E-14	9.56E-12
Panel B: CME(t-1) with OSE, SGX						
Sample A			3.53E-13	6.31E-15	4.90E-12	4.00E-15
Sample B			5.75E-06	7.56E-16	2.81E-05	1.75E-15

Notes: The table contains the results of the LM-type linearity tests for bilateral Nikkei futures pairs (OSE, SGX), (OSE, CME) and (SGX, CME). An auxiliary regression, equation (5.10) is run for market 1:

$$\Delta f_{1,t} = \beta_{00} + \sum_{j=1}^{p} (\beta_{0j} x_{t-j} + \beta_{1j} x_{t-j} z_{t-d} + \beta_{2j} x_{t-j} z_{t-d}^2 + \beta_{3j} x_{t-j} z_{t-d}^3) + v_t$$

Using $\Delta f_{2,t}$ as the dependent variable yields the regression of market 2. x_t contains $\Delta f_{1,t}$, $\Delta f_{2,t}$ and z_{t-1}; z_{t-1} is represented by the price differential (f_1 - f_2) at lag 1; all data detrended and free from the influence of outliers. The model lag p=7 (sample A) or 4 (sample B). Given the results in individual Nikkei markets, the delay parameter d is set to be 1. The null hypothesis of linearity is equivalent to H_0: $\beta_{1j}=\beta_{2j}=\beta_{3j}=0$, j=1,…, p, under which a LM-type test statistic follows $\chi^2(3p)$ asymptotically. The LM-type test statistic is constructed as $LM=T(RSS_L-RSS_A)/RSS_L$, where T is the sample size, RSS_L is the residual sum of squares from estimating the linear ECM, RSS_A is the residual sum of squares from estimating the auxiliary regression (5.10). Panel A provides the p-values of the LM-type test statistics in each market in each bilateral pair. Panel B provides additional evidence of nonlinearity: the CME on day t-1, denoted as CME(t-1), is aligned with the OSE, SGX on day t (the default time omitted), to test for nonlinearity with an alternative trading sequence. The model lag used is 6 (sample A) or 4 (sample B). The associated p-values of the LM-type test statistics are placed under the relevant markets.

Given that I selected a unit delay parameter in the individual Nikkei markets, I test for the smooth transition nonlinearity across the futures markets only with d=1. In this way, the linearity tests become more or less a specification check of the linear ECM-GARCH, and I expect to reject the null hypothesis of linearity as in the individual markets. Table 5.11 displays the linearity test results for the bilateral futures pairs. It is clear that the LM-type statistics are all highly significant, thereby supporting the smooth transition error correction behaviour across the futures markets.

The estimation results of the nonlinear ESTECM-EGARCH are listed in Table 5.12. Panel A shows the parameter estimates. It is interesting that the model lags in the nonlinear model are merely 1 or 2, much shorter than the model lags in the linear model. This is likely to reflect more nearly the actual price dependence of the Nikkei futures contracts on a daily basis and the high speed of information transmission across the markets. Note that the longer lags in the linear framework are necessary to remove the residual autocorrelations. This also implies that the nonlinear model may better fit my data. Compared with the ESTECM lags of the spot-futures pairs (Table 5.9), those of the futures price interactions are still shorter. As futures transactions incur fewer costs and risks, faster adjustments and shorter price dependence across the futures markets are not surprising.

Panel A of Table 5.12 shows the estimated error correction coefficients. Their negative signs are expected, and the foreign markets generally have smaller α in magnitude than the domestic market. With the smallest α in both samples, the CME remains the quickest market in the nonlinear adjustment process towards equilibrium. The SGX react faster to price differentials than the OSE in sample A (the magnitude of α is smaller in the SGX than in the OSE), but the two markets show similar speed of adjustments in sample B, with the OSE slightly quicker. There is also evidence of long-run bidirectional causality between the OSE and the CME in sample B. Overall, as in the linear model, the CME is the most dominant market in the cross-border price discovery process, in terms of price adjustments within a single regime.

Table 5.12 Estimation results across the Nikkei futures markets: the nonlinear ESTECM-EGARCH model

Panel A: Parameter estimates						
	(OSE, SGX)		(OSE, CME)		(SGX, CME)	
Dependent variable	OSE	SGX	OSE	CME	SGX	CME
Sample A						
p	2	1	1	1	1	1
α	-3.4355	-1.0656	-0.8532	0.0708	-0.8437	0.0819
	(-2.7324)	(-1.1475)	(-22.3866)	(0.4059)	(-22.1564)	(0.3915)
γ	0.3945	0.2535	3024.3838	0.1930	18347.6705	0.1483
	(1.5462)	(0.9728)	(0.7482)	(0.7645)	(0.5265)	(0.6808)
θ	-66.8270	-68.2985	203.2291	-71.9725	-133.0122	-27306.5802
	(-0.0003)	(-0.0001)	(0.1075)	(0.0000)	(-0.1643)	(0.0000)
λ	-0.0732	-0.0739	-0.0381	-0.0594	-0.0359	-0.0595
	(-6.0012)	(-6.0412)	(-3.2108)	(-4.9907)	(-3.0292)	(-4.9871)
Sample B						
p	1	1	2	1	2	1
α	-0.3714	0.3917	-0.8867	-0.1731	-0.8477	-0.0866
	(-0.8084)	(0.7475)	(-16.8463)	(-2.3674)	(-16.0663)	(-1.6029)
γ	5.4304	2.8788	42.7342	5.2953	49.0643	3331.5697
	(1.0068)	(0.8938)	(1.6484)	(0.6480)	(1.8682)	(0.9340)
θ	-5.1529	-3.8982	43.3605	58.0112	25.8319	42.5430
	(-0.3041)	(-0.2923)	(0.0633)	(0.0017)	(0.2052)	(0.2703)
λ	-0.0912	-0.0908	-0.0881	-0.1098	-0.0958	-0.1175
	(-5.1735)	(-5.0157)	(-4.1879)	(-4.9301)	(-4.2181)	(-5.0784)

Panel B: Granger causality tests	Middle regime		Outer regime	
	Wald stat	p-value	Wald stat	p-value
Sample A				
OSE does not cause SGX	2.4497	0.1175	4.5126	0.1047
SGX does not cause OSE	14.1663	0.0008	22.3182	0.0002
OSE does not cause CME	2.3839	0.1226	2.6288	0.2686
CME does not cause OSE	1.7192	0.1898	1.8392	0.3987
SGX does not cause CME	1.8213	0.1772	2.0069	0.3666
CME does not cause SGX	0.9182	0.3379	0.9269	0.6291
Sample B				
OSE does not cause SGX	0.1767	0.6742	0.2041	0.9030
SGX does not cause OSE	0.0561	0.8128	0.2557	0.8800
OSE does not cause CME	0.3616	0.5476	2.9971	0.2235
CME does not cause OSE	3.9428	0.1393	13.4770	0.0092
SGX does not cause CME	5.3791	0.0204	7.1097	0.0286
CME does not cause SGX	3.2738	0.1946	12.8173	0.0122

Notes for Table 5.12: The table presents the estimation results of the nonlinear ESTECM-EGARCH model for bilateral Nikkei futures pairs (OSE, SGX), (OSE, CME) and (SGX, CME). The mean models are equations (5.6a) (5.6b):

$$\Delta f_{1,t} = k_1 + \sum_{j=1}^{p} \pi_{11,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j} \Delta f_{2,t-j} + (k_1^* + \sum_{j=1}^{p} \pi_{11,j}^* \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j}^* \Delta f_{2,t-j} + \alpha_1 z_{t-1}) \times T_1(z_{t-d}) + u_{1,t}$$

$$T_1(z_{t-d}) = 1 - \exp[-\gamma_1 (z_{t-d} - c^*)^2 \times g_1(z_{t-d})],\ g_1(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_1 (z_{t-d} - c^*)]\}$$

$$\Delta f_{2,t} = k_2 + \sum_{j=1}^{p} \pi_{21,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j} \Delta f_{2,t-j} + (k_2^* + \sum_{j=1}^{p} \pi_{21,j}^* \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j}^* \Delta f_{2,t-j} + \alpha_2 z_{t-1}) \times T_2(z_{t-d}) + u_{2,t}$$

$$T_2(z_{t-d}) = 1 - \exp[-\gamma_2 (z_{t-d} - c^*)^2 \times g_2(z_{t-d})],\ g_2(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_2 (z_{t-d} - c^*)]\}$$

The variance models are equations (5.11) (5.13): $u_t = \sigma_t \eta_t$, $\ln \sigma_t^2 = \omega + \lambda(u_{t-1}/\sigma_{t-1}) + a|u_{t-1}/\sigma_{t-1}| + b \ln \sigma_{t-1}^2$, or $\ln \sigma_t^2 = \omega + \lambda(u_{t-1}/\sigma_{t-1}) + a_1|u_{t-1}/\sigma_{t-1}| + a_2|u_{t-2}/\sigma_{t-2}| + b \ln \sigma_{t-1}^2$ is used instead of (5.13) to remove excessive ARCH effects. The model restriction is $k^*=c^*=0$. The model lag p is determined by the method of Haggan and Ozaki (1981). The futures returns $\Delta f_{1,t}$, $\Delta f_{2,t}$ are detrended and outlier-free. The error correction term z_{t-1} is represented by the detrended, outlier-free price differentials (f_1 - f_2) at lag 1. The delay parameter d=1. The estimation of the ESTECM is by NLS; the estimation of the EGARCH is by quasi-maximum likelihood. Panel A presents the most important parameter estimates (α, γ, θ, λ) in each market in each pair. Panel B presents the results of joint significance tests on the short-run autoregressive coefficient π's by Wald tests, with the null hypothesis of no causality from the past prices in one market to the current prices in the other market. The Wald statistics and the associated p-values are reported in the middle regime and the outer regime. Numbers in parentheses are z-statistics. More results such as the individual significant tests on the short-run autoregressive coefficients are reported in Table A5.3 in the Appendix.

The rate of transition between the regimes, the smoothness parameter γ, is compared in relative terms, to find out which market has a relatively larger γ in each of the bilateral pairs. From Panel A of Table 5.12, in the pairs (OSE$_t$, SGX$_t$) and (OSE$_t$, CME$_t$), the larger estimates of γ are in the OSE; in (SGX$_t$, CME$_t$), the larger estimates of γ are in the SGX (sample A) or the CME (sample B). These results can be sorted as OSE>SGX>CME before the crisis, OSE>CME>SGX after the crisis, in terms of the transition speed in descending order. As such, the OSE is followed by the other two markets in the relative value of γ.[78] This probably reveals that the OSE has the most homogeneous structure of transaction costs among the three markets. After the crisis, the CME takes over the SGX to be the second place in that order, suggesting a possible increase in the value of γ in the CME. As higher γ means more rapid adjustments between the regimes and thus reduced transaction costs in the market, the CME transaction costs may be lower after the crisis. As a further check, I compare the value of γ between the two samples in each pair. In the pair (OSE$_t$, SGX$_t$), both smoothness parameters increase from

[78] One may notice the enormous estimates of the smoothness parameters in the pairs (OSE$_t$, CME$_t$) and (SGX$_t$, CME$_t$). Several sets of starting values are tried but the estimates are very similar. The literature agrees that the estimation of the smoothness parameter is difficult: the precise estimates are difficult to obtain and very often the estimates are insignificant (e.g. Franses and van Dijk, 2000). However, what I am concerned about is the relative size of the parameter in the three markets. The precise magnitude of the parameter in each market is deemed less important.

sample A to sample B, which indicates that the transaction costs in the two markets are decreasing. In the other two pairs, there is also a rise in γ in the CME, which confirms the reduced transaction costs in the CME. Compared with the CME, however, the OSE and the SGX have smaller γ in the two pairs of the CME in the post-crisis period. This could be that the CME cuts down its transaction costs to a very low level in this period so that any normal decline in the transaction costs in the OSE and the SGX appears less obvious. The common increasing trend of γ in the three futures markets from sample A to sample B is indicative of the decreasing futures transaction costs in the post-crisis period. Worthy of note is that, this should by no means be taken as a contradictory argument to the finding of the generally higher transaction costs in the spot-futures arbitrage after the crisis. The previous estimates of the spot-futures pairs indeed imply higher transaction costs after the crisis, but the higher transaction costs could come from the spot market - for example, the adjustment costs of dividends (OSE, SGX and CME) and exchange rate (CME), and the costs related to short sale in the post-crisis regulation. Considering the futures markets alone, I find that the transaction costs therein are actually falling in the post-crisis period, notably in the CME.

The first-moment asymmetry parameter θ is found to be consistently negative between the OSE and the SGX in both samples, as shown in Panel A of Table 5.12. Hence, in the arbitrage between the two markets, more investors respond to negative price differentials than equally sized positive price differentials. In the pairs pertaining to the CME, it is mostly negative in sample A but positive in sample B. Recall that the spot-futures arbitrage generally has positive θ in sample A, negative θ in sample B. It can be seen that the nonlinear asymmetric behaviour of the futures prices can be quite different once the spot market is involved. The futures prices exhibit predictive asymmetry to various extents and in changing nature. However, this does not mean that I cannot draw anything from the results. Rather, they suggest that bad news may have a larger impact after the crisis in the spot-futures arbitrage; given that more investors respond to positive futures price differentials of the CME after the crisis, the larger impact of bad news observed in the spot-futures arbitrage could be associated with the spot market. The EGARCH parameter λ is significantly negative in each futures pair, which confirms the leverage effect in the Nikkei variances.

Since, to the best of my knowledge, there are no previous studies on Granger causality tests on parameters of a nonlinear smooth transition model, in each bilateral pair of futures prices, the causality tests of one market are performed by imposing zero restrictions on the lagged returns of the other market, with the null hypothesis that each market is only affected by its own lagged returns. The restrictions are tested by Wald statistics. In the nonlinear model, the causal relationships can be examined in the middle regime and the outer regime. As displayed in Panel B of Table 5.12, one-way causality from the SGX to the OSE is found significant in both regimes before the crisis. After the crisis, there is unidirectional causality from the CME to the OSE, though significant only in the outer regime. Between the foreign markets, feedback relationships exist in both regimes, with the causality from the CME to the SGX stronger. Again, the foreign markets are more dominant in the cross-market information transmission, and the CME plays a leading role among the three markets. Comparing the significant Wald statistics associated with the *p*-values in the middle regime and those in the outer regime, I find that, in general, the short-run non-causalities are more strongly rejected in the outer regime. This lends support to the transaction cost argument that larger price differentials which locate in the outer regime tend to be adjusted more quickly, given that cointegration implies causality.

The evaluation results of the linear ECM-GARCH and the nonlinear ESTECM-EGARCH are summarised in Table 5.13. The models are not affected by residual autocorrelations or excessive ARCH effects, despite that the normality test results remain significant as in the spot-futures case. Significant asymmetric test results are found in the linear model between (OSE_t, SGX_t) in both samples and in the CME in sample B, but they almost disappear in the nonlinear model. To compare model fit, I check whether the RSS of the nonlinear model is smaller than the RSS of the corresponding linear model. However, the RSS measure yields mixed results: the nonlinear RSS is smaller in three pairs but larger in the rest. As the linear model has longer lag lengths than those of the nonlinear model, the small linear RSS may simply result from the many parameters used in the linear model. Thus, I switch to compare the information criteria, AIC and SBC, between the linear model and the corresponding nonlinear model. Table 5.13 shows that the AIC and SBC of the nonlinear model are always smaller.

Therefore, it is deemed that both models are able to depict the error correction dynamics in the Nikkei futures price interactions, but the nonlinear ESTECM-EGARCH may better characterise my data in terms of the remaining asymmetry and model fit.

Table 5.13 Evaluation results of the linear and nonlinear models in Nikkei futures markets

	(OSE, SGX)		(OSE, CME)		(SGX, CME)	
Dependent variable	OSE	SGX	OSE	CME	SGX	CME
Sample A						
Linear model: ECM-GARCH						
RSS	0.6245	0.6054	0.4719	0.6412	0.4500	0.6406
Q(24) for η_t	[0.9782]	[0.9847]	[0.9249]	[0.9662]	[0.9367]	[0.9672]
Q(24) for η_t^2	[0.1350]	[0.1471]	[0.3175]	[0.9046]	[0.3488]	[0.9136]
JB	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Asymmetric tests						
sign bias test	[0.7731]	[0.4478]	[0.9395]	[0.8409]	[0.8483]	[0.7546]
neg. size bias test	[0.4631]	[0.6289]	[0.4455]	[0.9578]	[0.4840]	[0.9084]
pos. size bias test	[0.1166]	[0.2262]	[0.2303]	[0.2447]	[0.3896]	[0.2739]
joint test	[0.0521]	[0.0598]	[0.2072]	[0.3050]	[0.4550]	[0.3073]
Information criteria						
AIC	-5.6598	-5.6843	-5.9437	-5.6271	-5.9851	-5.6279
SBC	-5.6171	-5.6416	-5.9031	-5.5865	-5.9445	-5.5873
Nonlinear model: ESTECM-EGARCH						
RSS	0.6223	0.6052	0.4745	0.6424	0.4524	0.6426
Q(24) for η_t	[0.8606]	[0.8533]	[0.8673]	[0.7066]	[0.8523]	[0.7099]
Q(24) for η_t^2	[0.1790]	[0.1125]	[0.1352]	[0.9711]	[0.1884]	[0.9702]
JB	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Asymmetric tests						
sign bias test	[0.2163]	[0.2861]	[0.5144]	[0.9841]	[0.4697]	[0.9875]
neg. size bias test	[0.8691]	[0.6958]	[0.7365]	[0.6144]	[0.7450]	[0.6138]
pos. size bias test	[0.4882]	[0.4215]	[0.1865]	[0.6515]	[0.8729]	[0.6640]
joint test	[0.4289]	[0.4913]	[0.5046]	[0.8942]	[0.7558]	[0.9009]
Information criteria						
AIC	-5.6968	-5.7284	-5.9703	-5.6485	-6.0170	-5.6480
SBC	-5.6584	-5.6985	-5.9426	-5.6207	-5.9892	-5.6202

Table 5.13 continued

	(OSE, SGX)		(OSE, CME)		(SGX, CME)	
Dependent variable	OSE	SGX	OSE	CME	SGX	CME
Sample B						
Linear model: ECM-GARCH						
RSS	0.3216	0.3168	0.1950	0.3341	0.1890	0.3340
Q(24) for η_t	[0.8260]	[0.8296]	[0.6116]	[0.9865]	[0.7823]	[0.9864]
Q(24) for η_t^2	[0.7003]	[0.7594]	[0.8349]	[0.6058]	[0.9007]	[0.6203]
JB	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Asymmetric tests						
sign bias test	[0.6755]	[0.5554]	[0.8088]	[0.3464]	[0.3284]	[0.1578]
neg. size bias test	[0.4975]	[0.4425]	[0.5481]	[0.4620]	[0.1578]	[0.2936]
pos. size bias test	[0.0255]	[0.0321]	[0.6175]	[0.0016]	[0.8324]	[0.0007]
joint test	[0.0444]	[0.0546]	[0.6361]	[0.0721]	[0.1038]	[0.0432]
Information criteria						
AIC	-5.7133	-5.7282	-6.2256	-5.6241	-6.2490	-5.6242
SBC	-5.6657	-5.6807	-6.1745	-5.5766	-6.2015	-5.5766
Nonlinear model: ESTECM-EGARCH						
RSS	0.3225	0.3165	0.1951	0.3376	0.1893	0.3358
Q(24) for η_t	[0.8439]	[0.8307]	[0.3985]	[0.9734]	[0.5429]	[0.9758]
Q(24) for η_t^2	[0.5630]	[0.7755]	[0.8159]	[0.6326]	[0.9840]	[0.8219]
JB	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Asymmetric tests						
sign bias test	[0.7294]	[0.8447]	[0.3969]	[0.1620]	[0.2565]	[0.0541]
neg. size bias test	[0.9428]	[0.9573]	[0.2721]	[0.9598]	[0.1822]	[0.1948]
pos. size bias test	[0.5561]	[0.7031]	[0.5831]	[0.0043]	[0.5476]	[0.0064]
joint test	[0.8069]	[0.9378]	[0.1252]	[0.1150]	[0.1660]	[0.1298]
Information criteria						
AIC	-5.7470	-5.7658	-6.3091	-5.6943	-6.3398	-5.6980
SBC	-5.6995	-5.7183	-6.2469	-5.6468	-6.2777	-5.6468

Notes: The table summarises the diagnostic checks and model fit measures of the linear ECM-GARCH and the nonlinear ESTECM-EGARCH models for bilateral Nikkei futures pairs (OSE, SGX), (OSE, CME) and (SGX, CME). The diagnostics include the Ljung-Box (1978) portmanteau test (Q) for standardised residuals and squared standardised residuals up to order 24, the Jarque-Bera (1980) normality test (JB), and the asymmetric test of Engle and Ng (1993) which contains sign bias test, negative (neg.) size bias test, positive (pos.) size bias test, and joint test. The RSS and information criteria, AIC and SBC, are reported for comparing model fit. The AIC is calculated as $-2\ln(L)/T+2n/T$, the SBC is calculated as $-2\ln(L)/T+n\ln(T)/T$, where $\ln(L)$ is the maximised value of the log-likelihood function, n is the number of parameters, and T is the sample size. Numbers in square brackets are p-values.

5.7 Robustness checks

The above results of the cross-border futures price interactions appear to support the CME as the most dominant market in the transnational price discovery process. As mentioned, the results are based on data on day *t*, with which the three futures markets are assumed to have overlapping trading hours. Since the Central Standard Time (CST) used by the CME is 15 hours behind the Japan Standard Time (JST) used by the OSE and SGX,[79] using all the returns on day *t* makes a default time sequence whereby the OSE, SGX are well ahead of the CME. Obviously, it deserves consideration whether the dominance of the CME is associated with such sequence. Following Booth et al. (1996), I re-estimate the models with an alternative time sequence by which the CME acts as the earliest trading market to check the robustness of its price leadership.

On a typical trading day, the OSE opens 9.00-15.15, with an overnight session 16.30-3.00 (JST); the SGX opens 7.45-14.25, with an overnight session 15.15-2.00 (Singapore time, SGT). Given that SGT is 1 hour behind JST, the trading hours of the two markets are almost overlapping. Thus, for simplicity, I only compare the time differences between the OSE and the CME. Figure 5.3 illustrates the simultaneous trading hours of the OSE and the CME. It is clear that, with the aid of the CME Globex and the OSE overnight trading, there are fairly long periods during a day when both markets are open. Moreover, the futures settlement prices in the OSE and the CME are generated on the same day.[80] The prior use of the same-day returns is hence justified from two aspects: a) arbitrage activities across the markets can be quite active due to the common trading hours in the default time sequence; b) the CME settlement price on day *t* reflects the information on day *t*; from the perspective of the OSE investors, the OSE settlement price on day *t* also reflects the information on day *t* (although it is actually day *t*-1 from the perspective of the CME investors) - matching CME_t with OSE_t, SGX_t captures information on the same "nominal" day.

[79] The SGX uses Singapore time which is 1 hour behind the Japan time; as will be explained later, the OSE, SGX trading hours are almost overlapping, and thus I can regard the SGX as using the Japan time.

[80] This also holds when the Central Daylight Time (CDT) is observed by the CME during summer. The CDT reduces the time differences between the OSE and the CME to 14 hours, so that the settlement prices OSE_t are generated at 1.15 in Chicago on day *t* under the CDT.

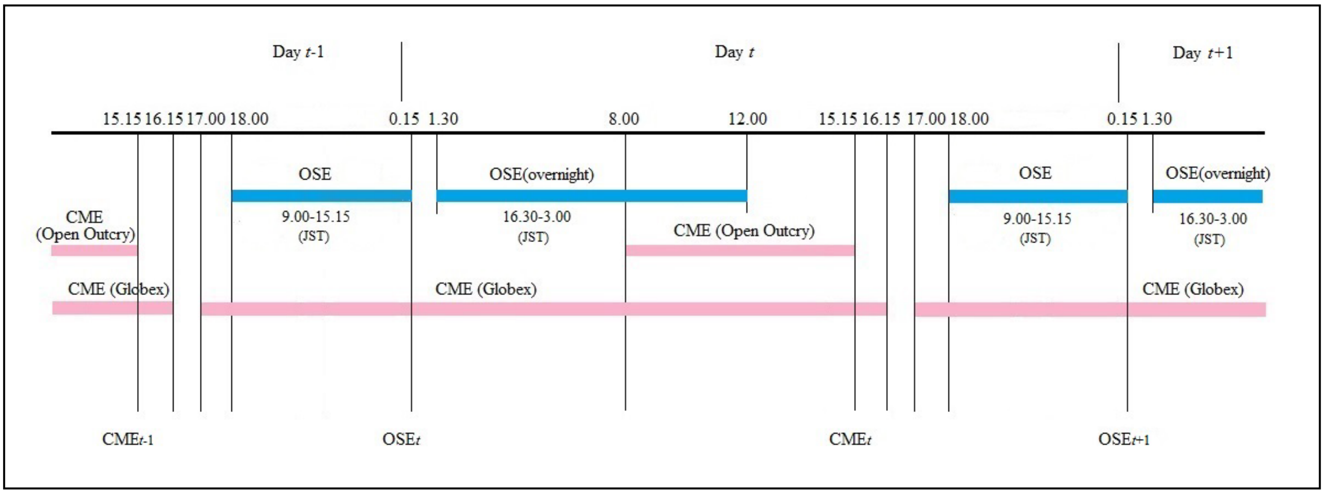


Figure 5.3 Trading hours of the OSE and the CME Nikkei futures markets

Notes: This figure illustrates the trading hours of the OSE (including the overnight session) and the CME (Globex and open outcry) as of 31/12/2014. The time is CST unless otherwise marked. The bottom shows the time when the OSE, CME settlement prices are generated; the subscripts *t*-1, *t* and *t*+1 indicate the timing differences.

Alternatively, CME_{t-1} can be aligned with OSE_t, SGX_t so that the CME becomes the earliest trading market in this time sequence, and all the returns are able to reveal information within the same 24-hour time intervals (Booth et al., 1996). Table 5.14 shows the estimation results of the linear ECM-GARCH using the alternative trading sequence. Contrary to the outcomes in Table 5.10, however, the CME takes the adjustment roles with relatively large error correction coefficients, and the OSE, SGX show much faster adjustments towards futures price parity. The long-run feedback relationships absent in Table 5.10 are also found in sample B. The Wald tests for short-run causality again indicate stronger influences of the OSE, SGX. Combining the previous results of the SGX leading the OSE, which is not affected by the timing issues, I find that the SGX now becomes the leading market, followed by the OSE, and finally the CME. With the alternative time sequence, the information leadership of the CME seems to be transferred to the SGX. Note that the results with the different time sequences are still consistent in the sense that the last trading market in each time sequence reflects information the most quickly, and that the foreign markets lead the domestic market in the cross-border information transmission.

Table 5.14 Robustness checks: the linear ECM-GARCH across the Nikkei futures markets

Panel A: Parameter estimates				
	(OSE, CME)		(SGX, CME)	
Dependent variable	OSE	CME	SGX	CME
Sample A				
α	-0.0876	0.9663	-0.0645	0.9987
	(-0.8486)	(20.2841)	(-0.5979)	(20.9107)
Sample B				
α	-0.1868	0.8573	-0.1883	0.9195
	(-2.1171)	(7.7796)	(-2.1128)	(6.7818)

Panel B: Granger causality tests		
	Wald stat	*p*-value
Sample A		
OSE does not cause CME	5502.1624	0.0000
CME does not cause OSE	16.0325	0.0248
SGX does not cause CME	5611.5337	0.0000
CME does not cause SGX	16.5222	0.0208
Sample B		
OSE does not cause CME	1495.1841	0.0000
CME does not cause OSE	13.4686	0.0194
SGX does not cause CME	1498.9699	0.0000
CME does not cause SGX	11.8033	0.0376

Notes: The table presents the estimation results of the linear ECM-GARCH model for bilateral Nikkei futures pairs (OSE, CME) and (SGX, CME), with the CME on day *t*-1 aligned with the OSE, SGX on day *t* to make the alternative time sequence by which the CME is the earliest trading market. The models and estimation details are the same as in Table 5.10, except that the model lags are 6 (sample A), 4 (sample B) in first differences. Panel A presents the estimated error correction coefficients (α) in each market in each pair. Panel B presents the results of Wald tests for Granger causality, by the augmented lag method of Toda and Yamamoto (1995), Dolado and Lütkepohl (1996), with the null hypothesis that the past prices in one market do not Granger-cause the current prices in the other market in the short run (Covrig et al., 2004). The Wald statistics are asymptotically distributed as $\chi^2(7)$ in sample A, $\chi^2(5)$ in sample B, reported with the associated *p*-values. Numbers in parentheses are *z*-statistics.

Nevertheless, the results with the alternative time sequence should be interpreted with caution. From Figure 5.3, there is a non-trading interval after the OSE overnight session closes and before the OSE normal session opens, lasting about 6 hours. Although the CME is still open during the interval, the OSE, SGX are both closed such that the spread arbitrage across the futures markets is not available. In fact, the spot market remains closed during the interval,[81] making the spot-futures arbitrage impossible. As such, trading activities in the Nikkei markets are expected to be low in those hours. Matching CME_{t-1} with OSE_t, SGX_t includes the thinly traded period in the estimation. Besides, clustered volatilities or risks are often reported when markets close and re-open in response to news that arrives during the non-trading gap.[82] Such news in the Nikkei markets can only manifest itself via the CME during the gap when the other markets are all closed. This may explain some autocorrelated residuals observed in the re-timed linear CME model, especially in sample B. The problem becomes severe when the nonlinear ESTECM-EGARCH is estimated with the alternative time sequence, as the CME generates poorly conditioned estimates with excessive residual autocorrelations which cannot be removed by increasing model lags. Since the smooth transition models may not be able to appropriately describe such information, the nonlinear results with the alternative time sequence are not reported. The results of the re-timed linear models should be interpreted with caution.

5.8 Discussion and conclusion

The chapter studies the international price discovery process in the Nikkei 225 stock index futures markets; specifically, the linear and nonlinear price adjustments towards equilibrium between the spot and futures prices in individual Nikkei markets, and across the equivalent Nikkei futures prices. With a 19-year sample covering a pre-crisis period and a post-crisis period, the Nikkei spot and futures markets are found to be intrinsically linked, and in fact cointegrated, in the sense that the spot and futures prices are cointegrated with the cointegrating vector [1, -1] in individual Nikkei markets, and that the three Nikkei futures prices are cointegrated with one common stochastic trend. Given the cointegrating relationships of the

---

[81] The trading hours of the Nikkei spot market are 9.00-11.30, 12.30-15.00 (JST), corresponding to 18.00-20.30, 21.30-0.00 (CST).

[82] That is, the widely documented U-shaped intraday pattern in volatility. Possible explanations include the discretionary liquidity traders of Admati and Pfleiderer (1988) and the portfolio rebalancing strategies of Brock and Kleidon (1992).

Nikkei markets, the error correction mechanisms are employed to describe the spot-futures price adjustments towards the cost of carry equilibrium, and the futures price adjustments towards the price parity condition across the equivalent futures markets. The linear ECM acts as a benchmark specification for modelling such adjustment processes. The nonlinear ESTECM is further used to capture the possible smooth transition error correction behaviour in the Nikkei markets, given the effects of transaction costs, heterogeneity and predictive asymmetry. Specification tests and evaluation criteria indicate the presence of smooth transition error correction dynamics and the nonlinear model more appropriate.

In individual Nikkei markets, with the linear ECM, there is considerable evidence of long-run bidirectional causality between the spot and futures prices; besides, the futures market generally assumes the price discovery function, except that the spot market plays a leading role in the OSE market in the post-crisis period. By contrast, with the nonlinear ESTECM, I find that the majority of the causalities are one-way, running from the futures to the spot in the pre-crisis period and from the spot to the futures in the post-crisis period. As the finding of futures leading spot is in agreement with the theoretical prediction, the crucial role of the spot market in the process of price discovery after the crisis is interesting. This type of price adjustments takes place within a single regime. More importantly, quicker movements between the regimes, which take place in the futures market before the crisis, are found in the spot market after the crisis. This means that the Nikkei spot market is quicker in adjustments within one regime and between the regimes. Among the consistently downsized rates of smooth transition which imply higher transaction costs of the spot-futures arbitrage in the Nikkei markets after the crisis, the transition speed in the Nikkei spot market is actually rising, probably reflecting the more uniform structure of the spot transaction costs. Recall that the effect of heterogeneous index arbitrageurs is rather weak in the Nikkei markets (see section 4.4.4, Chapter 4). Hence, the lower level of heterogeneity, not only in investor structure but also in transaction costs, may contribute to the major part played by the spot market in information dissemination after the crisis. To understand this, the interactions between noise traders and fundamental traders affect the nature of the price adjustments. Noise traders who divert prices away from equilibrium tend to follow market sentiment in rising markets; in the period of market downturns, as in the Nikkei markets after the crisis, they pay more attention to fundamental information, and prices are driven by fundamental traders to equilibrium (McMillan and Speight, 2006). If investors are by and large similar, they are likely to behave in a similarly conservative manner after the crisis, facing less various transaction costs. The aggregate market response to pricing errors may also subject to fewer risks of cognitive biases and deviation persistence (Shleifer, 2000), resulting in more rapid mean-reverting behaviour. This is in relative terms, however. The point made here is that the Nikkei spot market, with many different investors and transaction costs, may exhibit a lower level of heterogeneity in the investors and transaction costs than the Nikkei futures markets in the post-crisis period.

Across the Nikkei futures markets, the linear and nonlinear models show consistent results that the CME has the strongest influence on the other markets, and that the foreign markets lead the domestic market in the cross-border information transmission. The nonlinear ESTECM is further examined as to the speed of smooth transition across the futures markets. The OSE is found to exhibit the least heterogeneous structure of transaction costs, again in relative terms. It turns out that both the spot and futures markets in Japan show a lower level of heterogeneity, compared with the offshore markets. The common increasing trend of the transition speed indicates the decreasing transaction costs in the three futures markets in recent years, especially in the CME. Therefore, the information advantage enjoyed by the CME in the cross-border price discovery process may be explained by its role as a global financial centre and more lenient trading environment, such as lower (and more heterogeneous) transaction costs, and longer trading hours facilitated by the CME Globex. When an alternative time sequence is used, the price leadership of the CME seems to be transferred to the SGX. Like the CME, the SGX is a global financial centre and provides investors with greater heterogeneity and longer trading hours than the OSE. As such, my results consistently support the international centre hypothesis that the offshore information centre more strongly disseminates information to the other markets than the reverse, and thus acts as the main price discovery vehicle across the border. My results are also consistent with network/platform literature (e.g. Rochet and Tirole, 2003), which holds that information gravitates to the most ubiquitous international platform - in this case, the CME or the SGX. The last trading market in each time sequence may have more opportunities to absorb information that already exists in the earlier markets, which contributes to its price dominance. This is consistent with the finding of Booth et al. (1996).

Predictive asymmetry is present in the Nikkei prices and more investors respond to bad news than to good news of the same size. In individual Nikkei markets, such asymmetry is most evident in the post-crisis period; across the Nikkei futures markets, it is found in all the three markets in the pre-crisis period. The Nikkei variances also exhibit asymmetric behaviour, and bad news has a larger impact on volatility than equally sized good news. The asymmetry may reflect the various interactions of heterogeneous investors and transaction costs in the Nikkei markets. Sentana and Wadhwani (1992) put forward a theoretical model in which the activities of noise traders are closely associated with market volatility. Bad news induces investors to sell their holdings to meet obligations and to reduce exposure to any further falls in prices. This leads to more noise trading that increases volatility. However, the higher costs related to short sale, which lasted until November 2013 in Japan, may have alleviated the impact of bad news on the spot market. It is still found that more investors respond to positive price deviations in the index arbitrage before the crisis and in the spread arbitrage of the CME after the crisis. Among other factors, the heterogeneity in investors and transaction costs may contribute to the asymmetry observed in the Nikkei prices and variances.

Two implications from the chapter are as follows. Despite higher transaction costs in index arbitrage activities in the post-crisis period, which largely come from the Nikkei spot market as the Nikkei futures transaction costs are actually falling, the spot prices lead the futures prices in information dissemination in the period, probably due to the lower level of heterogeneity in investor structure and transaction costs in the spot market. The CME and SGX, however, with higher level of heterogeneity as one of their many advantages, dominate the cross-border price discovery process. The level of heterogeneity as a futures market characteristic has not received much academic interest in an international setting. Here it is obvious that it provides an important perspective at least for market regulation in separate countries and exchange competition across the border. On the other hand, the information leadership of the CME and SGX demonstrate the key functions of offshore markets in futures market globalisation. As more and more futures contracts become listed on multiple venues, it is no doubt a valuable task for investors and regulators to understand and make use of the price interaction mechanisms between the home market and the equivalent, offshore markets.

The chapter has focussed on the first-moment price dynamics in the Nikkei markets. The conditional variance equations used in the chapter are univariate GARCH or EGARCH models, simple representations to get rid of the excessive ARCH effects in the residuals. The second-moment volatility dynamics in the Nikkei markets will be addressed in more depth in the next chapter.

Appendix

Table A5.1 Estimation results in individual Nikkei markets: the nonlinear ESTECM-EGARCH model with delay parameter *d*>1

	SGX				CME			
	Sample A		Sample B		Sample A		Sample B	
	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat
ESTECM coefficients								
Spot								
p	3		2		4		5	
d	3		3		2		2	
k_s	-0.0002	-0.8688	0.0007	2.1951	0.0003	1.7086	-0.0002	-0.8107
$\pi_{ss,1}$	-0.5187	-3.9395	-0.2900	-1.6726	-0.5368	-3.4984	-0.7207	-4.6848
$\pi_{ss,2}$	-0.3758	-2.7015	-0.3038	-1.6040	-0.3628	-1.5191	0.0232	0.1127
$\pi_{ss,3}$	-0.1289	-0.9774			-0.0518	-0.2885	-0.0330	-0.2069
$\pi_{ss,4}$					0.0852	0.6924	-0.1923	-1.3853
$\pi_{ss,5}$							-0.2419	-2.7513
$\pi_{sf,1}$	0.5051	4.0047	0.3269	1.8274	0.5524	4.4281	0.7795	8.3357
$\pi_{sf,2}$	0.3853	2.8287	0.4667	2.2812	0.3606	1.4324	0.1793	0.8504
$\pi_{sf,3}$	0.1852	1.4234			0.3439	1.8017	-0.1874	-0.9013
$\pi_{sf,4}$					-0.0465	-0.3296	0.0695	0.4425
$\pi_{sf,5}$							0.1944	1.7863
$\pi_{ss,1}^*$	-0.0461	-0.2099	0.0070	0.0352	0.3540	2.1176	0.4204	2.4649
$\pi_{ss,2}^*$	0.0443	0.2111	0.2276	1.0546	0.2433	0.9679	-0.2305	-1.0357
$\pi_{ss,3}^*$	-0.1173	-0.5633			-0.0414	-0.2167	-0.0729	-0.4152
$\pi_{ss,4}^*$					-0.1453	-1.1333	0.1327	0.8867
$\pi_{ss,5}^*$							0.2220	2.3271
$\pi_{sf,1}^*$	0.0248	0.1141	-0.0952	-0.4680	-0.3985	-2.8532	-0.5355	-4.5251
$\pi_{sf,2}^*$	-0.0781	-0.3768	-0.3923	-1.7452	-0.2190	-0.8275	0.0293	0.1267
$\pi_{sf,3}^*$	0.0433	0.2088			-0.2620	-1.3010	0.3316	1.4836
$\pi_{sf,4}^*$					0.1161	0.7796	-0.0008	-0.0048
$\pi_{sf,5}^*$							-0.1604	-1.3339
α_s	0.3342	1.7774	0.2373	2.4316	0.6213	10.1967	0.5624	8.5703
γ_s	1.7548	0.9376	19.6767	0.9767	224.0359	1.3885	43.4930	1.6229
θ_s	4.7226	0.1993	-37.5042	-0.0308	-96.3074	-0.0698	1891.9147	0.0000

Table A5.1 continued

	SGX				CME			
	Sample A		Sample B		Sample A		Sample B	
	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat
Futures								
p	1		1					
d	3		3					
k_f	0.0000	0.1756	0.0004	1.2674				
$\pi_{fs,1}$	0.0838	0.9786	0.1966	1.6761				
$\pi_{ff,1}$	-0.1033	-1.2398	-0.1752	-1.5358				
$\pi_{fs,1}^*$	-0.8995	-2.3119	-0.3088	-1.7215				
$\pi_{ff,1}^*$	0.8436	2.2130	0.2373	1.3159				
α_f	-0.7082	-1.7207	-0.1436	-1.1671				
γ_f	0.2978	1.1109	3.4897	0.6312				
θ_f	-22.4422	-0.0031	-22.6416	-0.0132				
EGARCH coefficients								
Spot								
ω_s	-0.3727	-6.8785	-0.4919	-5.5268	-0.3398	-4.0604	-0.5755	-2.9984
λ_s	-0.0837	-7.2583	-0.0978	-5.6770	-0.0429	-2.8764	-0.0343	-1.0497
$a_{s,1}$	-0.0295	-0.6360	-0.0870	-1.3588	0.1024	1.6526	0.1917	3.5984
$a_{s,2}$	0.1876	4.0348	0.2541	4.0675	0.0556	0.9288		
b_s	0.9710	176.5954	0.9582	105.3115	0.9755	127.6515	0.9532	51.6799
Futures								
ω_f	-0.3214	-6.4049	-0.5059	-5.4916				
λ_f	-0.0784	-7.0409	-0.1049	-6.4500				
$a_{f,1}$	0.1365	7.1166	-0.0686	-1.0834				
$a_{f,2}$			0.2353	3.7209				
b_f	0.9748	194.3441	0.9569	103.6616				

Notes: This table shows the estimation results of the nonlinear ESTECM-EGARCH with d determined by the standard approach in the LM-type linearity tests in individual Nikkei markets, the SGX and the CME. The mean models are equations (5.3a) (5.3b):

$$\Delta s_t = k_s + \sum_{j=1}^{p} \pi_{ss,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j} \Delta f_{t-j} + (k_s^* + \sum_{j=1}^{p} \pi_{ss,j}^* \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j}^* \Delta f_{t-j} + \alpha_s z_{t-1}) \times T_s(z_{t-d}) + u_{s,t},$$

$$T_s(z_{t-d}) = 1 - \exp[-\gamma_s (z_{t-d} - c^*)^2 \times g_s(z_{t-d})],\ g_s(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_s (z_{t-d} - c^*)]\}$$

$$\Delta f_t = k_f + \sum_{j=1}^{p} \pi_{fs,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j} \Delta f_{t-j} + (k_f^* + \sum_{j=1}^{p} \pi_{fs,j}^* \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j}^* \Delta f_{t-j} + \alpha_f z_{t-1}) \times T_f(z_{t-d}) + u_{f,t},$$

$$T_f(z_{t-d}) = 1 - \exp[-\gamma_f (z_{t-d} - c^*)^2 \times g_f(z_{t-d})],\ g_f(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_f (z_{t-d} - c^*)]\}$$

The variance models are equations (5.11) (5.13): $u_t = \sigma_t \eta_t$, $\ln \sigma_t^2 = \omega + \lambda (u_{t-1}/\sigma_{t-1}) + a|u_{t-1}/\sigma_{t-1}| + b \ln \sigma_{t-1}^2$, or $\ln \sigma_t^2 = \omega + \lambda (u_{t-1}/\sigma_{t-1}) + a_1 |u_{t-1}/\sigma_{t-1}| + a_2 |u_{t-2}/\sigma_{t-2}| + b \ln \sigma_{t-1}^2$ is used instead of (5.13) to remove the excessive ARCH effects in the residuals. The model restriction is $k^*=c^*=0$. The estimation details are the same as in Table 5.9, except that the delay parameter d is determined as the candidate that generates the smallest p-value of the linearity test. That is, d=3 for the SGX, d=2 for the CME spot (Table 5.8). The coefficient estimates followed by z-statistics are reported for each market in each sample.

Table A5.2 Estimation results across the Nikkei futures markets: more parameters of the linear ECM-GARCH model

	(OSE, SGX)				(OSE, CME)				(SGX, CME)			
Dependent variable	OSE		SGX		OSE		CME		SGX		CME	
(Market 1)	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat
Sample A												
k	0.0002	0.8791	0.0002	0.8820	0.0010	4.5640	0.0002	0.7635	0.0010	4.6075	0.0002	0.6209
Market 1 lags												
π_1	0.1079	0.1941	-0.1972	-0.3736	0.0727	0.8840	-0.0864	-1.2535	0.0854	1.0374	-0.0581	-0.8264
π_2	0.2168	0.4338	-0.2712	-0.5806	0.0959	1.3516	-0.0756	-1.2406	0.1019	1.4570	-0.0534	-0.8623
π_3	0.0273	0.0608	-0.0531	-0.1255	0.0835	1.3667	-0.0707	-1.2705	0.0925	1.5237	-0.0539	-0.9630
π_4	0.2778	0.6835	-0.3078	-0.7992	0.0787	1.5120	-0.0576	-1.0578	0.0691	1.3505	-0.0423	-0.7715
π_5	0.1480	0.4386	-0.1335	-0.4150	0.1026	2.2194	-0.0732	-1.4177	0.0922	2.0344	-0.0574	-1.1069
π_6	0.1445	0.5350	-0.1699	-0.6471	0.0722	1.8946	-0.0902	-1.9633	0.0717	1.8703	-0.0836	-1.8104
π_7	-0.1122	-0.6191	0.1005	0.5653	0.0432	1.5622	-0.1093	-2.9025	0.0454	1.6666	-0.1146	-3.0395
Market 2 lags												
π_1	-0.1322	-0.2372	0.1765	0.3354	-0.1003	-1.2047	0.0469	0.6908	-0.1055	-1.2630	0.0231	0.3309
π_2	-0.2374	-0.4748	0.2544	0.5446	-0.0975	-1.3223	0.0811	1.3486	-0.1042	-1.4206	0.0608	0.9984
π_3	-0.0202	-0.0448	0.0606	0.1439	-0.0887	-1.4154	0.0739	1.3180	-0.0951	-1.5336	0.0587	1.0405
π_4	-0.2987	-0.7327	0.2866	0.7462	-0.0937	-1.7177	0.0490	0.8903	-0.0864	-1.6098	0.0330	0.5924
π_5	-0.1399	-0.4142	0.1398	0.4350	-0.1054	-2.1905	0.0507	1.0012	-0.0946	-2.0113	0.0343	0.6731
π_6	-0.1855	-0.6813	0.1311	0.5039	-0.0852	-2.1496	0.0733	1.6192	-0.0842	-2.1444	0.0709	1.5471
π_7	0.1000	0.5510	-0.1130	-0.6366	-0.0842	-2.6100	0.0627	1.8774	-0.0856	-2.6732	0.0719	2.1496
GARCH coefficients												
ω	0.0000	3.3477	0.0000	3.2985	0.0000	2.9041	0.0000	3.0034	0.0000	2.8481	0.0000	2.9909
a_1	0.0241	1.0646	0.0242	1.0705	0.0625	5.5601	0.0641	5.9558	0.0632	5.5952	0.0640	5.9586
a_2	0.0567	2.3042	0.0553	2.2303								
b	0.9017	61.7580	0.9018	58.3953	0.9272	73.2666	0.9216	72.3634	0.9253	70.0018	0.9217	72.3402

Table A5.2 continued

	(OSE, SGX)				(OSE, CME)				(SGX, CME)			
Dependent variable	OSE		SGX		OSE		CME		SGX		CME	
(Market 1)	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat
Sample B												
k	0.0008	2.2815	0.0007	1.9236	-0.0006	-2.0795	0.0007	1.7279	-0.0007	-2.1191	0.0007	1.7097
Market 1 lags												
π_1	0.0952	0.1771	-0.1604	-0.2995	-0.1392	-2.1871	-0.0768	-0.8273	-0.1507	-2.3892	-0.0838	-0.8892
π_2	-0.1377	-0.3029	0.0935	0.2059	-0.0958	-1.7430	0.0130	0.1605	-0.1115	-1.9715	-0.0007	-0.0089
π_3	-0.3224	-0.8305	0.2305	0.5957	-0.0246	-0.5685	0.0407	0.6216	-0.0356	-0.8139	0.0291	0.4362
π_4	0.0528	0.1922	-0.1228	-0.4517	-0.0169	-0.5863	0.0617	1.2208	-0.0249	-0.8689	0.0587	1.1474
Market 2 lags												
π_1	-0.1077	-0.2000	0.1514	0.2834	0.0719	1.0212	0.0579	0.6314	0.0929	1.3744	0.0733	0.7834
π_2	0.1735	0.3783	-0.0624	-0.1385	0.0983	1.6738	-0.0315	-0.4101	0.1083	1.8122	-0.0175	-0.2242
π_3	0.3187	0.8167	-0.2380	-0.6200	0.0167	0.3555	-0.0888	-1.5015	0.0294	0.6264	-0.0781	-1.2834
π_4	-0.0796	-0.2892	0.0962	0.3543	0.0066	0.1751	-0.0713	-1.7952	0.0075	0.2027	-0.0744	-1.8799
GARCH coefficients												
ω	0.0000	3.0579	0.0000	3.0969	0.0000	2.0898	0.0000	2.5124	0.0000	2.6575	0.0000	2.5039
a_1	0.1025	4.3095	0.1029	4.1745	0.1558	2.2574	0.0767	3.3181	0.1034	2.7579	0.0760	3.3075
a_2					-0.0972	-1.4142						
b	0.8662	31.8214	0.8653	30.7821	0.9087	29.3026	0.8781	25.7397	0.8411	17.7008	0.8795	25.9872

Notes: The table contains more parameter estimates of the linear ECM-GARCH model for bilateral Nikkei futures pairs (OSE, SGX), (OSE, CME) and (SGX, CME). The mean models are equations (5.5a) (5.5b):

$$\Delta f_{1,t} = k_1 + \sum_{j=1}^{p}\pi_{11,j}\Delta f_{1,t-j} + \sum_{j=1}^{p}\pi_{12,j}\Delta f_{2,t-j} + \alpha_1 z_{t-1} + u_{1,t}, \quad \Delta f_{2,t} = k_2 + \sum_{j=1}^{p}\pi_{21,j}\Delta f_{1,t-j} + \sum_{j=1}^{p}\pi_{22,j}\Delta f_{2,t-j} + \alpha_2 z_{t-1} + u_{2,t}$$

The variance models are equations (5.11) (5.12): $u_t = \sigma_t \eta_t$, $\sigma_t^2 = \omega + a u_{t-1}^2 + b\sigma_{t-1}^2$, or a GARCH (2,1) model $\sigma_t^2 = \omega + a_1 u_{t-1}^2 + a_2 u_{t-2}^2 + b\sigma_{t-1}^2$ is used instead of (5.12) to remove the excessive ARCH effects in the residuals. The estimation details are the same as in Table 5.10. In each bilateral pair, the short-run autoregressive coefficients are sorted by market 1 and 2, where market 1 is the market of the dependent variable, and market 2 is the other market. For example, if OSE is the dependent variable in the pair (OSE, SGX), OSE is the market 1 and SGX is the market 2; if SGX is the dependent variable in the pair (OSE, SGX), SGX is the market 1 and OSE is the market 2. This arrangement enables most subscripts to be omitted without loss of clarity. The parameter estimates followed by *z*-statistics are reported in each market in each pair. The estimated error correction coefficients and the joint significant test results on the short-run coefficients are not included but reported in Table 5.10.

Table A5.3 Estimation results across the Nikkei futures markets: more parameters of the nonlinear ESTECM-EGARCH model

	(OSE, SGX)				(OSE, CME)				(SGX, CME)			
Dependent variable	OSE		SGX		OSE		CME		SGX		CME	
(Market 1)	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat
Sample A												
k	0.0000	0.1491	0.0001	0.5366	0.0008	3.8991	0.0001	0.5338	0.0009	4.2339	0.0001	0.4731
Market 1 lags												
π_1	-0.9391	-3.8358	0.2790	1.4702	-0.1374	-0.5860	0.0116	0.2779	0.7820	1.0887	0.0013	0.0327
π_2	-0.4386	-2.1240										
π_1^*	3.3208	2.8313	-1.5647	-1.6706	0.0936	0.3953	-0.1839	-0.8148	-0.8261	-1.1503	-0.1738	-0.6859
π_2^*	1.8411	2.5201										
Market 2 lags												
π_1	0.9297	3.7383	-0.2882	-1.5652	0.4452	1.3112	-0.0578	-1.5440	-0.7395	-0.9582	-0.0491	-1.3495
π_2	0.4339	2.0679										
π_1^*	-3.4502	-2.8707	1.4290	1.5824	-0.4547	-1.3362	0.1512	0.8401	0.7417	0.9611	0.1435	0.7149
π_2^*	-1.8946	-2.5517										
EGARCH coefficients												
ω	-0.3515	-6.3769	-0.3485	-6.3031	-0.2682	-5.3312	-0.2776	-5.2814	-0.2626	-5.1956	-0.2777	-5.2818
λ	-0.0732	-6.0012	-0.0739	-6.0412	-0.0381	-3.2108	-0.0594	-4.9907	-0.0359	-3.0292	-0.0595	-4.9871
a_1	-0.01221	-0.2664	-0.0168	-0.3660	0.1403	7.4239	0.1234	6.7986	0.1381	7.2523	0.1232	6.7896
a_2	0.1596	3.5123	0.1643	3.6087								
b	0.9723	172.6033	0.9726	172.1142	0.9820	197.2234	0.9788	183.0125	0.9825	196.6311	0.9788	182.8828

Table A5.3 continued

Dependent variable (Market 1)	(OSE, SGX)				(OSE, CME)				(SGX, CME)			
	OSE		SGX		OSE		CME		SGX		CME	
	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat	Estimate	*z*-stat
Sample B												
k	0.0007	1.9763	0.0007	2.0241	-0.0005	-1.9136	0.0004	1.1801	-0.0006	-2.4185	0.0004	1.1365
Market 1 lags												
π_1	-0.0237	-0.0502	0.0643	0.1577	-0.1260	-0.8991	-0.0239	-0.2547	0.0397	0.2756	0.6903	1.1052
π_2					0.1443	1.4048			0.1577	1.3935		
π_1^*	-0.1041	-0.1551	-0.1036	-0.1521	-0.0068	-0.0444	-0.1182	-0.9319	-0.1942	-1.2476	-0.7619	-1.2154
π_2^*					-0.2605	-2.4272			-0.2737	-2.3248		
Market 2 lags												
π_1	-0.1128	-0.2368	-0.1734	-0.4204	0.1187	0.6685	-0.0465	-0.6013	-0.1202	-0.6595	-1.3337	-2.3193
π_2					-0.1206	-0.9821			-0.2292	-1.5980		
π_1^*	0.2978	0.4421	0.2914	0.4303	-0.0843	-0.4401	0.1468	1.4983	0.1934	0.9931	1.3811	2.4012
π_2^*					0.2203	1.6874			0.3414	2.2885		
EGARCH coefficients												
ω	-0.5259	-4.7780	-0.5320	-4.9267	-0.5062	-4.4539	-0.5691	-4.5150	-0.6178	-4.6089	-0.6648	-4.7004
λ	-0.0912	-5.1735	-0.0908	-5.0157	-0.0881	-4.1879	-0.1098	-4.9301	-0.0958	-4.2181	-0.1175	-5.0784
a_1	0.1843	5.3165	0.1848	5.4344	0.1240	4.2434	0.1707	5.0381	0.1402	4.4978	0.0730	1.0335
a_2											0.1267	1.7308
b	0.9557	86.2220	0.9552	87.2573	0.9551	82.4048	0.9487	71.0803	0.9443	68.7977	0.9402	62.7431

Notes: The table contains more parameter estimates of the nonlinear ESTECM-EGARCH model for bilateral Nikkei futures pairs (OSE, SGX), (OSE, CME) and (SGX, CME). The mean models are equations (5.6a) (5.6b):

$$\Delta f_{1,t} = k_1 + \sum_{j=1}^{p} \pi_{11,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j} \Delta f_{2,t-j} + (k_1^* + \sum_{j=1}^{p} \pi_{11,j}^* \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j}^* \Delta f_{2,t-j} + \alpha_1 z_{t-1}) \times T_1(z_{t-d}) + u_{1,t}, T_1(z_{t-d}) = 1 - \exp[-\gamma_1 (z_{t-d} - c^*)^2 \times g_1(z_{t-d})], g_1(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_1 (z_{t-d} - c^*)]\}$$

$$\Delta f_{2,t} = k_2 + \sum_{j=1}^{p} \pi_{21,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j} \Delta f_{2,t-j} + (k_2^* + \sum_{j=1}^{p} \pi_{21,j}^* \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j}^* \Delta f_{2,t-j} + \alpha_2 z_{t-1}) \times T_2(z_{t-d}) + u_{2,t}, T_2(z_{t-d}) = 1 - \exp[-\gamma_2 (z_{t-d} - c^*)^2 \times g_2(z_{t-d})], g_2(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_2 (z_{t-d} - c^*)]\}$$

The variance models are equations (5.11) (5.13): $u_t = \sigma_t \eta_t$, $\ln \sigma_t^2 = \omega + \lambda (u_{t-1}/\sigma_{t-1}) + a|u_{t-1}/\sigma_{t-1}| + b \ln \sigma_{t-1}^2$, or $\ln \sigma_t^2 = \omega + \lambda (u_{t-1}/\sigma_{t-1}) + a_1 |u_{t-1}/\sigma_{t-1}| + a_2 |u_{t-2}/\sigma_{t-2}| + b \ln \sigma_{t-1}^2$ is used instead of (5.13) to remove excessive ARCH effects. The model restriction is $k^*=c^*=0$. The estimation details are the same as in Table 5.12. In each bilateral pair, the short-run autoregressive coefficients are sorted by market 1 and 2, where market 1 is the market of the dependent variable, and market 2 is the other market. For example, if OSE is the dependent variable in the pair (OSE, SGX), OSE is the market 1 and SGX is the market 2; if SGX is the dependent variable in the pair (OSE, SGX), SGX is the market 1 and OSE is the market 2. This arrangement enables most subscripts to be omitted without loss of clarity. The parameter estimates followed by *z*-statistics are reported in each market in each pair. The estimated error correction coefficients, smoothness parameters, asymmetry parameters and the joint significant test results on the short-run coefficients are not included but reported in Table 5.12.

Chapter 6

Volatility transmission in the Nikkei 225 futures markets

6.1 Introduction

Chapter 5 looked into the first-moment price dynamics in the Nikkei 225 stock index futures markets. Apart from price, another and arguably even more important conduit for cross-market information linkages is price volatility. The theoretical model of Ross (1989) suggests that the variance of price change is equal to the variance of information flow in a no-arbitrage economy, which reveals the mechanism whereby price volatility and the rate of information flow are directly related. A considerable amount of information disseminates through second-moment interdependencies that involve the dynamics of conditional variances and covariances. It is accepted in the literature that focusing only on the first-moment price dynamics could lead to specification errors and false inferences about the interactions between spot and futures prices (Chan et al., 1991). Empirical evidence is ample that the second-moment dependence is much more significant than the first-moment dependence, and in some situations, the second-moment serves as the only information channel in the absence of the first-moment (e.g. Hamori, 2003).

Based on one common stock index market (Tokyo Stock Exchange, TSE), the Nikkei 225 stock index futures contracts are traded on three equivalent yet different markets: Osaka Exchange (OSE), Singapore Exchange (SGX) and Chicago Mercantile Exchange (CME). However, research is still very limited on the volatility dynamics of the triple-listed Nikkei futures contracts, and thus the second-moment information transmission process in the Nikkei markets is not as adequately understood as is the first-moment. Studying the information linkages through the second-moments may provide further insights into the cross-border information transmission mechanism in the Nikkei markets. There are two possible hypotheses as to the location of the information leadership in transnational information dissemination: the home-bias hypothesis and the international centre hypothesis (e.g. Fung et al., 2001; Covrig et al., 2004). The home-bias hypothesis argues that domestic or home investors enjoy a battery of advantages such as geographic proximity to the underlying spot market, familiarity with local trading environment and regulation, and fewer trading barriers, and thus the domestic market should dominate the information transmission across borders.[83] By contrast, the international centre hypothesis argues if a foreign market is a global financial centre, then we might expect it to dominate transnational information dissemination because of the better trading conditions it can provide. Higher efficiency in processing and sharing information, and more opportunities for risk management by trading other financial instruments are also available on the foreign market. The second-moment information channel can exist with or without the first-moment information channel, and thus it is not clear which hypothesis is more relevant for the Nikkei volatilities. More importantly, the triple-listing nature of the Nikkei futures contracts necessitates a proper understanding of the Nikkei volatility dynamics, in that information shocks can be contagious from one market to the other such that the Nikkei volatilities become predictable, and that volatility co-movements between the markets have important implications for portfolio management strategies and maintaining financial stability in the course of futures market globalisation. In addition, the different trading hours of the CME Nikkei futures may affect the dynamic linkages between the CME and the other Nikkei futures markets, but this issue has not been treated explicitly in the literature. This chapter is therefore motivated to explore the second-moment volatility dynamics between Nikkei spot and futures markets, and across the Nikkei futures markets.

The chapter aims to investigate the international volatility transmission process in the Nikkei markets from two perspectives: a) the volatility interactions in individual Nikkei markets and across the Nikkei futures markets; and b) the time-varying behaviour of dynamic conditional correlations for Nikkei spot-futures pairs and futures-futures pairs. For volatility interactions, using the exponential smooth transition error correction model (ESTECM) as the conditional mean and univariate exponential GARCH (EGARCH) as the conditional variance, I perform

[83] Following Board and Sutcliffe (1996), I define the domestic or home futures market as the exchange where the futures contracts are traded in the same country as the stocks underlying the index, i.e. the OSE; the corresponding foreign or offshore futures market as the exchange in whose country the futures contracts are traded but the stocks underlying the index are not, i.e. the SGX and the CME.

the cross-correlation function (CCF) test of Cheung and Ng (1996), which is a diagnostic, two-stage approach for testing causality-in-variance, or the volatility spillover effect. If $\mathbf{r_t}$ is a 2×1 vector of asset returns at time t with elements r_{1t} and r_{2t}, r_2 does not cause r_1 in variance means $V\left[r_{1t}\left|\Omega_{t-1}^{\mathbf{r}}\right.\right]=V\left[r_{1t}\left|\Omega_{t-1}^{r_1}\right.\right]$, where $\Omega_{t\text{-}1}$ is the information set at time t-1 for $\mathbf{r}$ (or r_1), and $V[\cdot]$ denotes conditional variance (Comte and Lieberman, 2000). In other words, the notion of causality-in-variance indicates that volatilities are not restricted in one market but can spill over to other markets, and thus volatilities become predictable on the basis of volatilities in the related markets. With the CCF test, I find bidirectional volatility spillover between Nikkei spot and futures markets, with some evidence that the causality-in-variance originating from futures to spot is stronger than the reverse. Across the Nikkei futures markets, the CME causes the other Nikkei markets in variance the most strongly and is the leading market in the international volatility transmission. More generally, it is the foreign Nikkei markets (the CME and SGX) that act as the main source of information flow in the cross-border information dissemination mechanism. Consistent with conclusions in Chapter 5, the volatility results lend further support to the international centre hypothesis and confirm the key role of equivalent, offshore futures markets in the transnational information transmission process.

The most significant result of the CCF test is the contemporaneous correlations of the Nikkei returns, suggesting that the majority of information is transmitted in the Nikkei markets simultaneously. This finding points to the critical importance of the dynamic linkages between the Nikkei markets. As such, I use the Dynamic Conditional Correlation (DCC) multivariate GARCH model of Engle (2002) to examine the Nikkei market co-movements over time. Overall, the Nikkei markets are highly integrated, and the majority of information is absorbed jointly. The Nikkei conditional correlations are strongly persistent and stable, but there is evidence that the Nikkei spot-futures correlations exhibit more dynamics and their level of persistence declines from the pre-crisis period to the post-crisis period. The effect of different trading hours of the CME futures is checked by re-estimating the DCC model with an alternative time sequence. I notice that the time effect generates a different correlation pattern between the CME and the other markets, but this may merely reflect a thinly traded period incorporated in the sequence rather than the true market linkages. The time differences among the Nikkei markets do not affect the main characteristics of the Nikkei conditional correlations such as high level, strong persistence and stability.

The chapter contributes to the literature in the following ways. First, existing studies tend to look at the potential destabilising effects of Nikkei futures trading on the underlying stock volatility, e.g. Bacha and Vila (1994), Chang et al. (1999); or the first-moment price dynamics across the Nikkei futures markets, e.g. Booth et al. (1996). Few works have focused on the volatility transmission process of all of the three Nikkei futures markets. The chapter studies the volatility transmission in individual Nikkei markets and across the three Nikkei futures markets, which provides comprehensive new evidence on the Nikkei volatility dynamics and therefore helps deepen the understanding of the second-moment information linkages in the Nikkei markets. Second, with the univariate CCF test and the multivariate DCC model, the chapter shows the consistent result of the predominance of the foreign Nikkei markets in the cross-border information dissemination. The result is in agreement with the conclusions in Chapter 5 and continually supports the international centre hypothesis. In this way, I am able to confirm the important contributions of offshore futures exchanges in spreading first-moment and second-moment information to the information dissemination mechanism across the border. Third, there is little research on the dynamic Nikkei market linkages over time. By analysing the time-varying behaviour of Nikkei market co-movements, the chapter reports that the Nikkei markets are all very closely related to each other and the close relationships are strongly persistent and stable over time. Undoubtedly, the finding has important implications at least for investors and policy makers in the Nikkei markets. Fourth, the effect of different trading hours of the CME Nikkei futures has been largely ignored in the literature. The chapter explicitly considers the effect of different trading hours of the CME on the Nikkei conditional correlations, and shows that the time differences do not affect the main characteristics of the Nikkei conditional correlations, despite that they generate a different correlation pattern between the CME and the other markets, which may merely reflect low trading volume rather than the dynamic Nikkei market linkages.

The rest of the chapter is organised as follows. Section 6.2 describes data and presents preliminary analysis. The CCF test and the results of the volatility spillover effect are provided in section 6.3. The DCC methodology and its estimation results are provided in section 6.4. Section 6.5 discusses the main findings and concludes the chapter.

6.2 Data and preliminary analysis

Data used in this chapter are daily closing prices of Nikkei 225 index and daily settlement prices of Nikkei 225 index futures traded on the OSE, SGX and CME, which are obtained from the respective exchanges and Datastream over the period 20/06/1996-31/12/2014 (OSE and SGX); 01/01/1997-31/12/2014 (CME). This is the same dataset as that used in the last chapter. The contract months of the Nikkei futures contracts follow the usual quarterly cycle - March, June, September and December, and the futures price series is compiled using the nearest futures contracts and moving onto the next nearest contract at the start of the contract month. Daily returns for Nikkei spot (S_t) and futures prices (F_t) are calculated as $\Delta s_t = \ln(S_t/S_{t-1})$ and $\Delta f_t = \ln(F_t/F_{t-1})$, respectively. For individual spot-futures pairs, the local holiday schedule is applied and holidays are excluded from the data, as I assume that both markets need to be open to make index arbitrage available. Figure 5.1 in Chapter 5 plots the Nikkei spot and futures return series. An obvious spike is observed in each market in October-November 2008 during the financial crisis, with the Quandt-Andrews breakpoint test suggesting structural changes (see Chapter 4, p.136). As such, the overall sample is divided into a pre-crisis period (sample A) and a post-crisis period (sample B), excluding a short turmoil interval in the middle of the crisis.

Pre-crisis period (sample A):

28/06/1996-09/10/2008 (OSE, SGX); 09/01/1997-12/09/2008 (CME)

Post-crisis period (sample B):

04/11/2008-31/12/2014 (OSE, SGX); 02/12/2008-31/12/2014 (CME)

For futures-futures pairs, observations of the Nikkei futures returns are retained only when all of the three markets are open. This is because the three markets adopt different holiday schedules, and for simplicity I do not consider the information transmissions associated with closed markets. Moreover, the starting and ending dates of the sample periods are altered to ensure that the three futures series have the same length. The starting date of sample A is also adjusted to allow for the estimated lag parameters in the conditional mean. Therefore, a different sample division is employed for the futures-futures interactions.

Pre-crisis period (sample A):

17/01/1997-12/09/2008

Post-crisis period (sample B):

02/12/2008-30/12/2014

Table 6.1 presents descriptive statistics of Nikkei spot and futures returns. The means of the returns are very close in value and with the same signs, suggesting that the Nikkei markets may be potentially linked. The standard deviations of the returns are also broadly comparable. The futures standard deviations are slightly higher than the spot standard deviations before the crisis, but this is not so obvious after the crisis. In other words, the evidence is weak that the Nikkei futures markets are more volatile than the underlying spot market. Most of the Nikkei returns are negatively skewed and leptokurtic, suggesting departures from normality. Besides, the Jarque-Bera (1980) statistics decisively reject the null hypothesis of normal distribution in all the Nikkei markets. The Ljung-Box (1978) Q-statistics for the returns and squared returns indicate the presence of linear and nonlinear dependencies in the data, respectively. The much larger size and stronger significance of the Q-statistics for the squared returns also imply more influential nonlinear dependencies. It is well established in the literature that nonlinear (higher-moment) dependencies can be attributed to conditional heteroskedasticity (Koutmos and Tucker, 1996).

Table 5.2 in Chapter 5 displays the unconditional correlation coefficients for pair-wise Nikkei spot and futures returns. The Nikkei spot, OSE and SGX futures show close relationships with correlations larger than 0.96. The highest level of co-movement emerges between the OSE and SGX futures, correlated at 0.99 in both samples. This can be explained by the fact that the OSE, SGX contracts based on the same index are denominated in the same currency and traded almost at the same time. As a result, spread arbitrage between OSE and SGX incurs fewer hurdles, and most information can be transmitted and shared simultaneously between the two exchanges. By contrast, the CME futures show relatively low co-movements with the other Nikkei returns, due perhaps to their relatively small trading volume and/or extra risks involved in the CME arbitrage. As an additional check, the CME correlations are computed again by matching the CME returns on day t-1 with any one of the other returns on day t, to allow for a possible alternative time sequence by which the CME is the earliest trading market (Booth et al., 1996); and the last row of each sample in Table 5.2 shows even smaller correlations. As will be discussed in section 6.4, however, the unconditional correlations tend to underestimate the true associations among the Nikkei markets; these associations are represented by conditional correlations estimated from bivariate DCC models.

The cost of carry relationship requires that the spot and futures prices should be cointegrated with the cointegrating vector [1, -1]. Table 5.3 in Chapter 5 tests for cointegration in individual Nikkei markets using the two-step procedure of Engle and Granger (1987). Augmented Dickey-Fuller (ADF) tests and Phillips-Perron (PP) tests for unit roots are applied to the log-prices (s_t, f_t) and returns in each market. I find that the spot and futures prices are I(1), and the log-basis b_t, defined as (f_t - s_t), is I(0). In other words, the spot and futures prices are cointegrated with the cointegrating vector [1, -1] in individual Nikkei markets. Likewise, for futures contracts traded on more than one exchange, futures price parity requires that these exchanges should be cointegrated with one common stochastic trend. Table 5.4 in Chapter 5 tests for cointegration across the Nikkei futures markets using the Johansen (1988; 1991) procedure. It is clear that the three Nikkei futures markets are cointegrated with one common stochastic factor, and each bilateral pair of Nikkei futures prices is cointegrated with the cointegrating vector [1, -1].[84] Given that the Nikkei markets are cointegrated, an error correction mechanism is justified to act as the conditional mean equation in the subsequent analysis. For individual spot-futures pairs, the log-basis b_t will be used as the error correction term. For bilateral futures pairs, the futures price differential (f_1 - f_2) will be used as the error correction term, where 1, 2 denote any two Nikkei futures markets for brevity.

[84] See section 5.4.2, Chapter 5 for more details about the test procedures and the test results.

Table 6.1 Descriptive statistics of Nikkei 225 spot and futures returns

	S	OSE	SGX	CME
Sample A				
Mean	-0.0003	-0.0003	-0.0003	-0.0001
SD	0.0147	0.0153	0.0150	0.0149
Skewness	-0.1902	-0.3257	-0.2724	-0.0471
Kurtosis	5.2172	6.1591	6.1722	4.5263
JB	637.6581**	1310.9621**	1303.1264**	286.8665**
Q(12) for r_t	13.4092	25.5513**	17.3270	23.6483**
Q(12) for r_t^2	406.2301**	353.9619**	334.8531**	400.6054**
Sample B				
Mean	0.0005	0.0005	0.0005	0.0005
SD	0.0153	0.0154	0.0150	0.0149
Skewness	-0.5398	-0.3991	-0.3605	0.0366
Kurtosis	6.9314	6.5969	6.6591	5.3772
JB	1045.0729**	853.5288**	905.8228**	361.7884**
Q(12) for r_t	18.9721*	16.9911	18.9153*	12.0514
Q(12) for r_t^2	369.8906**	548.5039**	604.9055**	243.6330**

Notes: The table presents descriptive statistics of Nikkei 225 price returns in spot (S) and futures (OSE, SGX, CME) markets, including mean, standard deviation (SD), skewness, kurtosis, Jarque-Bera (1980) statistics (JB) of testing the null hypothesis of normal distribution, and Ljung-Box (1978) Q-statistics up to order 12 for returns (r_t) and squared returns (r_t^2). The price returns are calculated as the first-order differences in logarithmic prices. ** denotes significance at the 5% level. * denotes significance at the 10% level.

Trends and outliers in the data are removed by regressing each of the return series and error correction terms on a constant, time to maturity[85] and dummy variables which represent the outliers. I define outliers as observations larger than 6 standard deviations in absolute value of each of the series. The regression residuals, detrended and free from the outliers, are to be used as their dependent variables in the following estimation. In individual Nikkei markets, the number of outliers removed is 4(OSE), 8(SGX) and 2(CME), leaving the total amount of observations for estimation to 4533(OSE), 4582(SGX) and 4479(CME). Across the futures markets, the number of outliers is 3 when the timing issues of the CME are ignored, 4 when the timing issues are considered, leaving the total number of observations for estimation to 2776 (sample A) and 1443 (sample B). Table 5.3 in Chapter 5 shows that the log-basis without the effect of trends or outliers, denoted as b_t^*, is also I(0), which confirms the Nikkei spot-futures cointegrating relationship.

6.3 Volatility interdependencies in the Nikkei markets

6.3.1 The cross-correlation function (CCF) test

I study the second-moment, cross-market linkages in the Nikkei markets using the CCF test designed by Cheung and Ng (1996). The CCF test in itself is a diagnostic method based on the squared standardised residuals estimated from univariate conditional variance models. In the last chapter, I demonstrated the suitability of the exponential smooth transition error correction model (ESTECM) with univariate EGARCH in describing first-moment price dynamics in the Nikkei markets. Given this, the CCF test will be conducted based on the squared standardised residuals estimated from the ESTECM-EGARCH model. The CCF approach has an advantage that it allows the model estimations and the calculation of sample cross-correlations to be undertaken in two separate stages rather than simultaneously, making it convenient to implement in practice. Compared with multivariate GARCH models, the CCF test avoids excessive parameters which are difficult to interpret and computational burdens. More importantly, the CCF test results can provide helpful guidance on formulating a multivariate

[85] Time to maturity is the number of calendar days remaining in a futures contract until expiration. Time to maturity is found to exert significant impact on my data for maturity and rollover effects. However, time-related patterns or the calendar effect is ignored as the effect is not important on my data. See section 5.4.3, Chapter 5 for more discussions.

model. As will be shown later, my CCF test results provide justification for DCC multivariate GARCH specifications. In fact, multivariate GARCH models should not be estimated without checking for such effects in the data *a priori* by diagnostic tests (Soriano and Climent, 2005), a widely adopted one of which is the CCF test.

6.3.2 The conditional mean and conditional variance models

Recall that in Chapter 5 I discussed the ESTECM-EGARCH model. The same specification will be used in performing the CCF test. For convenience, a brief review of the conditional mean (ESTECM) and the conditional variance (EGARCH) is provided below. Following from Chapter 5, I assume that the nonlinear adjustments of spot and futures returns in individual Nikkei markets follow an ESTECM, given as follows:

$$\Delta s_t = k_s + \sum_{j=1}^{p} \pi_{ss,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j} \Delta f_{t-j} + (k_s^* + \sum_{j=1}^{p} \pi_{ss,j}^* \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j}^* \Delta f_{t-j} + \alpha_s z_{t-1}) \times T_s(z_{t-d}) + u_{s,t}$$

$$T_s(z_{t-d}) = 1 - \exp[-\gamma_s (z_{t-d} - c^*)^2 \times g_s(z_{t-d})]$$

$$g_s(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_s (z_{t-d} - c^*)]\} \tag{6.1a}$$

$$\Delta f_t = k_f + \sum_{j=1}^{p} \pi_{fs,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j} \Delta f_{t-j} + (k_f^* + \sum_{j=1}^{p} \pi_{fs,j}^* \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j}^* \Delta f_{t-j} + \alpha_f z_{t-1}) \times T_f(z_{t-d}) + u_{f,t}$$

$$T_f(z_{t-d}) = 1 - \exp[-\gamma_f (z_{t-d} - c^*)^2 \times g_f(z_{t-d})]$$

$$g_f(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_f (z_{t-d} - c^*)]\} \tag{6.1b}$$

where k, k^* are constants; π, π^* are the short-run autoregressive coefficients; the model residual u_t is iid with zero mean and finite variance; the model lag j=1, 2, …, p, with p as a positive integer. The error correction term is z_{t-1}, and the error correction coefficient α measures the long-run speed of adjustments and direction of causality. I generally expect α_s>0, α_f<0, and the market with a slower (quicker) speed of information transmission to have significant (insignificant) and larger (smaller) α in magnitude.[86] $T(\cdot)$ is an exponential smooth transition function bounded between 0, the middle regime where no investor will trade, and 1, the outer regime where all investors will trade. z_{t-d} is the transition variable with the delay parameter d,

[86] The sign of α_s depends on the net outcome of the two opposing effects of arbitrage and momentum (Zhong et al., 2004; Bohl et al., 2011), and therefore the sign of α_s is not necessarily positive in some markets.

d>0. The rate of the transition between the regimes is governed by the smoothness parameter γ, γ>0. If $\gamma \to 0$ or $\gamma \to \infty$, $T(\cdot)$ converges to 0 or 1, respectively, and the ESTECM converges to a linear error correction model (van Dijk et al., 2002). The location parameter c^* gives the centre of $T(\cdot)$. $g(\cdot)$ is an asymmetry function bounded between 0.5 and 1.5. The asymmetry parameter θ measures the asymmetric market response to positive and negative pricing deviations. Equations (6.1a) (6.1b) are used to model the conditional mean in individual Nikkei markets.

For a bilateral pair of futures prices (f_1, f_2), the nonlinear price adjustments across the futures markets are assumed to follow a similar ESTECM as below:

$$\Delta f_{1,t} = k_1 + \sum_{j=1}^{p} \pi_{11,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j} \Delta f_{2,t-j} + (k_1^* + \sum_{j=1}^{p} \pi_{11,j}^* \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j}^* \Delta f_{2,t-j} + \alpha_1 z_{t-1}) \times T_1(z_{t-d}) + u_{1,t}$$

$$T_1(z_{t-d}) = 1 - \exp[-\gamma_1 (z_{t-d} - c^*)^2 \times g_1(z_{t-d})]$$

$$g_1(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_1 (z_{t-d} - c^*)]\} \tag{6.2a}$$

$$\Delta f_{2,t} = k_2 + \sum_{j=1}^{p} \pi_{21,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j} \Delta f_{2,t-j} + (k_2^* + \sum_{j=1}^{p} \pi_{21,j}^* \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j}^* \Delta f_{2,t-j} + \alpha_2 z_{t-1}) \times T_2(z_{t-d}) + u_{2,t}$$

$$T_2(z_{t-d}) = 1 - \exp[-\gamma_2 (z_{t-d} - c^*)^2 \times g_2(z_{t-d})]$$

$$g_2(z_{t-d}) = 0.5 + 1/\{1 + \exp[-\theta_2 (z_{t-d} - c^*)]\} \tag{6.2b}$$

Most model parameters above are the same as those in equations (6.1a) and (6.1b), and thus extensions of their interpretations to the futures markets are straightforward. For example, the smoothness parameter γ controls the rate of the regime switch in each of the futures markets, and the asymmetry parameter θ captures the asymmetric market response to positive and negative futures spreads. Equations (6.2a) (6.2b) describe the conditional mean across the Nikkei futures markets.

The ESTECM residual u_t is assumed to follow a univariate EGARCH process of Nelson (1991) in the Nikkei markets. The EGARCH model is selected as it takes into account the different impacts of good news and bad news on volatility. Compared with other asymmetric GARCH models, the EGARCH model specifies the conditional variance as an exponential function, consistent with the exponential transition function which contains the asymmetry function in the first moment. Let σ_t^2 be the conditional variance, which is a time-varying, positive and measurable function of the information set at time t-1. An EGARCH (1, 1) model can be formulated as follows:[87]

$$u_t = \sigma_t \eta_t \tag{6.3}$$

$$\ln \sigma_t^2 = \omega + \lambda(u_{t-1} / \sigma_{t-1}) + a\left|u_{t-1} / \sigma_{t-1}\right| + b \ln \sigma_{t-1}^2 \tag{6.4}$$

where η_t ~ iid(0,1); there are no constraints on the non-negativity of the coefficients ω, a and b; the coefficient λ sheds light on the presence of the predictive asymmetry of asset prices. The impact of any price innovations on the logarithmic conditional variance is a linear combination of λ and a. For a positive shock, $u_{t-1}/\sigma_{t-1}>0$, the impact is (λ+a); for a negative shock, $u_{t-1}/\sigma_{t-1}<0$, the impact is (-λ+a) (Enders, 2010). Thus, a negative λ is required for negative shocks to trigger higher volatility, or the leverage effect. Equations (6.3) (6.4) are the conditional variance model in the Nikkei markets.

6.3.3 The CCF test for testing causality-in-variance

As noted earlier, the CCF test consists of two stages. In the first stage, univariate time series models are estimated that allow for time variation in the conditional mean and conditional variance. In the second stage, the squared residuals standardised by conditional variances are constructed and the cross-correlation functions are calculated to test the null hypothesis of no causality-in-variance. Consistent sample estimates of the models, and sample estimators of the squared standardised residuals should be used in practice. In my study, the series $\{\eta_t^2\}$ obtained from estimating the ESTECM-EGARCH in the first stage is used to calculate the sample cross-correlation. For a bilateral pair of futures prices (f_1, f_2), as an example, denote $\eta_{1,t}^2, \eta_{2,t}^2$ as their respective squared standardised residuals.[88] The sample cross-correlation coefficient at lag l, $r_{1,2}(l)$, is computed as:

[87] Model residuals are checked for excessive ARCH effects. If an EGARCH (2, 1) model is found necessary to remove the excessive ARCH effects, equation (6.4) is modified to: $\ln \sigma_t^2 = \omega + \lambda(u_{t-1} / \sigma_{t-1}) + a_1\left|u_{t-1} / \sigma_{t-1}\right| + a_2\left|u_{t-2} / \sigma_{t-2}\right| + b \ln \sigma_{t-1}^2$, where the impact of price innovations is a linear combination of λ, a_1 and a_2. The predictive asymmetry exists if $\lambda<0$.

[88] Note that $\eta_{1,t}^2, \eta_{2,t}^2, \bar{\eta}_1^2, \bar{\eta}_2^2$ and $r_{1,2}(l)$ in the context are all estimated from samples; I omit the "^" symbol used to denote estimated values for simplicity.

$$r_{1,2}(l)=\frac{c_{1,2}(l)}{\sqrt{c_{1,1}(0)c_{2,2}(0)}}$$

where $c_{1,2}(l)$ is the sample cross-covariance at lag l, given by

$$c_{1,2}(l)=\frac{1}{T}\sum\left(\eta_{1,t}^2-\overline{\eta}_1^2\right)\left(\eta_{2,t-l}^2-\overline{\eta}_2^2\right),\ l=0,\ \pm1,\ \pm2,...,$$

and $c_{1,1}(0)$, $c_{2,2}(0)$ are the sample variances of $\eta_{1,t}^2$, $\eta_{2,t}^2$, respectively; T is the sample size.

Under regularity conditions, Cheung and Ng (1996) prove that:

$$\sqrt{T}\left(r_{1,2}(l_1),...,r_{1,2}(l_m)\right)\rightarrow N\left(\mathbf{0},\mathbf{I_m}\right)$$

as $T\rightarrow\infty$, where $l_1,\ldots,l_m$ are m different integers. To test for causality-in-variance at a specified lag l, the test statistic $\sqrt{T}\left(r_{1,2}(l)\right)$ is compared with a standard normal distribution. If it falls outside the critical values of the standard normal distribution at a certain significance level, I reject the null hypothesis of no causality-in-variance and find evidence of cross-border volatility interactions. If all cross-correlations of squared standardised residuals at all possible lags are not significantly different from zero, then there is no causal relationship in variance. The CCF test for the Nikkei spot-futures pairs can be conducted analogously.

6.3.4 Estimation procedure

The two-stage approach of Cheung and Ng (1996) is followed to examine the second-moment causal relationships in the Nikkei markets. The first stage of the CCF test involves estimating conditional mean and conditional variance models. The estimation of the ESTECM, equations (6.1a) (6.1b) and (6.2a) (6.2b), is by nonlinear least squares (NLS). The model restriction $k^*=c^*=0$ is imposed because the adjusted price returns Δs_t, Δf_t and $\Delta f_{1,t}$, $\Delta f_{2,t}$ do not contain constants, and the transition functions are usually centred at zero. The error correction term z_{t-1} is represented by the log-basis b_t^* at lag 1, or by the futures price differentials (f_1 - f_2) at lag 1, both detrended and free of outliers. The transition variable z_{t-d} has a delay parameter d=1.[89] To provide a scale-free environment for the nonlinear parameters, I standardise the smoothness parameter γ by dividing it by the sample variance of z_{t-d}, and standardise the asymmetry parameter θ by dividing it by the sample standard deviation of z_{t-d}. The standardisation is a

[89] The delay parameter d=1 is determined by linearity tests and model evaluations. See section 5.5.1, Chapter 5 for details.

common practice in studies with smooth transition models (e.g. Teräsvirta, 1994; Anderson, 1997).

To estimate the model lag p in the ESTECM, I follow Haggan and Ozaki (1981) to grid search for possible combinations of (γ, θ). With fixed (γ, θ), the ESTECM becomes linear, and the resultant linear model is estimated with different lags. The model lag p is determined as the lag that yields the minimal Akaike Information Criterion (AIC); also, that minimum needs to be stable for different combinations of (γ, θ). The NLS estimation of the ESTECM is equivalent to maximum likelihood if the model residual u_t is assumed to be normally distributed; otherwise the NLS estimates can be interpreted as quasi-maximum likelihood estimates (van Dijk et al., 2002).[90] The NLS estimates are conditional upon starting values. A two-dimensional grid search over γ and θ is performed to obtain different sets of starting values. Among the models whose algorithms converge and parameter estimates look reasonable, the final model is decided as the one with the lowest residual variance. The estimation of EGARCH, equations (6.3) (6.4), is by quasi-maximum likelihood to generate consistent estimates under the assumption of conditional t-distribution. The joint estimation of the ESTECM as the conditional mean and the EGARCH as the conditional variance is difficult. Instead, I first estimate the ESTECM, and then estimate the EGARCH using the residual obtained from the ESTECM. The separate estimation is in the spirit of Chan and McAleer (2002) and would not bias the models. See section 5.5.2, Chapter 5 for more details.

Results of the ESTECM-EGARCH are reported in Table 5.9 and Table 5.12 in Chapter 5. Analyses of these results are given in section 5.6, Chapter 5 and thus are not repeated here. As Cheung and Ng (1996) point out, autocorrelations in standardised residuals or in their squares affect the size of the CCF test. I apply Ljung-Box (1978) Q-statistics for η_t and η_t^2 to check the model adequacy and find that there are no remaining residual autocorrelations or excessive ARCH effects, as seen in Panel B of Table 5.9 and Table 5.13, Chapter 5. Hence, I believe that the proposed ESTECM-EGARCH framework is able to reasonably describe the dynamics

[90] For conditions of consistency and asymptotical normality of the NLS estimates I refer to Klimko and Nelson (1978) and Tong (1990).

inherent in the data, and construct the series of squared standardised residuals and calculate sample cross-correlation coefficients as required in the second stage of the CCF test.

The longest lag l in the CCF test is selected to be 10. This is because the maximal lag length p in the conditional mean model is 4 (Table 5.9 in Chapter 5), suggesting that the Nikkei price dependence lasts for approximately a week. Although causality-in-variance can exist with or without causality-in-mean, many studies report that the second-moment dependence is much stronger than the first-moment dependence, e.g. Hamori (2003). Therefore, I extend the longest lag in the cross-correlation functions to 10 trading days to allow for the probably more influential, persistent volatility interactions in the Nikkei markets. However, lags longer than 10 are not investigated as I do not think that major second-moment dependence would last for more than two weeks, considering the development of technology in futures trading. 10 lags should be sufficiently long for capturing any volatility spillovers between the Nikkei series. As a result of calculating the cross-correlations for up to 10 lags, I discard 10 observations at each end of each sample to keep the sample size T fixed, such that the sample means, sample variances of the squared standardised residuals are also fixed for different lags l.

6.3.5 The CCF test results

6.3.5.1 Spot-futures volatility interactions

Table 6.2 shows the sample cross-correlation coefficients of the squared standardised residuals estimated from the ESTECM-EGARCH model in individual Nikkei markets. The "lag" refers to a positive *l*, i.e. the number of periods the Nikkei futures market lags behind the underlying stock market. The "lead" refers to a negative *l*, i.e. the number of periods the Nikkei futures market leads the underlying stock market. Statistically significant cross-correlations indicate rejecting the null hypothesis of no causality-in-variance and thus spot-futures volatility interactions. Significant cross-correlation at a certain lag suggests volatility spillovers from spot to futures, while significant cross-correlation at a certain lead suggests volatility spillovers from futures to spot. Note that the Nikkei spot and CME returns are not synchronised in time while performing the CCF test, i.e. the spot on day *t* is aligned with the CME on day *t*, because the different trading hours between the two markets are not important on a daily basis (see section 4.2.4, Chapter 4), and because studies on international volatility linkages tend to use same-day data, not merely those using the CCF method, e.g. Fung et al. (2001), Hamori (2003). As such, significant cross-correlations at lag 0 are interpreted as contemporaneous relationships, and significant cross-correlations at other leads and lags are interpreted as lead-lag relationships in volatility, in the CME the same way as in the OSE and SGX.

The most obvious finding of Table 6.2 is the high level and strong significance of the sample cross-correlations at lag 0 in all Nikkei spot-futures pairs. The contemporaneous correlations are over 0.9 in the OSE and SGX, and about 0.6 in the CME, all significant at the 5% level. The OSE has the highest spot-futures correlation at 0.98 in sample B, and there is an increase in the contemporaneous correlation from sample A to sample B in all the markets. At non-zero leads and lags, the cross-correlations are much smaller in magnitude, and many of them are not significant. This means that the contemporaneous spot-futures relationships are the most important and much information is transmitted between the Nikkei spot and futures markets simultaneously.

As shown in Table 6.2, there exist volatility feedbacks in both samples between the Nikkei spot and the OSE. The Nikkei spot causes the OSE in variance at lag 7 and the OSE causes the spot in variance at lag 3 in the pre-crisis period, and the two-way causal relationships are at lag 9 in the post-crisis period, although it is less easy to identify the direction in which the causality is stronger. The SGX has a similar causation pattern. The Nikkei spot has a spillover effect on the SGX at lags 1 and 7, and the SGX has a spillover effect on the spot at lag 3 in sample A. In sample B, the bidirectional volatility spillovers are found at lag 9. The larger size and stronger significance of the lead implies stronger causality-in-variance running from the futures, and thus the futures' leadership in volatility transmission; however, this may not matter much for investors as it is 9 trading days afterwards. The lead-lag relationships in volatility between the spot and the CME are somewhat different. The cross-correlations at lag 1 in sample A are both significant at the 5% level, suggesting an important information transmission channel between the two markets. Before the crisis, spot leads futures in variance at lag 1, and futures leads spot in variance up to lag 7. After the crisis, spot causes futures in variance at lag 8, and the reverse causality occurs at lag 4. Despite volatility feedbacks, there is again some evidence that causality-in-variance and information flows originating from the futures market are stronger.

Table 6.2 Sample cross-correlations of squared standardised residuals for individual Nikkei spot-futures pairs

l	Lag S and OSE(+*l*)	Lead S and OSE(-*l*)	Lag S and SGX(+*l*)	Lead S and SGX(-*l*)	Lag S and CME(+*l*)	Lead S and CME(-*l*)
Sample A						
0	0.9478**		0.9371**		0.5681**	
1	-0.0288	0.0136	-0.0346*	0.0167	0.0429**	0.0382**
2	-0.0201	-0.0129	-0.0250	-0.0151	0.0170	-0.0154
3	0.0295	0.0366*	0.0242	0.0367*	0.0141	0.0099
4	-0.0034	-0.0126	-0.0046	0.0156	0.0040	0.0385**
5	0.0002	-0.0143	0.0010	-0.0065	-0.0096	0.0142
6	0.0135	0.0219	0.0050	0.0025	0.0297	0.0026
7	0.0377**	0.0258	0.0348*	0.0255	0.0285	0.0441**
8	0.0005	-0.0068	0.0051	-0.0053	0.0029	0.0032
9	-0.0083	0.0130	-0.0124	0.0103	0.0114	-0.0089
10	0.0178	0.0071	0.0087	-0.0060	-0.0174	0.0005
Sample B						
0	0.9805**		0.9529**		0.5998**	
1	0.0063	0.0149	0.0064	0.0088	0.0168	0.0391
2	0.0037	0.0169	-0.0023	0.0133	0.0000	0.0219
3	-0.0108	-0.0046	-0.0015	-0.0071	0.0284	0.0179
4	-0.0234	-0.0198	-0.0181	-0.0125	-0.0027	0.0512*
5	0.0122	0.0239	0.0173	0.0408	0.0044	0.0173
6	-0.0054	-0.0053	0.0086	0.0008	-0.0320	0.0026
7	0.0032	0.0133	0.0005	0.0084	-0.0080	-0.0106
8	0.0073	0.0097	0.0043	0.0059	0.0452*	0.0007
9	0.0456*	0.0475*	0.0435*	0.0640**	0.0082	-0.0069
10	-0.0202	-0.0208	-0.0205	-0.0139	0.0281	0.0057

Notes: This table shows the sample cross-correlation coefficients of the squared standardised residuals estimated from the ESTECM-EGARCH model (Table 5.9) for individual spot-futures pairs. The "lag" refers to a positive *l*, i.e. the number of periods the Nikkei futures market lags behind the underlying stock market. The "lead" refers to a negative *l*, i.e. the number of periods the Nikkei futures market leads the underlying stock market. ** denotes significance at the 5% level. * denotes significance at the 10% level.

Table 6.3 Sample cross-correlations of squared standardised residuals for bilateral Nikkei futures pairs

	(OSE, SGX)		(OSE, CME)		(SGX, CME)	
l	Lag	Lead	Lag	Lead	Lag	Lead
	SGX and OSE(+*l*)	SGX and OSE(-*l*)	CME and OSE(+*l*)	CME and OSE(-*l*)	CME and SGX(+*l*)	CME and SGX(-*l*)
Sample A						
0	0.9842**		0.6100**		0.6072**	
1	0.0185	0.0156	0.0525**	-0.0118	0.0637**	-0.0066
2	-0.0170	-0.0223	0.0095	0.0061	0.0042	0.0056
3	0.0157	0.0124	0.0143	0.0095	0.0121	0.0101
4	-0.0095	-0.0132	0.0460**	0.0171	0.0415**	0.0144
5	-0.0086	-0.0123	0.0162	0.0017	0.0169	-0.0019
6	0.0053	0.0027	-0.0078	0.0162	-0.0086	0.0166
7	0.0235	0.0236	0.0452**	0.0182	0.0403**	0.0212
8	0.0041	0.0048	-0.0133	0.0024	-0.0101	0.0019
9	-0.0032	0.0015	0.0154	0.0029	0.0109	-0.0009
10	0.0108	0.0023	0.0167	-0.0135	0.0169	-0.0111
Sample B						
0	0.9901**		0.6379**		0.5894**	
1	-0.0049	-0.0056	0.0242	0.0294	0.0096	0.0537*
2	0.0152	0.0055	0.0374	-0.0054	0.0213	-0.0101
3	-0.0005	0.0076	0.0523*	0.0228	0.0511*	0.0178
4	0.0177	0.0090	0.0227	-0.0025	0.0280	-0.0085
5	-0.0145	-0.0165	0.0066	-0.0179	0.0048	-0.0195
6	0.0177	0.0219	0.0048	-0.0122	0.0104	-0.0097
7	0.0006	0.0014	-0.0006	-0.0138	-0.0030	-0.0084
8	0.0380	0.0280	0.0059	0.0334	-0.0015	0.0403
9	0.0434	0.0509*	-0.0124	-0.0092	-0.0074	-0.0130
10	-0.0064	-0.0055	0.0240	0.0323	0.0329	0.0334

Notes: This table shows the sample cross-correlation coefficients of the squared standardised residuals estimated from the ESTECM-EGARCH model (Table 5.12) for bilateral futures pairs (f_1, f_2). The "lag" refers to a positive *l*, i.e. the number of periods market 1 lags behind market 2. The "lead" refers to a negative *l*, i.e. the number of periods market 1 leads market 2. ** denotes significance at the 5% level. * denotes significance at the 10% level.

6.3.5.2 Cross-border futures volatility interactions

Table 6.3 gives the sample cross-correlation coefficients of the squared standardised residuals estimated from the ESTECM-EGARCH model across the Nikkei futures markets. For each bilateral futures pair (f_1, f_2), the "lag" refers to a positive l, i.e. the number of periods market 1 lags behind market 2. The "lead" refers to a negative l, i.e. the number of periods market 1 leads market 2. Statistically significant cross-correlations indicate rejecting the null hypothesis of no causality-in-variance and therefore cross-border volatility spillovers. For example, the OSE is the market 1 and the SGX is the market 2 in the pair (OSE, SGX). Significant cross-correlation at a certain lag suggests volatility spillovers from the SGX to the OSE, while significant cross-correlation at a certain lead suggests volatility spillovers from the OSE to the SGX. As in the previous table, I do not synchronise the OSE, SGX returns and the CME returns in time, i.e. the OSE or SGX on day t is aligned with the CME on day t. To consider the effect of time differences, the ESTECM-EGARCH model is re-estimated with an alternative time sequence whereby the OSE or SGX on day t is matched with the CME on day t-1 such that the CME becomes the earliest trading market in the sequence, but this leads to severe model problems such as poorly conditioned estimates and excessive residual autocorrelations in the CME (results not reported; see section 5.7, Chapter 5). As a consequence, the CME squared standardised residuals cannot be generated to carry out the CCF test and timing issues are ignored here. For all the futures pairs, significant cross-correlations at lag 0 are interpreted as contemporaneous relationships, and significant cross-correlations at other leads and lags are interpreted as lead-lag relationships in volatility across the border.

Similar to the results in individual Nikkei markets, the cross-correlation coefficients at lag 0 are high and strongly significant across the Nikkei futures markets, as displayed in Table 6.3. The contemporaneous correlations between the OSE and the SGX are higher than 0.98 in sample A and 0.99 in sample B, implying that the information transmission between the OSE and the SGX is almost simultaneous. The very close link between the two futures is not surprising as they are based on the same index, and use the same currency and time zone. The CME correlations are relatively lower, at around 0.6. Moreover, there is an increase in the OSE contemporaneous correlations, and yet a slight decrease in the SGX-CME contemporaneous correlations in recent years. Overall, the Nikkei cross-correlations at lag 0 are far more important than those at other leads and lags, in terms of size and significance. Consistent with the results in individual spot-futures pairs, the CCF test indicates that the majority of information is transmitted across the Nikkei futures markets in a simultaneous manner.

In Table 6.3, the CCF test results for the pair (OSE, SGX) suggest that there is no evidence of causality-in-variance between the two futures, except that the OSE causes the SGX in variance at lag 9 in the post-crisis sample. But the only causal relationship may not be of practical importance to investors as it occurs 9 trading days later. The virtual absence of cross-market spillovers between the OSE and the SGX again implies that information is shared almost simultaneously between the two markets within the same day. Different are the cross-market causation patterns related to the CME futures. For the pair (OSE, CME), the CME causes the OSE in variance at lags 1, 4 and 7 in sample A, at lag 3 in sample B. Yet I do not find evidence of reverse causality. The CCF test results for the pair (SGX, CME) indicate that the CME leads the SGX in variance up to lag 7 in sample A, and that volatility spillovers are bidirectional in sample B: the CME causes the SGX in variance at lag 3 and the SGX causes the CME in variance at lag 1. The causal relationships between the CME and the OSE or SGX are somewhat stronger in the pre-crisis period than in the post-crisis period.

The above results can be sorted as CME>SGX>OSE, in terms of information leadership in descending order in the volatility transmission mechanism across the Nikkei futures markets. The CME has the strongest influence on the other markets, in that the CME has a spillover effect on the other markets up to lag 7 and the reverse spillover effect is weaker. The SGX is second to the CME for I find evidence of the SGX causing the CME in variance at lag 1 in sample B. In contrast, the OSE tends to lag behind the CME and SGX in transmitting volatility. Recall that the foreign Nikkei futures markets (the CME and SGX) play a leading role in the first-moment information transmission process (see section 5.8, Chapter 5). The CCF test results consistently show that they still lead the domestic futures market (the OSE) in the second-moment information transmission process. The information advantage of the foreign futures markets can be mainly attributed to the more lenient trading environment they provide, such as longer trading hours and lower transaction costs. Therefore, I repeatedly support the international centre hypothesis that global financial centres are likely to dominate cross-border information dissemination - in fact, I find that the dominance exists in both first-moment price discovery and second-moment volatility spillovers in the Nikkei markets.

To summarise, the volatility causation patterns in the Nikkei markets are as follows. First, the contemporaneous relationships are much more important than any lead-lag relationships in volatility, which means that the majority of information is impounded into the Nikkei markets simultaneously. Second, in individual Nikkei markets, volatility spillovers are bidirectional, with some evidence that the information flows from the futures market are stronger. Third, across the Nikkei futures markets, the CME causes the other markets in variance the most strongly and thus enjoys the information leadership; foreign Nikkei futures exchanges, the CME and SGX, act as the main source of information flow in the cross-border information transmission process. Using the CCF method, I find that multivariate GARCH models are appropriate for my data as volatility interactions are present in and across the Nikkei markets. The critical importance of the contemporaneous relationships justifies the DCC multivariate GARCH specifications to be employed in the next section.

6.4 The dynamics of Nikkei conditional correlations

Univariate GARCH models have been applied so far to investigate volatility dynamics in the univariate setting. They are, however, unable to depict the variances and covariances of several assets jointly. More often than not, information hits several assets simultaneously, and asset volatilities move together and affect each other. For example, the CCF test suggests volatility feedbacks between the Nikkei spot and futures markets, i.e. volatility shocks to the Nikkei futures intensify the underlying stock volatility, and *vice versa*. Moreover, asset managers may wish to construct well diversified portfolios for different kinds of assets, in which case the covariances and correlations among these assets become crucial. Multivariate GARCH models are used in this section to model the volatilities and volatility co-movements of the Nikkei series. In particular, I select the DCC multivariate GARCH model of Engle (2002). The contemporaneous relationships between the Nikkei volatilities are the most important, based on the CCF test in the previous section. Following this, one would naturally ask how the contemporaneous market linkages evolve over time. An understanding of the time-varying dynamics of Nikkei conditional correlations is essential for investors as changes in the volatility co-movements necessitates changes in their strategies of international portfolio management. This is even more relevant for regulators, as fluctuations in the conditional correlations are indicative of changes in the market stability and integration in the global context.

The DCC model is a standard method in the literature for estimating volatility co-movements among markets. It allows the conditional correlations to evolve over time, such that the time-varying dynamics of the interrelations among the Nikkei volatilities are not lost as in the Constant Conditional Correlation (CCC) model of Bollerslev (1990) which assumes that the conditional correlations are time-invariant. The DCC model has an advantage over other multivariate GARCH models such as VECH of Bollerslev et al. (1988) and BEKK of Engle and Kroner (1995) for involving far less parameters; in a bivariate DCC-GARCH (1, 1) model, for instance, only nine parameters need to be estimated within the whole framework. Estimation of the DCC model consists of two separate stages, and the two-stage parameter estimates are consistent and asymptotically normal (Engle and Sheppard, 2001). The parsimony and tractability of the DCC model outweighs its potential drawback that the conditional correlations in the DCC model obey the same dynamics regulated by two scalar parameters, which is difficult to justify when the number of variables is large (Bauwens et al., 2006). This should not be a problem in this study anyway, as I will examine the dynamics of Nikkei conditional correlations in a bivariate system, or in other words, for individual spot-futures pairs and bilateral futures pairs.

6.4.1 The bivariate DCC-GARCH (1, 1) framework

Let $\mathbf{r_t}$ be the 2×1 vector of asset returns in a given spot-futures pair or futures-futures pair at time t; $\Omega_{t\text{-}1}$ the information set available at time t-1; $\mathbf{u_t}$ the 2×1 vector of residuals; $\boldsymbol{\eta}_\mathbf{t}$ the 2×1 vector of standardised residuals assumed to be iid with zero mean and identity variance. The bivariate DCC-GARCH (1, 1) framework can be represented as follows:

$$\mathbf{r_t} = E(\mathbf{r_t} | \Omega_{t-1}) + \mathbf{u_t} \tag{6.5}$$

$$\mathbf{u_t} = \sqrt{\mathbf{H_t}}\boldsymbol{\eta}_\mathbf{t} \tag{6.6}$$

$$\mathbf{H_t} = \mathbf{D_t R_t D_t} \tag{6.7}$$

$$\mathbf{R_t} = \mathbf{Q_t^{*\text{-}1} Q_t Q_t^{*\text{-}1}} \tag{6.8}$$

Equation (6.5) is the conditional mean model. Based on Chapter 5 and the CCF analysis above, a natural candidate for the conditional mean is the smooth transition model, equations (6.1a) (6.1b) and (6.2a) (6.2b). However, preliminary estimations show that they are difficult to converge in the multivariate GARCH context, irrespective of the use of different starting values or optimisation algorithms. To deal with the problem, I tried to estimate the smooth transition models without GARCH models at first, and then estimate the bivariate GARCH using the residuals obtained from the smooth transition models. Unfortunately, estimating smooth transition models alone without GARCH effects turns out to be problematic, as neglected heteroskedasticity does affect the lag parameters of the smooth transition models and hence the residuals of the smooth transition models. Therefore, I impose an additional restriction, γ=0 (zero smoothness parameter), on the smooth transition models to assist convergence. With the restriction, equations (6.1a) (6.1b) reduce to the following linear error correction model (ECM) for individual Nikkei spot-futures pairs:[91]

[91] Note that the error correction term $z_{t\text{-}1}$ should be included in both the linear and nonlinear parts of a complete specification of the ESTECM to allow for error corrections in the middle regime and the outer regime. If that is the case, with γ=0, equations (6.1a) (6.1b) collapse exactly to equations (6.9a) (6.9b), (6.2a) (6.2b) exactly to equations (6.10a) (6.10b). However, I decide to retain $z_{t\text{-}1}$ only in the nonlinear section, or the outer regime of the ESTECM for the following reasons: a) arbitrage would be too costly to exist for small pricing errors $z_{t\text{-}1}$ in the middle regime, yet arbitrage is expected to be active for large $z_{t\text{-}1}$ in the outer regime, and so the error correction in the outer regime is more interesting and deserves more attention; b) the ESTECM is simpler to estimate with one error correction term; c) this is the practice in most studies with the ESTECM. This explains why, with γ=0, equations (6.1a) (6.1b) and (6.2a) (6.2b) merely reduce to a linear ECM that appears without an error correction term. I retain the error correction term in equations (6.9a) (6.9b) and (6.10a) (6.10b).

$$\Delta s_t = k_s + \sum_{j=1}^{p} \pi_{ss,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j} \Delta f_{t-j} + \alpha_s z_{t-1} + u_{s,t} \qquad (6.9a)$$

$$\Delta f_t = k_f + \sum_{j=1}^{p} \pi_{fs,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j} \Delta f_{t-j} + \alpha_f z_{t-1} + u_{f,t} \qquad (6.9b)$$

Similarly, equations (6.2a) (6.2b) reduce to the following linear ECM under the restriction γ=0, for bilateral Nikkei futures pairs:

$$\Delta f_{1,t} = k_1 + \sum_{j=1}^{p} \pi_{11,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j} \Delta f_{2,t-j} + \alpha_1 z_{t-1} + u_{1,t} \qquad (6.10a)$$

$$\Delta f_{2,t} = k_2 + \sum_{j=1}^{p} \pi_{21,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j} \Delta f_{2,t-j} + \alpha_2 z_{t-1} + u_{2,t} \qquad (6.10b)$$

The linear ECM is a simple specification to describe the dynamics in the Nikkei price returns. Although some dynamics such as the regime-switching nature is ignored, the linear ECM is still appropriate in this context, because the error correction term is preserved whose coefficient α measures the speed of adjustment towards long-run equilibrium. Estimating the linear ECM by OLS will also be much easier than estimating the ESTECM by NLS which entails a grid search for starting values, and thus I can focus more on the second-moment dynamics exhibited by conditional variances and conditional correlations. The DCC literature often uses a simple, linear conditional mean such as constant mean, AR and reduced-form VAR, as long as it is able to fit the data, e.g. Koch (2014), Jones and Olson (2013). I apply the linear ECM to the Nikkei series and report no autocorrelations or remaining ARCH effects in the model residuals (see Table 5.7 and Table 5.13, Chapter 5). Therefore, the restricted ESTECM or linear ECM, equations (6.9a) (6.9b) and (6.10a) (6.10b), will act as the conditional mean model (6.5) in individual Nikkei markets and across the Nikkei futures markets, respectively.

The residual vector $\mathbf{u_t}$ has a 2×2 full rank conditional variance-covariance matrix $\mathbf{H_t}$, as shown in equation (6.6). The elements of $\mathbf{H_t}$ are conditional variances and covariances estimated from univariate GARCH-class models. EGARCH models were used as the conditional variance model for asymmetric and exponential considerations. The conditional variance model was the same for all Nikkei series when results of the conditional mean were of interest; a fixed conditional variance model enables me to compare the mean results among different markets, eliminating the possibility that any differences might come from the differences in the conditional variance specifications. Since I specially focus on the conditional variances here (thus the linear ECM acts as the conditional mean for all the series), I no longer want to limit the conditional variance model to EGARCH. Instead, I use the AIC and Schwartz Bayesian Criterion (SBC) to select the univariate conditional variance model for each spot-futures pair and futures-futures pair, from the most commonly used GARCH-class models. These models include GARCH, GJR-GARCH and EGARCH models, all at the order (1, 1). An EGARCH (1, 1) specification is given by equations (6.3) (6.4). Let σ_t^2 be the conditional variance as in equation (6.3), a GARCH (1, 1) model of Bollerslev (1986) is given as below:

$$\sigma_t^2 = \omega + a u_{t-1}^2 + b\sigma_{t-1}^2 \tag{6.11}$$

where $\omega>0$; $a\geq 0$; $b\geq 0$; $a+b<1$. I consider the GARCH (1, 1) process as it is simple enough to provide a benchmark for other candidate conditional variance models. However, it is not able to allow for the different impacts of good news and bad news on volatility, or the leverage effect. Such predictive asymmetry can be found in the EGARCH and GJR-GARCH processes. A GJR-GARCH (1, 1) model of Glosten et al. (1993) can be represented as:

$$\sigma_t^2 = \omega + a u_{t-1}^2 + \lambda I_{t-1} u_{t-1}^2 + b\sigma_{t-1}^2 \tag{6.12}$$

where the dummy variable $I_{t-1}=1$ if $u_t<0$ and 0 otherwise. The coefficient λ sheds light on the presence of the leverage effect. For a positive shock, $u_{t-1}/\sigma_{t-1}>0$, $I_{t-1}=0$, the impact of the positive shock on σ_t^2 is a; for a negative shock, $u_{t-1}/\sigma_{t-1}<0$, $I_{t-1}=1$, the impact of the negative shock on σ_t^2 is $(a+\lambda)$ (Enders, 2010). Thus, provided that $\lambda>0$, a negative shock increases volatility more than a positive shock of the same magnitude.

Equation (6.7) shows a possible decomposition of $\mathbf{H_t}$. $\mathbf{D_t}$ is the 2×2 diagonal matrix of conditional standard deviations estimated from univariate GARCH-class models, or $\mathbf{D_t} = diag(\sigma_{1t}, \sigma_{2t})$. $\mathbf{R_t}$ is the time-varying conditional correlation matrix with 1 on the diagonal, conditional correlation coefficients $\rho_{12,t}$ off the diagonal. Engle (2002) and Engle and Sheppard (2001) suggest estimating $\mathbf{H_t}$ in two separate stages. Univariate GARCH-class models are selected and estimated in the first stage, and the univariate residuals divided by their standard deviations estimated in the first stage are used to estimate the conditional correlations in the second stage. The two-stage estimation maintains the consistency and asymptotic normality of the parameter estimates in the DCC model.

The estimation of the conditional correlations is based on equation (6.8), which governs the evolution of $\mathbf{R_t}$. For the positive definiteness of $\mathbf{H_t}$, it is sufficient to require $\mathbf{R_t}$ to be positive definite. For the positive definiteness of $\mathbf{R_t}$, I only need to ensure that $\mathbf{Q_t}$ in equation (6.8) is positive definite (Engle and Sheppard, 2001). $\mathbf{Q_t} = (1-m-n)\bar{\mathbf{Q}} + mu_{t-1}u'_{t-1} + n\mathbf{Q_{t-1}}$, where $\bar{\mathbf{Q}}$ is the 2×2 unconditional correlation matrix of the standardised residuals, and *m*, *n* are scalar parameters that provide a GARCH-like dynamic structure for $\mathbf{Q_t}$: *m* captures the impact of past shocks and *n* captures the impact of past dynamic correlations. The positive definiteness of $\mathbf{Q_t}$ and hence the positive definiteness of $\mathbf{H_t}$ is satisfied if *m*, *n* are non-negative, and have a sum less than 1. If $m+n=0$, the correlations are constant in time, and the DCC reduces to the CCC model of Bollerslev (1990). $\mathbf{Q}^* = diag(\sqrt{q_{11,t}}, \sqrt{q_{22,t}})$ is the 2×2 diagonal matrix that contains the square roots of the diagonal elements of $\mathbf{Q_t}$. Given the positive definiteness of $\mathbf{Q_t}$, $\mathbf{Q}^*$ guarantees that $\mathbf{R_t}$ is a conditional correlation matrix with 1 on the diagonal, $\rho_{12,t}$ off the diagonal no larger than 1 in absolute value (Cappiello et al., 2006). The conditional correlation coefficient is calculated as $\rho_{12,t} = q_{12,t} / \sqrt{q_{11,t}q_{22,t}}$ in $\mathbf{R_t}$, which is of my primary interest.

6.4.2 The DCC estimation

I apply the two-stage approach of Engle (2002) and Engle and Sheppard (2001) to estimate the bivariate DCC models in the Nikkei markets. Initially, the linear ECM, equations (6.9a) (6.9b) and (6.10a) (6.10b), act as the conditional mean model for Nikkei spot-futures pairs and bilateral futures pairs, respectively. The SBC selects the lag parameter $p=1$ for spot-futures pairs, with which the mean residuals are not autocorrelated. The SBC still selects $p=1$ for bilateral futures pairs, but this seems too short to capture the price dynamics related to the CME. I then consider the AIC which suggests $p=7$ (sample A) and $p=4$ (sample B). With 7 (sample A) and 4 (sample B) lags the mean residuals are not autocorrelated, and thus 7 (sample A) and 4 (sample B) lags are used in the conditional mean for bilateral futures pairs.

The first stage of the DCC estimation procedure involves specifying and estimating univariate conditional variance models. The AIC and SBC are used to select from univariate GARCH, GJR-GARCH and EGARCH models for each pair. In addition, the selected models should be well specified, i.e. the univariate residuals should not exhibit remaining autocorrelations or ARCH effects. In the course of estimating the univariate models, the Nikkei returns are assumed to be conditionally normal, i.e. $\mathbf{r_t}|\Omega_{t-1}\sim N(\mathbf{0},\mathbf{H_t})$, and the estimation is by quasi-maximum likelihood with Bollerslev-Wooldridge (1992) robust standard errors and covariance; however, if a model fails to converge under the normality assumption, then a conditional *t*-distribution is assumed, because distributional assumptions do not affect the consistency and asymptotic normality of the DCC estimates (Engle and Sheppard, 2001). The optimisation algorithm is Berndt-Hall-Hall-Hausman (BHHH). The selection results are shown in Table 6.4. The GJR-GARCH models are selected in most cases, and the GARCH models are selected for the spot-OSE pair and for the OSE-SGX pair in sample B.

The second stage of the DCC estimation procedure involves estimating the parameters of dynamic correlations from the univariate residuals standardised by their standard deviations estimated during the first stage. The DCC-GJR-GARCH (1, 1) models are fitted in most cases, and the DCC-GARCH (1, 1) models are fitted for the spot-OSE pair and for the OSE-SGX pair in sample B. As with univariate models, a bivariate conditional normal distribution is assumed, or a bivariate conditional *t*-distribution is assumed provided that a DCC model fails to converge under the normality assumption. The DCC estimation is by (quasi-)maximum likelihood. The optimisation algorithm is BHHH. Model adequacy is checked by the ARCH-LM test of Engle (1982). Likelihood ratio tests are performed to test the null hypothesis of constant correlation against the alternative hypothesis of DCC.

Prior to analysis of the DCC results, it is noteworthy that the default time sequence is applied in the DCC estimation in which the CME returns on day *t* is aligned with any other market returns on day *t*. The different trading hours of the CME futures are ignored at the moment, and the Nikkei futures markets are assumed to be simultaneous. Section 6.4.5 examines the effect of the different trading hours of the CME futures on the DCC and provides the DCC estimation results with the alternative time sequence whereby the CME returns on day *t*-1 is matched with any other market returns on day *t*.

Table 6.4 Univariate GARCH-class models

Models selected for spot-futures pairs			
	(Spot, OSE)	(Spot, SGX)	(Spot, CME)
Sample A	GJR-GARCH	GJR-GARCH	GJR-GARCH
Sample B	GARCH	GJR-GARCH	GJR-GARCH
Models selected for futures-futures pairs			
	(OSE, SGX)	(OSE, CME)	(SGX, CME)
Sample A	GJR-GARCH	GJR-GARCH	GJR-GARCH
Sample B	GARCH	GJR-GARCH	GJR-GARCH

Notes: This table shows the model selection results of the univariate GARCH-class models: GARCH, GJR-GARCH and EGARCH, all at the order (1, 1). The selection criteria are the AIC and SBC; in addition, the selected models should be well specified, i.e. the univariate residuals should not exhibit remaining autocorrelations or ARCH effects.

6.4.3 The DCC results: spot-futures conditional correlations

6.4.3.1 Spot-OSE

Table 6.5 contains the DCC estimation results for the pair (spot, OSE). There is evidence of error correction dynamics in the conditional mean, as the error correction coefficients α_s>0, α_f<0 in sample A, and both are negative in sample B. In sample A, the error correction coefficients are significant in the two markets, indicating bidirectional causality-in-mean in the long run. In terms of the long-run speed of adjustment, α_f is smaller than α_s in magnitude and thus the futures market is quicker in transmitting price information. Besides, the significant autoregressive coefficient π_{sf} suggests futures leading spot in the short run. In sample B, the significant and larger α_f in magnitude suggests that the spot market is quicker in transmitting price information in the long run. Yet the significant autoregressive coefficients π_{sf} and π_{fs} suggest bidirectional causality-in-mean in the short run. The conditional variance is the GJR-GARCH (1, 1) model in the pre-crisis period. The asymmetry coefficients are significantly positive in the two markets, indicating the presence of the leverage effect, i.e. bad news increases market volatility more than equally sized good news. The GARCH (1, 1) model is selected for the post-crisis sample, which implies that the leverage effect may not be prevalent over the period in the two markets.

In both samples, the DCC parameters in the conditional covariance equation are significant, which proves the time-varying nature of the conditional correlations between the two markets. The DCC parameters also imply strong effect of past dynamic correlations: the news parameter m is quite small while the persistence parameter n is large. The persistence of conditional correlations is an increasing function of (m+n) (Aielli, 2013), and this sum is close to 1, although it is still less than 1 so that the variance-covariance matrix $\mathbf{H_t}$ remains positive definite. Highly persistent conditional correlations are often reported in the DCC literature, e.g. Engle and Sheppard (2001). Nevertheless, I notice that the conditional correlations may have become less persistent in recent years, as the sum (m+n) reduces to a lower level in sample B. According to the ARCH-LM test, there is no evidence of any remaining ARCH effects in the model standardised residuals. The null hypothesis of constant correlation is strongly rejected by the likelihood ratio test.

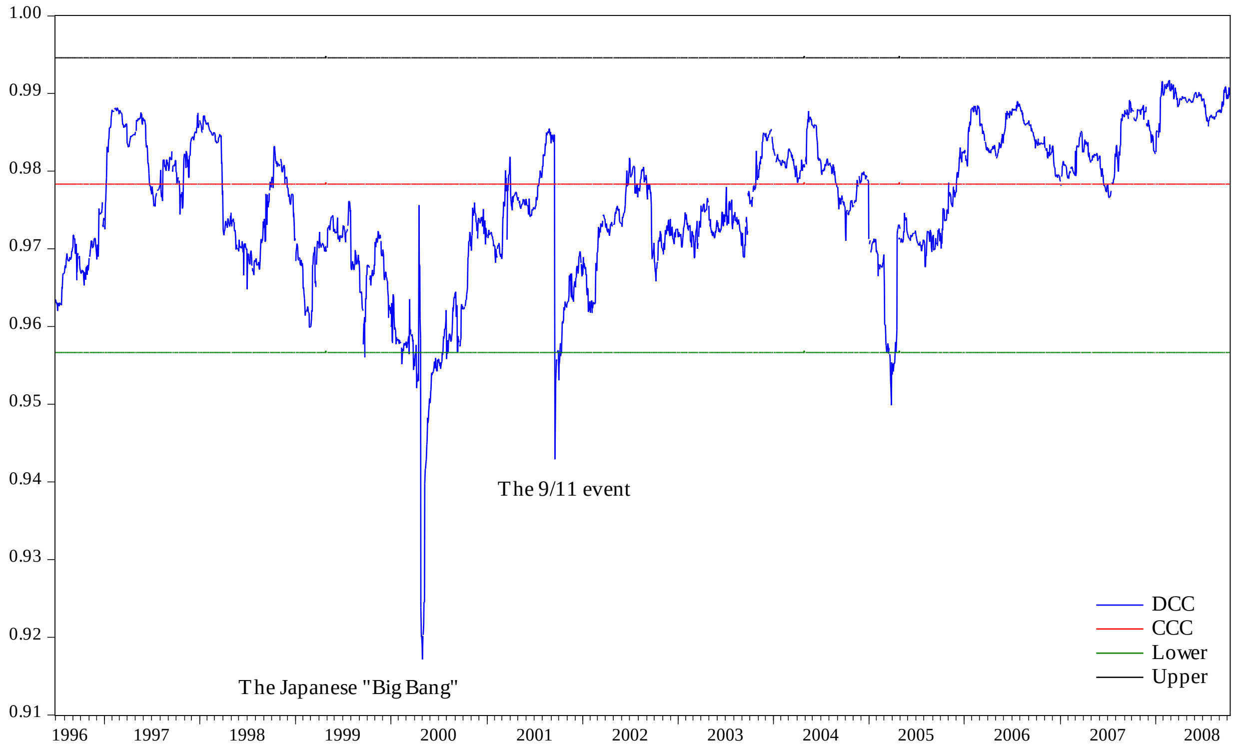
Figure 6.1 shows the conditional correlations between the two markets over time. The spot-futures correlations are high, with the average level of the DCC 0.9756 (sample A) and 0.9845 (sample B). The correlations generally fluctuate within the two-standard-error bands, especially in the post-crisis sample. In sample A, the DCC series is a V-shaped curve with the sharpest spike during April-May 2000, close to the finishing time of the Japanese "Big Bang".[92] The decreasing spot-futures correlations during the "Big Bang" may be related to market adaptations to a set of deregulatory policies that sequentially came into effect in financial markets in Japan. As of the completion of the "Big Bang", however, the spot-futures correlations show an overall uprising trend. The terrorist attacks on 11/09/2001 also cause a temporary drop of the spot-futures relationship but its effect is smaller and shorter than the "Big Bang" effect. In sample B, the correlations remain at a very high level with quite a few minor dynamics. The correlations between the two markets show a slightly decreasing trend over time.

[92] The Japanese "Big Bang" is a five-year financial deregulatory reform proposed by Japan's government in November 1996, aimed at eliminating all partitions in Japanese financial markets no later than 2001. During the "Big Bang" period, a series of policies came into effect to remove barriers and increase competition among financial intermediaries (Flath, 2014).

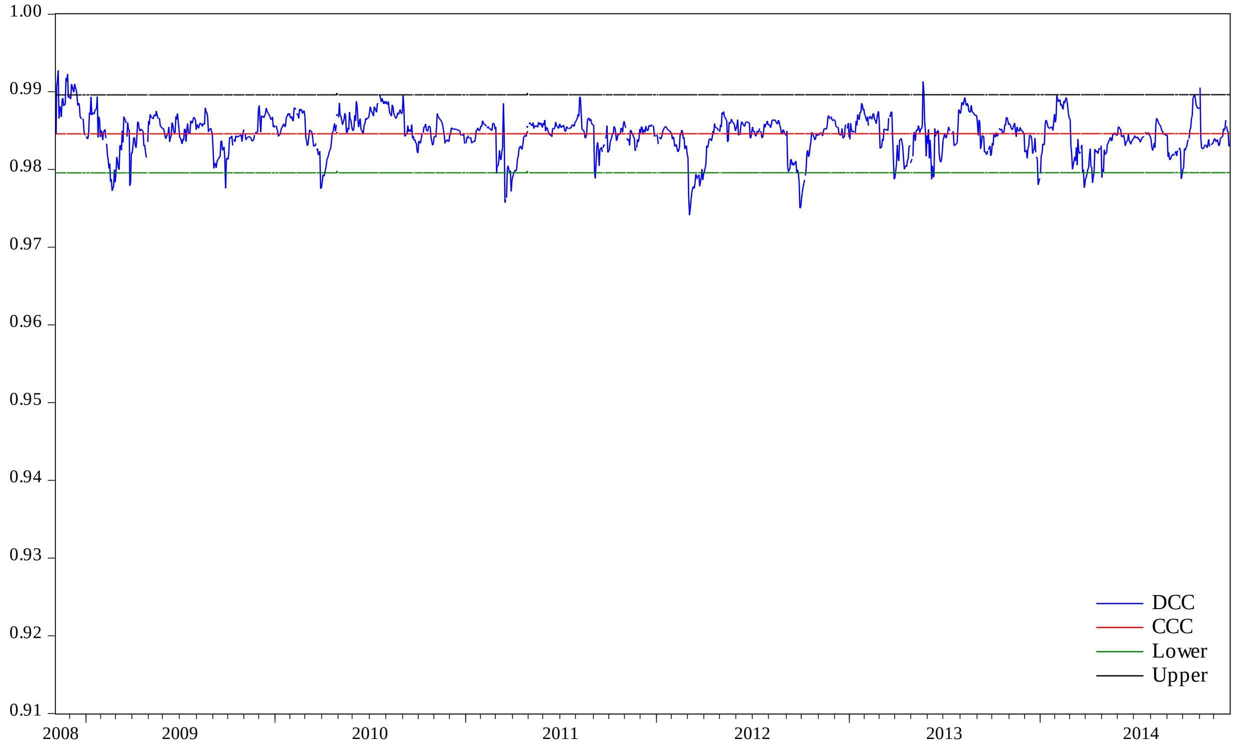
Table 6.5 Estimation results of the DCC models: Spot and OSE

Sample A	Spot		Futures		Sample B	Spot		Futures	
	Estimate	*t*-stat	Estimate	*t*-stat		Estimate	*t*-stat	Estimate	*t*-stat
ECM coefficients					ECM coefficients				
k	0.0000	0.0472	0.0002	1.1047	k	0.0005	1.4116	0.0004	1.0234
π_s	-0.2375	-3.4625	-0.0642	-0.9023	π_s	-0.5699	-3.9433	-0.3578	-2.4454
π_f	0.1988	2.8997	0.0163	0.2283	π_f	0.5044	3.5129	0.2819	1.9396
α	0.3313	3.7469	-0.2501	-2.7459	α	-0.0640	-0.4191	-0.4779	-3.0926
GJR-GARCH coefficients					GARCH coefficients				
ω	0.0000	4.6083	0.0000	4.9811	ω	0.0000	6.3900	0.0000	6.8898
a	0.0360	5.4495	0.0293	4.4185	a	0.1082	12.3637	0.1051	12.8911
b	0.9295	134.9893	0.9343	144.8005	b	0.8570	78.0296	0.8585	83.0827
λ	0.0446	4.9952	0.0449	5.1977					
DCC-GJR-GARCH coefficients					DCC-GARCH coefficients				
m	0.0200	6.3113			m	0.0353	4.2636		
n	0.9789	282.0148			n	0.8927	22.3700		
$m+n$	0.9989				$m+n$	0.9280			
ARCH-LM(10)	[0.4597]		[0.8122]		ARCH-LM(10)	[0.2770]		[0.4448]	
	LR stat		*p*-value			LR stat		*p*-value	
Testing for CCC	75.2333		0.0000		Testing for CCC	16.3600		0.0001	

Notes: This table contains the DCC estimation results for the pair (spot, OSE). The conditional mean is the linear ECM, equations (6.9a) (6.9b): $\Delta s_t = k_s + \sum_{j=1}^{p}\pi_{ss,j}\Delta s_{t-j} + \sum_{j=1}^{p}\pi_{sf,j}\Delta f_{t-j} + \alpha_s z_{t-1} + u_{s,t}$, $\Delta f_t = k_f + \sum_{j=1}^{p}\pi_{fs,j}\Delta s_{t-j} + \sum_{j=1}^{p}\pi_{ff,j}\Delta f_{t-j} + \alpha_f z_{t-1} + u_{f,t}$. The first letter in the subscripts of the ECM parameters indicates the market to which the parameters belong: *s* means spot and *f* means futures, and this is omitted in the table presentation for brevity. But the second letter (if any) in the subscripts of the ECM parameters is retained in the table presentation. The conditional variance in sample A is the GJR-GARCH (1, 1), equations (6.3) and (6.12): $u_t = \sigma_t \eta_t$, $\sigma_t^2 = \omega + a u_{t-1}^2 + \lambda I_{t-1} u_{t-1}^2 + b\sigma_{t-1}^2$, where the dummy variable I_{t-1}=1 if u_t<0 and 0 otherwise; the conditional variance in sample B is the GARCH (1, 1), equations (6.3) and (6.11): $u_t = \sigma_t \eta_t$, $\sigma_t^2 = \omega + a u_{t-1}^2 + b\sigma_{t-1}^2$. The conditional correlation is equation (6.8): $\mathbf{R_t} = \mathbf{Q_t^{*-1} Q_t Q_t^{*-1}}$, where $\mathbf{Q_t} = (1-m-n)\bar{\mathbf{Q}} + m u_{t-1} u_{t-1}' + n\mathbf{Q_{t-1}}$. The DCC model adequacy is checked by the ARCH-LM test of Engle (1982) up to order 10, and the significance levels are in square brackets. The bottom line reports the likelihood ratio (LR) test statistics and the associated *p*-values of testing the null hypothesis of constant correlation (CCC) against the alternative hypothesis of DCC.



Sample A



Sample B

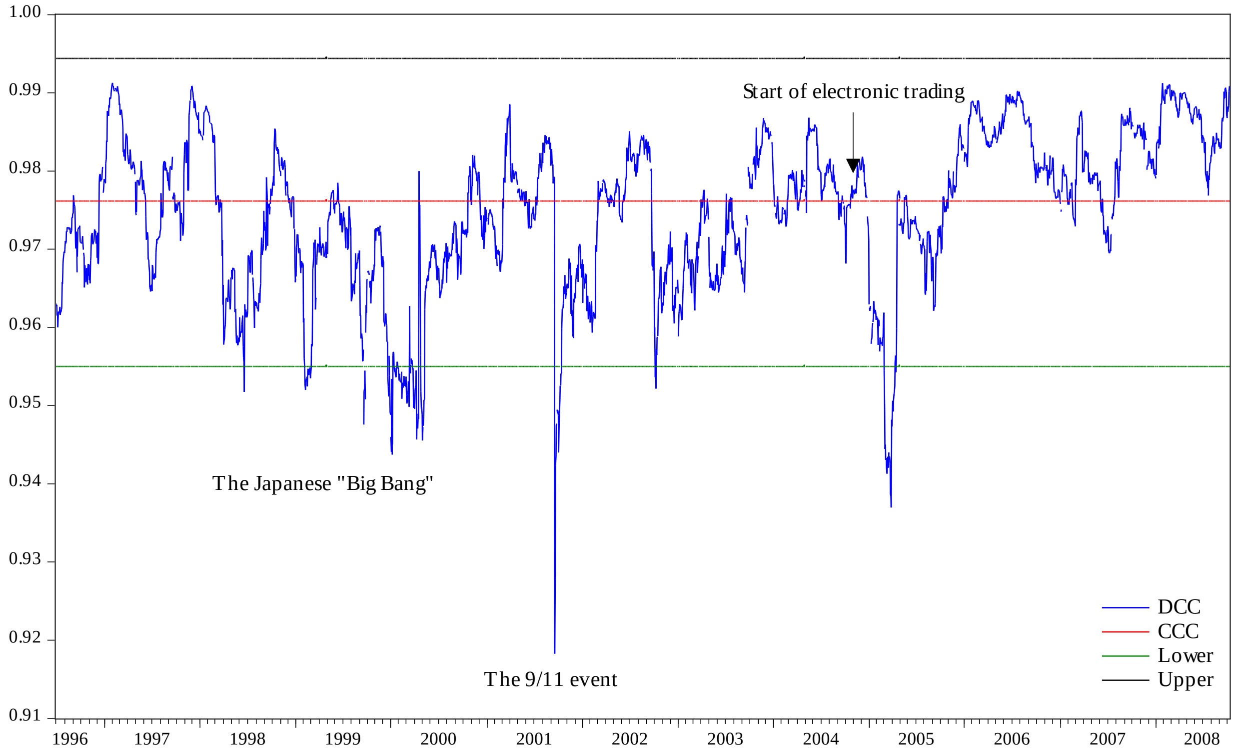
Figure 6.1 Conditional correlations between Nikkei spot and OSE

Notes: This figure shows the conditional correlations between the spot and OSE. “DCC” denotes the conditional correlations estimated from the DCC-GJR-GARCH (1, 1) model in sample A; the DCC-GARCH (1, 1) model in sample B. “CCC” denotes the constant correlations estimated from the CCC-GJR-GARCH (1, 1) model in sample A; the CCC-GARCH (1, 1) model in sample B. “Lower” and “Upper” denote the two-standard-error lower and upper bands of the estimated DCC, respectively. The mean of the estimated DCC is 0.9756 (sample A) and 0.9845 (sample B). The estimated CCC is 0.9783 (sample A) and 0.9845 (sample B).

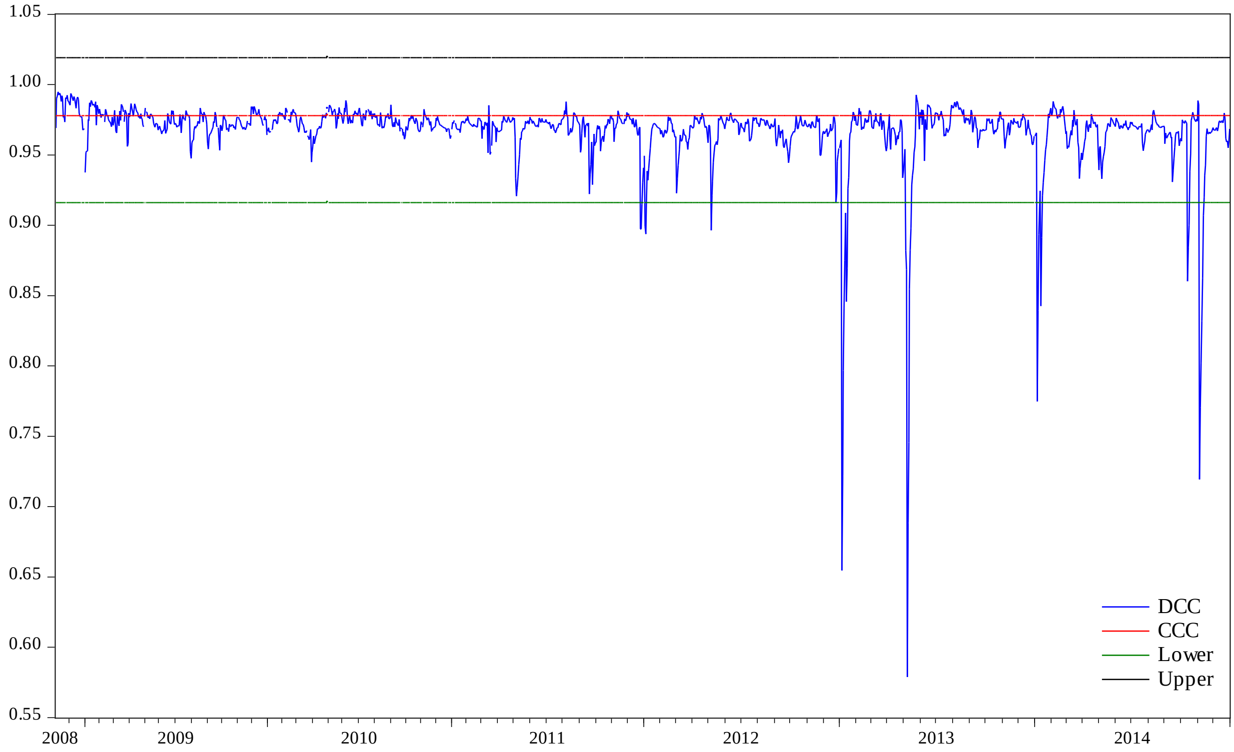
Table 6.6 Estimation results of the DCC models: Spot and SGX

Sample A	Spot		Futures		Sample B	Spot		Futures	
	Estimate	*t*-stat	Estimate	*t*-stat		Estimate	*t*-stat	Estimate	*t*-stat
ECM coefficients					ECM coefficients				
k	-0.0002	-0.9440	0.0000	0.0967	k	0.0007	1.7404	0.0004	0.9909
π_s	-0.2228	-3.4709	-0.0548	-0.8268	π_s	-0.2744	-2.6352	-0.1254	-1.2023
π_f	0.2053	3.1432	0.0339	0.5017	π_f	0.2136	2.0405	0.0654	0.6244
α	0.4178	4.9313	-0.1810	-2.0625	α	0.2054	1.6244	-0.2899	-2.2899
GJR-GARCH coefficients					GJR-GARCH coefficients				
ω	0.0000	6.2662	0.0000	7.9452	ω	0.0000	4.1721	0.0000	4.4345
a	0.0403	7.6895	0.0287	6.0625	a	0.0624	3.8482	0.0595	3.9415
b	0.9162	156.8142	0.9238	184.1715	b	0.8742	44.9796	0.8711	45.9876
λ	0.0624	9.6084	0.0641	11.1277	λ	0.0459	2.3965	0.0512	2.7352
DCC-GJR-GARCH coefficients					DCC-GJR-GARCH coefficients				
m	0.0326	10.4035			m	0.1111	5.4831		
n	0.9648	273.0598			n	0.7093	13.8930		
m+n	0.9974				m+n	0.8204			
ARCH-LM(10)	[0.6437]		[0.8687]		ARCH-LM(10)	[0.4155]		[0.1713]	
Testing for CCC	LR stat		*p*-value		Testing for CCC	LR stat		*p*-value	
	116.3013		0.0000			14.8967		0.0001	

Notes: This table contains the DCC estimation results for the pair (spot, SGX). The conditional mean is the linear ECM, equations (6.9a) (6.9b): $\Delta s_t = k_s + \sum_{j=1}^{p} \pi_{ss,j}\Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j}\Delta f_{t-j} + \alpha_s z_{t-1} + u_{s,t}$, $\Delta f_t = k_f + \sum_{j=1}^{p} \pi_{fs,j}\Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j}\Delta f_{t-j} + \alpha_f z_{t-1} + u_{f,t}$. The first letter in the subscripts of the ECM parameters indicates the market to which the parameters belong: s means spot and f means futures, and this is omitted in the table presentation for brevity. But the second letter (if any) in the subscripts of the ECM parameters is retained in the table presentation. The conditional variance is the GJR-GARCH (1, 1), equations (6.3) and (6.12): $u_t = \sigma_t \eta_t$, $\sigma_t^2 = \omega + a u_{t-1}^2 + \lambda I_{t-1} u_{t-1}^2 + b\sigma_{t-1}^2$, where the dummy variable I_{t-1}=1 if u_t<0 and 0 otherwise. The conditional correlation is equation (6.8): $\mathbf{R_t} = \mathbf{Q_t^{*-1} Q_t Q_t^{*-1}}$, where $\mathbf{Q_t} = (1-m-n)\bar{\mathbf{Q}} + m u_{t-1} u_{t-1}' + n\mathbf{Q_{t-1}}$. The DCC model adequacy is checked by the ARCH-LM test of Engle (1982) up to order 10, and the significance levels are in square brackets. The bottom line reports the likelihood ratio (LR) test statistics and the associated *p*-values of testing the null hypothesis of constant correlation (CCC) against the alternative hypothesis of DCC.



Sample A



Sample B

Figure 6.2 Conditional correlations between Nikkei spot and SGX

Notes: This figure shows the conditional correlations between the spot and SGX. "DCC" denotes the conditional correlations estimated from the DCC-GJR-GARCH (1, 1) model. "CCC" denotes the constant correlations estimated from the CCC-GJR-GARCH (1, 1) model. "Lower" and "Upper" denote the two-standard-error lower and upper bands of the estimated DCC, respectively. The mean of the estimated DCC is 0.9747 (sample A) and 0.9674 (sample B). The estimated CCC is 0.9762 (sample A) and 0.9778 (sample B).

6.4.3.2 Spot-SGX

The DCC estimation results for the pair (spot, SGX) are provided in Table 6.6. In the conditional mean equation, the error correction coefficients are with expected signs, i.e. $\alpha_s>0$, $\alpha_f<0$, which is indicative of the error correction mechanism. In sample A, the error correction coefficients are significant in the two markets, suggesting bidirectional causality-in-mean in the long run. The fact that α_f is smaller than α_s in magnitude also suggests futures leading spot in reflecting price information. In the short run, the futures still plays a leading role in price discovery as π_{sf} is significant. In sample B, the significant and larger α_f in magnitude indicate spot leading futures in the long run, while the significant π_{sf} indicates the primary role of the futures market in the short run. The conditional variance in both samples is described by the GJR-GARCH (1, 1) model. The significantly positive asymmetry coefficient λ indicates the more pronounced impact of bad news on volatility.

Turning to the conditional covariance, I find that the DCC parameters are significant in both samples, meaning that the conditional correlations between the spot and futures vary through time. The large persistence parameter n suggests highly persistent conditional correlations between the spot and SGX. The sum (m+n) is over 0.99 in sample A, and this also confirms the persistent nature of the DCC between the two markets. However, I find that the sum reduces to around 0.82 in sample B, as a result of the decrease in the persistence parameter n. The relatively lower level of persistence in the conditional correlations may reflect the fact that information is disseminated more quickly in the two markets in the post-crisis period than in the pre-crisis period, and hence, the conditional correlation pattern exhibits more dynamics in sample B. The estimated DCC-GJR-GARCH (1, 1) models do not suffer from excessive ARCH in the standardised residuals. Furthermore, I test the null hypothesis of constant correlation, and the null hypothesis is rejected decisively in both samples.

Figure 6.2 plots the conditional correlations between the two markets over time. The spot-SGX correlations are slightly smaller than the spot-OSE correlations, yet still high, with the average DCC 0.9747 (sample A) and 0.9674 (sample B). The spot-futures relationship is generally stable, though at times it becomes temporarily loose, as represented by several spikes from 2012. A detailed examination indicates a V-shaped correlation pattern in sample A. The deepest valley of the correlations occurs a few days after the terrorist attacks on 11/09/2001. The generally decreasing correlations between the spot and SGX during 1996-2000 is probably caused by the Japanese "Big Bang", which also leads to the fall of the spot-OSE correlations at the same time. However, the DCC between the spot and SGX is apparently affected by the 9/11 event to a larger extent than by the "Big Bang". Given that the SGX is a global financial centre, worldwide incidents are more likely to exert a larger impact on the SGX, while the financial reforms at the national level are more likely to exert a larger impact on the Japanese markets. Moreover, it is interesting to observe that the switch from floor trading to electronic trading of the SGX Nikkei futures contracts on 01/11/2004 does not have a discernible effect on the conditional correlations between the spot and SGX. In sample B (note the scale difference), the volatility of the correlations increases over time, which is consistent with the lower level of persistence found in the correlation process over the sample, implying more rapid absorption of information shocks in the two markets.

6.4.3.3 Spot-CME

The DCC estimation results for the pair (spot, CME) are presented in Table 6.7. The error correction coefficients α_s>0, α_f<0 suggest the presence of error correction mechanism. Before the crisis, the error correction coefficients are significant in the two markets, showing the evidence of feedback in the mean. In terms of the long-run speed of adjustment, α_f is smaller than α_s in magnitude, and thus the futures leads the spot in price discovery. The autoregressive coefficients π_{sf} and π_{fs} are both significant, indicating bidirectional causality-in-mean between the spot and futures markets in the short run. After the crisis, the futures market plays a leading role in reflecting price information both in the long run (α_f is insignificant and smaller than α_s in magnitude) and in the short run (π_{sf} is significant). The conditional variance is the GJR-GARCH (1, 1) specification. The volatility asymmetry coefficients are significantly positive in the two markets, which is indicative of the presence of the leverage effect.

Table 6.7 Estimation results of the DCC models: Spot and CME

Sample A	Spot		Futures		Sample B	Spot		Futures	
	Estimate	*t*-stat	Estimate	*t*-stat		Estimate	*t*-stat	Estimate	*t*-stat
ECM coefficients					ECM coefficients				
k	0.0004	1.9242	-0.0002	-0.8565	k	-0.0006	-2.0287	0.0006	1.4575
π_s	-0.0628	-2.7291	-0.0565	-2.0088	π_s	-0.1247	-5.1056	0.0325	0.9832
π_f	0.0462	1.7802	0.0239	0.7343	π_f	0.0939	3.0018	-0.0519	-1.2242
α	0.7052	23.6674	-0.1384	-3.8394	α	0.6844	19.5121	-0.0049	-0.1026
GJR-GARCH coefficients					GJR-GARCH coefficients				
ω	0.0000	6.7656	0.0000	6.6470	ω	0.0000	3.6049	0.0000	3.4996
a	0.0383	8.4856	0.0277	5.1738	a	0.0206	1.7777	0.0225	1.6041
b	0.9202	174.3678	0.9232	136.1029	b	0.9101	53.6314	0.8903	44.5940
λ	0.0551	6.5185	0.0575	7.0522	λ	0.0598	3.1331	0.1044	4.3135
DCC-GJR-GARCH coefficients					DCC-GJR-GARCH coefficients				
m	0.0294	9.0753			m	0.0159	2.3983		
n	0.9661	248.4066			n	0.9698	62.9043		
m+n	0.9955				m+n	0.9857			
ARCH-LM(10)	[0.1067]		[0.9463]		ARCH-LM(10)	[0.9462]		[0.8978]	
Testing for CCC	LR stat		*p*-value		Testing for CCC	LR stat		*p*-value	
	61.2937		0.0000			10.8947		0.0010	

Notes: This table contains the DCC estimation results for the pair (spot, CME). The conditional mean is the linear ECM, equations (6.9a) (6.9b): $\Delta s_t = k_s + \sum_{j=1}^{p} \pi_{ss,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{sf,j} \Delta f_{t-j} + \alpha_s z_{t-1} + u_{s,t}$, $\Delta f_t = k_f + \sum_{j=1}^{p} \pi_{fs,j} \Delta s_{t-j} + \sum_{j=1}^{p} \pi_{ff,j} \Delta f_{t-j} + \alpha_f z_{t-1} + u_{f,t}$. The first letter in the subscripts of the ECM parameters indicates the market to which the parameters belong: *s* means spot and *f* means futures, and this is omitted in the table presentation for brevity. But the second letter (if any) in the subscripts of the ECM parameters is retained in the table presentation. The conditional variance is the GJR-GARCH (1, 1), equations (6.3) and (6.12): $u_t = \sigma_t \eta_t$, $\sigma_t^2 = \omega + a u_{t-1}^2 + \lambda I_{t-1} u_{t-1}^2 + b \sigma_{t-1}^2$, where the dummy variable I_{t-1}=1 if u_t<0 and 0 otherwise. The conditional correlation is equation (6.8): $\mathbf{R_t} = \mathbf{Q_t^{*-1} Q_t Q_t^{*-1}}$, where $\mathbf{Q_t} = (1 - m - n)\bar{\mathbf{Q}} + m u_{t-1} u'_{t-1} + n \mathbf{Q_{t-1}}$. The DCC model adequacy is checked by the ARCH-LM test of Engle (1982) up to order 10, and the significance levels are in square brackets. The bottom line reports the likelihood ratio (LR) test statistics and the associated *p*-values of testing the null hypothesis of constant correlation (CCC) against the alternative hypothesis of DCC.

Sample A

Sample B

Figure 6.3 Conditional correlations between Nikkei spot and CME

Notes: This figure shows the conditional correlations between the spot and CME. “DCC” denotes the conditional correlations estimated from the DCC-GJR-GARCH (1, 1) model. “CCC” denotes the constant correlations estimated from the CCC-GJR-GARCH (1, 1) model. “Lower” and “Upper” denote the two-standard-error lower and upper bands of the estimated DCC, respectively. The mean of the estimated DCC is 0.7570 (sample A) and 0.6319 (sample B). The estimated CCC is 0.7835 (sample A) and 0.6527 (sample B).

In the conditional covariance equation, the DCC parameters are significant, meaning that the conditional correlations are indeed time-varying. Besides, the small news parameter *m* and large persistence parameter *n* imply the strong influence of previous dynamic correlations. The sum (m+n) is close to 1, which suggests the highly persistent conditional correlations between the spot and CME. I also notice a decrease in the sum from sample A to sample B, which implies that information shocks may have a more immediate effect in recent years, and as a result, the conditional correlations exhibit more dynamics. The DCC-GJR-GARCH (1, 1) models are free from excessive ARCH effects in the standardised residuals. The null hypothesis of constant correlation is tested against the alternative hypothesis of DCC, and the likelihood ratio test is able to reject the null hypothesis at conventional significance level.

The time-varying conditional correlations between the two markets generally exhibit a decreasing trend in sample A and an increasing trend in sample B, as depicted in Figure 6.3. The average level of the DCC is 0.7570 (sample A) and 0.6319 (sample B), which are lower than those of the previous pairs. In sample A, the conditional correlations between the spot and the CME experience three major drops - the first drop is during 1997-2000 which can be related to the Japanese “Big Bang”, the second occurs within a short period after 11/09/2001 and the third starts from 2007. Like the previous spot-futures correlations, the spot-CME relationship falls during the five-year “Big Bang” and reaches a periodic bottom close to the completion of the “Big Bang”; and it is temporarily loosened by the 9/11 event. But there is an obvious decrease in the relationship from 2007, which is not found in the previous pairs. The CME futures market is probably affected by the credit crunch and hence its co-movement with the Nikkei spot market becomes weakened. In sample B, the correlations are generally growing, with a dramatic drop of the correlations in March 2011, the time of Japan earthquake followed by the Fukushima nuclear crisis.

6.4.4 The DCC results: futures-futures conditional correlations

6.4.4.1 OSE-SGX

Table 6.8 contains the estimation results for the pair (OSE, SGX). The error correction towards futures price parity is present for at least one error correction coefficient is negative in the two markets. In both samples, the SGX leads the OSE in the first-order information transmission process, in that α in the OSE is significant and larger in magnitude while α in the SGX is insignificant and smaller in magnitude. In other words, the OSE mainly makes adjustments to the OSE-SGX spreads and thus lags behind the SGX in the cross-border price formation process. Before the crisis, the short-run autoregressive coefficients indicate feedback causality-in-mean between the OSE and SGX, with the causality running from the SGX to the OSE being slightly stronger than the reverse. After the crisis, however, none of these are significant and therefore the short-run causalities are absent, which implies that the two markets are likely to be more efficient in the post-crisis period. The GJR-GRACH (1, 1) is the conditional variance in sample A. As expected, the asymmetry coefficient λ is significantly positive in the two markets, confirming the existence of the leverage effect. The GARCH (1, 1) model is the conditional variance in sample B, which implies that the volatility asymmetry may not be evident in the two markets in the post-crisis period.

The DCC-GJR-GARCH (1, 1) model cannot converge between the OSE and SGX in sample A. I tried to fit the DCC-GARCH (1, 1) and DCC-EGARCH (1, 1) models for the pair, but they show convergence problems as well. Since all the DCC models are difficult to converge, I estimate the conditional correlations in sample A by CCC models: CCC-GJR-GARCH, CCC-GARCH and CCC-EGARCH, all at the order (1, 1). The CCC-GJR-GARCH (1, 1) has a higher log-likelihood than the CCC-GARCH (1, 1), and the CCC-EGARCH (1, 1) does not converge. As such, I select the CCC-GJR-GARCH (1, 1) for the OSE-SGX pair in sample A. The CCC-GJR-GARCH (1, 1) can be viewed as the DCC-GJR-GARCH (1, 1) with the restriction m+n=0, i.e. the two DCC parameters sum up to zero. The estimated CCC is 0.9944 between the OSE and SGX. This reveals the close relationship between the two markets, and helps elucidate the DCC non-convergence over the sample. The OSE and SGX share the same underlying index, operate almost at the same time and adopt the same currency; hence, the conditional correlations between the OSE and SGX are likely to be highly stable and persistent, but not so dynamic as would be expected in the correlations between either of the two markets and the CME, for example. The DCC models may not be able to properly characterise the less dynamic conditional correlation structure. In sample B, the DCC-GARCH (1, 1) results show a small news parameter m and large persistence parameter n, and a nearly unitary (m+n), which indicate strong persistence in the conditional correlation process. The ARCH-LM test shows that the estimated models do not suffer from remaining ARCH effects. Given that the CCC-GJR-GARCH (1, 1) is selected for sample A, testing for constant correlation is conducted for sample B only. The null hypothesis of constant correlation is not rejected in sample B, because the DCC log-likelihood is smaller than the counterpart CCC log-likelihood, giving rise to a negative χ^2 statistic for which the likelihood ratio test cannot be performed. This suggests that, as in sample A, there is insufficient time variation in the correlations between the two markets. One might want to regard the correlations as constant (thus the CCC is reported and plotted together with the DCC in Figure 6.4). But the more important information conveyed is that the OSE and SGX are highly integrated in both samples.

Figure 6.4 illustrates the close relationship between the two markets. The estimated constant correlation is 0.9944 in sample A. The average DCC is 0.9952 and the estimated CCC is 0.9955 in sample B. The OSE-SGX relationship remains high and stable over the years. After the crisis, the dynamic conditional correlations are strongly persistent and growing. An obvious periodic fall is found in March 2011, suggesting that the Japan earthquake on 11/03/2011 and the following nuclear crisis temporarily weaken the degree of co-movement between the OSE and SGX. The estimated constant correlation is plotted for reference, given the non-rejection of the null hypothesis of constant correlation over the period.

Table 6.8 Estimation results of the DCC models: OSE and SGX

	OSE		SGX			OSE		SGX	
Sample A					Sample B				
	Estimate	*t*-stat	Estimate	*t*-stat		Estimate	*t*-stat	Estimate	*t*-stat
ECM coefficients					ECM coefficients				
k	0.0003	1.1442	0.0003	1.1358	k	0.0009	2.5768	0.0008	2.2583
OSE lags					OSE lags				
π_1	0.3006	1.3312	0.3523	1.5513	π_1	0.0859	0.1817	0.1320	0.2823
π_2	0.4327	2.0006	0.4599	2.1181	π_2	-0.1949	-0.4593	-0.1357	-0.3220
π_3	0.0880	0.4196	0.1099	0.5218	π_3	-0.3466	-1.0759	-0.2807	-0.8801
π_4	0.4516	2.2576	0.4510	2.2492	π_4	0.1323	0.5436	0.1695	0.7065
π_5	0.3099	1.4973	0.2919	1.4195					
π_6	0.3172	1.6270	0.3006	1.5465					
π_7	-0.1174	-0.7876	-0.1159	-0.7867					
SGX lags					SGX lags				
π_1	-0.3158	-1.3885	-0.3637	-1.5916	π_1	-0.0835	-0.1763	-0.1242	-0.2653
π_2	-0.4668	-2.1528	-0.4908	-2.2537	π_2	0.2100	0.4964	0.1468	0.3498
π_3	-0.0711	-0.3417	-0.0913	-0.4368	π_3	0.3375	1.0452	0.2710	0.8478
π_4	-0.4685	-2.3336	-0.4672	-2.3226	π_4	-0.1679	-0.6958	-0.2048	-0.8615
π_5	-0.3217	-1.5441	-0.3044	-1.4700					
π_6	-0.3503	-1.8052	-0.3326	-1.7188					
π_7	0.0984	0.6575	0.0967	0.6535					
α	-1.3964	-4.9874	-0.4382	-1.5566	α	-0.8759	-1.7170	0.0008	0.0015
GJR-GARCH coefficients					GARCH coefficients				
ω	0.0000	5.7655	0.0000	6.2956	ω	0.0000	6.3788	0.0000	6.4165
a	0.0282	7.0455	0.0284	8.0431	a	0.0668	9.0954	0.0646	8.4147
b	0.9479	285.9573	0.9489	309.0278	b	0.8842	75.5962	0.8840	72.1092
λ	0.0318	6.7115	0.0293	6.7710					
CCC-GJR-GARCH coefficients					DCC-GARCH coefficients				
CCC	0.9944	5502.1349			m	0.0034	4.0358		
					n	0.9966	1056.0266		
					$m+n$	0.99995			
ARCH-LM(10)	[0.8454]		[0.7098]		ARCH-LM(10)	[0.2930]		[0.2705]	
Testing for CCC	LR stat		*p*-value		Testing for CCC	LR stat		*p*-value	
	NA		NA			-6.1915		NA	

Table 6.9 Estimation results of the DCC models: OSE and CME

	OSE		CME			OSE		CME	
Sample A					Sample B				
	Estimate	*t*-stat	Estimate	*t*-stat		Estimate	*t*-stat	Estimate	*t*-stat
ECM coefficients					ECM coefficients				
k	0.0006	2.7052	-0.0002	-0.7506	k	-0.0004	-1.5530	0.0007	2.0706
OSE lags					OSE lags				
π_1	0.0099	0.2752	0.0173	0.2792	π_1	-0.1505	-2.6427	0.0329	0.4492
π_2	0.0463	1.2420	0.0577	0.9724	π_2	-0.0952	-1.9710	-0.0167	-0.2610
π_3	0.0489	1.3574	0.0652	1.2091	π_3	-0.0278	-0.6962	-0.0426	-0.7993
π_4	0.0476	1.4071	0.0356	0.7663	π_4	-0.0256	-1.0540	-0.0500	-1.4948
π_5	0.0689	2.1248	0.0601	1.4126					
π_6	0.0566	1.9297	0.0795	2.1938					
π_7	0.0332	1.5007	0.0583	2.1499					
CME lags					CME lags				
π_1	-0.0449	-1.1707	-0.0489	-0.7531	π_1	0.0778	1.2831	-0.0726	-0.9177
π_2	-0.0529	-1.4434	-0.0529	-0.8786	π_2	0.0895	1.6596	-0.0058	-0.0815
π_3	-0.0580	-1.5678	-0.0602	-1.0674	π_3	0.0234	0.5216	0.0219	0.3624
π_4	-0.0625	-1.8768	-0.0471	-0.9681	π_4	0.0254	0.7936	0.0675	1.5745
π_5	-0.0617	-1.9384	-0.0641	-1.5026					
π_6	-0.0699	-2.2874	-0.0976	-2.5489					
π_7	-0.0777	-3.3128	-0.1080	-3.6663					
α	-0.8840	-19.0771	0.0579	0.8063	α	-0.8425	-13.8794	-0.0839	-1.0624
GJR-GARCH coefficients					GJR-GARCH coefficients				
ω	0.0000	5.6394	0.0000	5.9814	ω	0.0000	4.1658	0.0000	3.6988
a	0.0338	5.7407	0.0281	5.1288	a	0.0197	1.3434	0.0178	1.3200
b	0.9143	126.7264	0.9221	125.7025	b	0.8907	47.8657	0.8903	45.3558
λ	0.0721	7.6373	0.0636	7.2777	λ	0.0769	3.7092	0.1048	4.3201
DCC-GJR-GARCH coefficients					DCC-GJR-GARCH coefficients				
m	0.0599	14.6957			m	0.0129	3.2902		
n	0.9306	187.7924			n	0.9870	241.7422		
m+n	0.9905				m+n	0.99996			
ARCH-LM(10)	[0.9228]		[0.9989]		ARCH-LM(10)	[0.3510]		[0.5705]	
Testing for CCC	LR stat		*p*-value		Testing for CCC	LR stat		*p*-value	
	109.9569		0.0000			10.4354		0.0012	

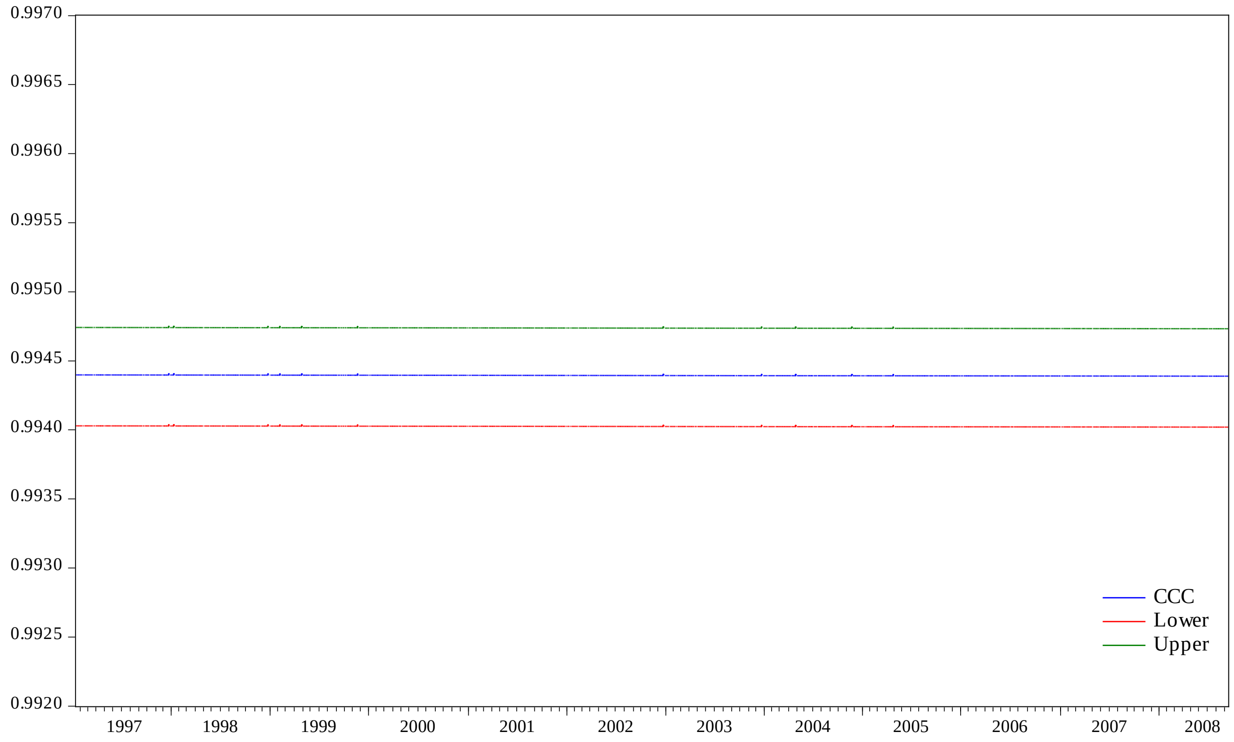
Table 6.10 Estimation results of the DCC models: SGX and CME

	SGX		CME			SGX		CME	
Sample A					Sample B				
	Estimate	*t*-stat	Estimate	*t*-stat		Estimate	*t*-stat	Estimate	*t*-stat
ECM coefficients					ECM coefficients				
k	0.0006	2.8578	-0.0003	-0.9766	k	-0.0005	-1.9630	0.0007	1.9789
SGX lags					SGX lags				
π_1	0.0360	0.9878	0.0161	0.2581	π_1	-0.1529	-2.6776	0.0289	0.3942
π_2	0.0661	1.7609	0.0546	0.9081	π_2	-0.0997	-2.0482	-0.0068	-0.1058
π_3	0.0709	2.0074	0.0640	1.1767	π_3	-0.0298	-0.7438	-0.0399	-0.7404
π_4	0.0466	1.3825	0.0314	0.6682	π_4	-0.0293	-1.2346	-0.0552	-1.6500
π_5	0.0626	1.9224	0.0474	1.0913					
π_6	0.0568	2.0005	0.0756	2.0669					
π_7	0.0349	1.6095	0.0690	2.5380					
CME lags					CME lags				
π_1	-0.0653	-1.7006	-0.0501	-0.7678	π_1	0.0858	1.4151	-0.0657	-0.8324
π_2	-0.0731	-2.0091	-0.0503	-0.8290	π_2	0.0915	1.6911	-0.0100	-0.1409
π_3	-0.0762	-2.0958	-0.0561	-0.9862	π_3	0.0298	0.6609	0.0174	0.2862
π_4	-0.0650	-1.9727	-0.0442	-0.9045	π_4	0.0293	0.9147	0.0673	1.5617
π_5	-0.0580	-1.8299	-0.0568	-1.3117					
π_6	-0.0693	-2.3165	-0.0928	-2.3978					
π_7	-0.0796	-3.5001	-0.1148	-3.9254					
α	-0.9019	-19.6424	0.0681	0.9374	α	-0.8330	-13.7773	-0.0761	-0.9649
GJR-GARCH coefficients					GJR-GARCH coefficients				
ω	0.0000	5.9896	0.0000	6.0007	ω	0.0000	4.5147	0.0000	3.7345
a	0.0345	6.0387	0.0285	5.0520	a	0.0197	1.2908	0.0187	1.3528
b	0.9149	132.8747	0.9221	122.9820	b	0.8756	43.8618	0.8873	44.4774
λ	0.0696	7.8744	0.0622	7.2920	λ	0.0843	3.7976	0.1072	4.3475
DCC-GJR-GARCH coefficients					DCC-GJR-GARCH coefficients				
m	0.0608	15.0541			m	0.0144	3.5566		
n	0.9301	190.8025			n	0.9856	234.1480		
$m+n$	0.9909				$m+n$	0.9999994			
ARCH-LM(10)	[0.9726]		[0.9985]		ARCH-LM(10)	[0.7697]		[0.5825]	
Testing for CCC	LR stat		*p*-value		Testing for CCC	LR stat		*p*-value	
	114.6106		0.0000			12.1371		0.0005	

Notes for Table 6.8: This table contains the DCC estimation results for the pair (OSE, SGX). The conditional mean is the linear ECM, equations (6.10a) (6.10b): $\Delta f_{1,t} = k_1 + \sum_{j=1}^{p} \pi_{11,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j} \Delta f_{2,t-j} + \alpha_1 z_{t-1} + u_{1,t}$, $\Delta f_{2,t} = k_2 + \sum_{j=1}^{p} \pi_{21,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j} \Delta f_{2,t-j} + \alpha_2 z_{t-1} + u_{2,t}$. The subscripts of the ECM parameters are omitted for brevity except that the model lags j of the autoregressive coefficients are retained in the table presentation. The conditional variance in sample A is the GJR-GARCH (1, 1), equations (6.3) and (6.12): $u_t = \sigma_t \eta_t$, $\sigma_t^2 = \omega + a u_{t-1}^2 + \lambda I_{t-1} u_{t-1}^2 + b \sigma_{t-1}^2$, where the dummy variable $I_{t\text{-}1}$=1 if u_t<0 and 0 otherwise; the conditional variance in sample B is the GARCH (1, 1), equations (6.3) and (6.11): $u_t = \sigma_t \eta_t$, $\sigma_t^2 = \omega + a u_{t-1}^2 + b \sigma_{t-1}^2$. The conditional correlation is equation (6.8): $\mathbf{R_t} = \mathbf{Q_t^{*\text{-}1} Q_t Q_t^{*\text{-}1}}$, where $\mathbf{Q_t} = (1-m-n)\bar{\mathbf{Q}} + m u_{t-1} u'_{t-1} + n \mathbf{Q_{t\text{-}1}}$. The DCC model adequacy is checked by the ARCH-LM test of Engle (1982) up to order 10, and the significance levels are in square brackets. The bottom line reports the likelihood ratio (LR) test statistics and the associated *p*-values of testing the null hypothesis of constant correlation (CCC) against the alternative hypothesis of DCC.

Notes for Table 6.9: This table contains the DCC estimation results for the pair (OSE, CME). The conditional mean is the linear ECM, equations (6.10a) (6.10b): $\Delta f_{1,t} = k_1 + \sum_{j=1}^{p} \pi_{11,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j} \Delta f_{2,t-j} + \alpha_1 z_{t-1} + u_{1,t}$, $\Delta f_{2,t} = k_2 + \sum_{j=1}^{p} \pi_{21,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j} \Delta f_{2,t-j} + \alpha_2 z_{t-1} + u_{2,t}$. The subscripts of the ECM parameters are omitted for brevity except that the model lags j of the autoregressive coefficients are retained in the table presentation. The conditional variance is the GJR-GARCH (1, 1), equations (6.3) and (6.12): $u_t = \sigma_t \eta_t$, $\sigma_t^2 = \omega + a u_{t-1}^2 + \lambda I_{t-1} u_{t-1}^2 + b \sigma_{t-1}^2$, where the dummy variable $I_{t\text{-}1}$=1 if u_t<0 and 0 otherwise. The conditional correlation is equation (6.8): $\mathbf{R_t} = \mathbf{Q_t^{*\text{-}1} Q_t Q_t^{*\text{-}1}}$, where $\mathbf{Q_t} = (1-m-n)\bar{\mathbf{Q}} + m u_{t-1} u'_{t-1} + n \mathbf{Q_{t\text{-}1}}$. The DCC model adequacy is checked by the ARCH-LM test of Engle (1982) up to order 10, and the significance levels are in square brackets. The bottom line reports the likelihood ratio (LR) test statistics and the associated *p*-values of testing the null hypothesis of constant correlation (CCC) against the alternative hypothesis of DCC.

Notes for Table 6.10: This table contains the DCC estimation results for the pair (SGX, CME). The conditional mean is the linear ECM, equations (6.10a) (6.10b): $\Delta f_{1,t} = k_1 + \sum_{j=1}^{p} \pi_{11,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j} \Delta f_{2,t-j} + \alpha_1 z_{t-1} + u_{1,t}$, $\Delta f_{2,t} = k_2 + \sum_{j=1}^{p} \pi_{21,j} \Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j} \Delta f_{2,t-j} + \alpha_2 z_{t-1} + u_{2,t}$. The subscripts of the ECM parameters are omitted for brevity except that the model lags j of the autoregressive coefficients are retained in the table presentation. The conditional variance is the GJR-GARCH (1, 1), equations (6.3) and (6.12): $u_t = \sigma_t \eta_t$, $\sigma_t^2 = \omega + a u_{t-1}^2 + \lambda I_{t-1} u_{t-1}^2 + b \sigma_{t-1}^2$, where the dummy variable $I_{t\text{-}1}$=1 if u_t<0 and 0 otherwise. The conditional correlation is equation (6.8): $\mathbf{R_t} = \mathbf{Q_t^{*\text{-}1} Q_t Q_t^{*\text{-}1}}$, where $\mathbf{Q_t} = (1-m-n)\bar{\mathbf{Q}} + m u_{t-1} u'_{t-1} + n \mathbf{Q_{t\text{-}1}}$. The DCC model adequacy is checked by the ARCH-LM test of Engle (1982) up to order 10, and the significance levels are in square brackets. The bottom line reports the likelihood ratio (LR) test statistics and the associated *p*-values of testing the null hypothesis of constant correlation (CCC) against the alternative hypothesis of DCC.

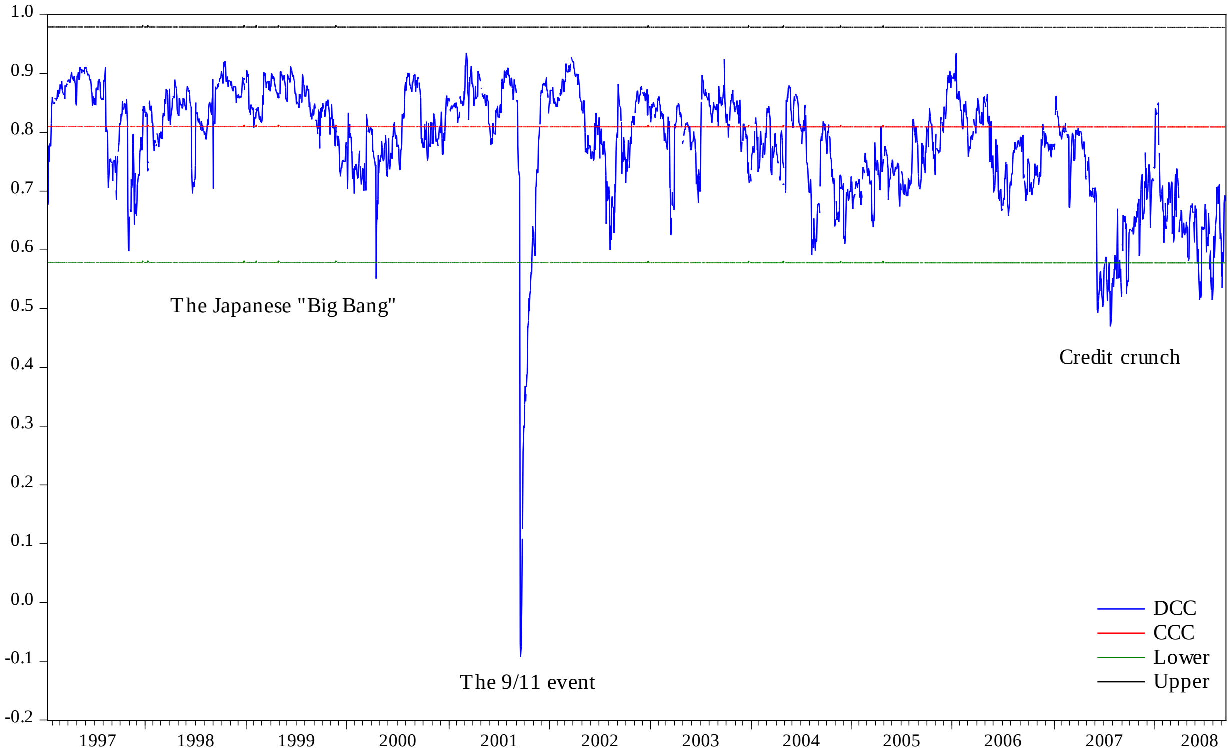


Sample A

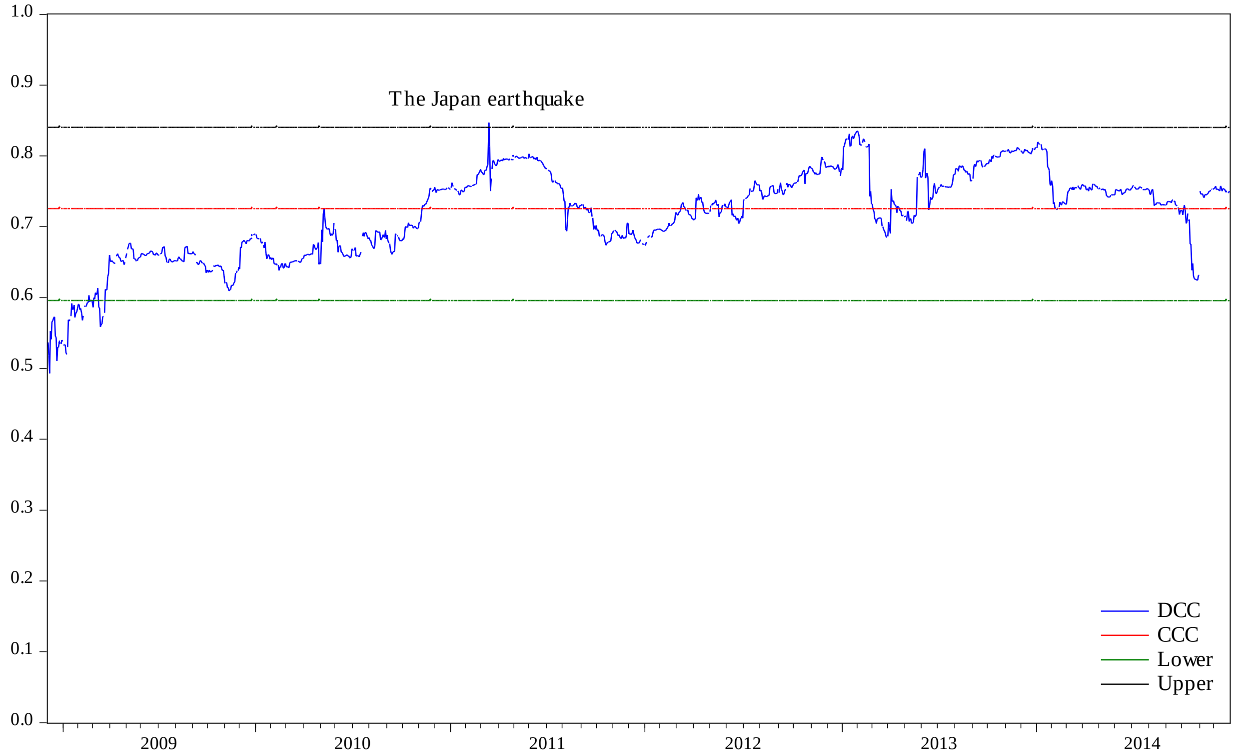
Sample B

Figure 6.4 Conditional correlations between the OSE and SGX

Notes: This figure shows the conditional correlations between the OSE and SGX. In sample A, "CCC" denotes the constant correlations estimated from the CCC-GJR-GARCH (1, 1) model. In sample B, "DCC" denotes the conditional correlations estimated from the DCC-GARCH (1, 1) model, and "CCC" denotes the constant correlations estimated from the CCC-GARCH (1, 1) model. "Lower" and "Upper" denote the two-standard-error lower and upper bands of the estimated CCC in sample A, and of the estimated DCC in sample B, respectively. The estimated CCC is 0.9944 in sample A. The mean of the estimated DCC is 0.9952 in sample B, and the estimated CCC is 0.9955 in sample B.



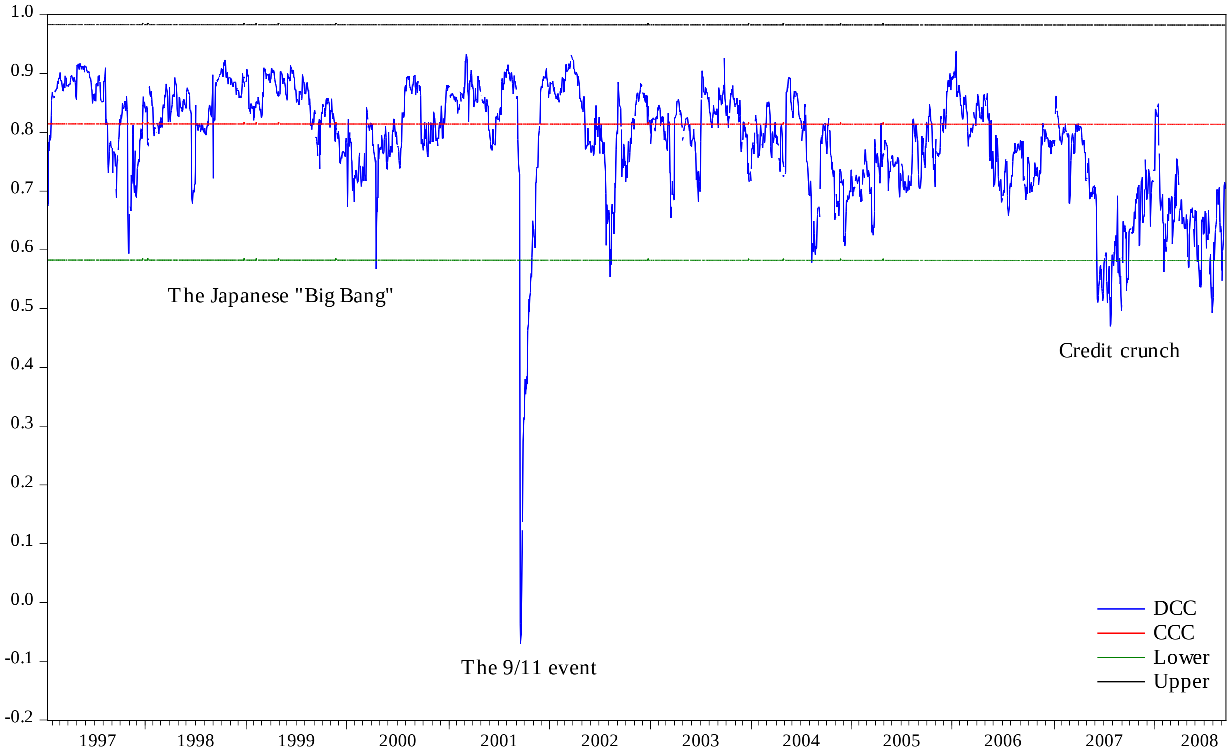
Sample A



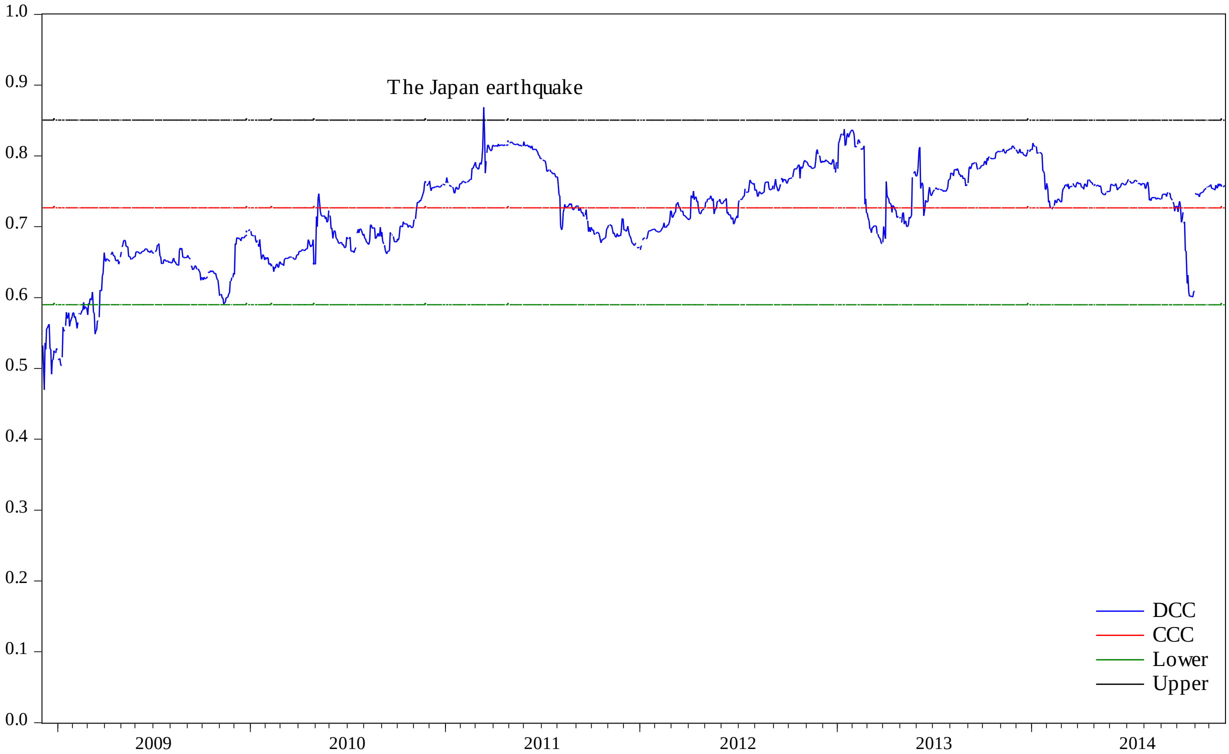
Sample B

Figure 6.5 Conditional correlations between the OSE and CME

Notes: This figure shows the conditional correlations between the OSE and CME. “DCC” denotes the conditional correlations estimated from the DCC-GJR-GARCH (1, 1) model. “CCC” denotes the constant correlations estimated from the CCC-GJR-GARCH (1, 1) model. “Lower” and “Upper” denote the two-standard-error lower and upper bands of the estimated DCC, respectively. The mean of the estimated DCC is 0.7806 (sample A) and 0.7186 (sample B). The estimated CCC is 0.8106 (sample A) and 0.7259 (sample B).



Sample A



Sample B

Figure 6.6 Conditional correlations between the SGX and CME

Notes: This figure shows the conditional correlations between the SGX and CME. "DCC" denotes the conditional correlations estimated from the DCC-GJR-GARCH (1, 1) model. "CCC" denotes the constant correlations estimated from the CCC-GJR-GARCH (1, 1) model. "Lower" and "Upper" denote the two-standard-error lower and upper bands of the estimated DCC, respectively. The mean of the estimated DCC is 0.7843 (sample A) and 0.7207 (sample B). The estimated CCC is 0.8149 (sample A) and 0.7270 (sample B).

6.4.4.2 OSE-CME

Table 6.9 presents the DCC estimation results for the pair (OSE, CME). Error correction towards the futures price parity between the two futures markets is active for at least one of the error correction coefficients in the pair is negative. The CME is the dominant market in reflecting price information across the border, as its error correction coefficient is insignificant and much smaller in magnitude than that of the OSE. Before the crisis, the short-run causality-in-mean is bidirectional, and it is clear that the causality running from the CME to the OSE is stronger than the reverse. After the crisis, the only significant cross-market autoregressive coefficient indicates the CME leading the OSE in the short run. The scarcity of short-run causalities implies that the informational efficiency of the two markets may have been improved in recent years. The GJR-GARCH (1, 1) is employed as the conditional variance model. In both samples, I find significantly positive asymmetry coefficients and thus evidence of the asymmetric behaviour of volatility in response to negative and positive information.

In the DCC-GJR-GARCH (1, 1) specifications, the significant DCC parameters suggest the time-varying nature of the conditional correlations between the OSE and CME. The small news parameter m and large persistence parameter n imply the strong influence of previous dynamic correlations. The sum (m+n) is over 0.99, and there is even an increase in the sum from sample A to sample B. These results suggest not only a highly persistent correlation structure but also an increase in the degree of persistence in the DCC between the two markets. The estimated DCC-GJR-GARCH (1, 1) models do not suffer from excessive ARCH in the standardised residuals. The null hypothesis of constant correlation can be strongly rejected in both samples.

Figure 6.5 plots the estimated time-varying conditional correlations between the OSE and CME. The average level of the DCC is 0.7806 (sample A) and 0.7186 (sample B). In sample A, the most obvious finding is a plunge in the correlations that occurs within a short period after the terrorist attacks on 11/09/2001. This event decreases the correlations dramatically, and makes the correlations negative at one time, with the lowest correlation -0.0933 on 17/09/2001. Yet the normal dynamics of the correlations is recovered shortly afterwards. Similar to the results of the spot-CME pair, the OSE-CME relationship declines during the "Big Bang" and the credit crunch. The general trend of the relationship in sample A is decreasing. In sample B, the conditional correlations have a much more persistent pattern and they are generally increasing. A periodic peak in March 2011 indicates that the level of co-movement between the two markets temporarily strengthens following the massive earthquake on 11/03/2011. In fact, the highest correlation between the two markets reaches 0.8469 on 15/03/2011.

6.4.4.3 SGX-CME

The DCC estimation results for the pair (SGX, CME) are provided in Table 6.10. There is error correction adjustment towards the futures price parity between the SGX and CME since at least one of the error correction coefficients in the pair is negative. In the long run, the CME leads the SGX in reflecting price information across the border, as its error correction coefficient is insignificant and much smaller in magnitude than that of the SGX. In the short run, I find bidirectional causality-in-mean in both samples, and the causality originating from the CME to the SGX is much stronger than the reverse. In addition, the short-run causalities become less in quantity and significance in sample B than in sample A, suggesting that the SGX and CME are probably more informationally efficient in the post-crisis period. The conditional variance is described by the GJR-GARCH (1, 1) model. Significantly positive asymmetry coefficients are found in each market, confirming the negative association between current returns and future volatility.

The conditional correlation pattern of the SGX and CME bears much resemblance to that of the OSE and CME. The time-varying dynamics of the conditional correlations are proved by the significant DCC parameters. The small news parameter m and large persistence parameter n imply strong persistence. The sum (m+n) is over 0.99 and even higher in the post-crisis sample. Obviously the strong persistence in the conditional correlation structure becomes even stronger in recent years, and the SGX-CME correlations are mainly driven by their history rather than information shocks. The ARCH-LM test does not detect excessive ARCH in the model standardised residuals. Also, the likelihood ratio tests strongly reject the null hypothesis of constant correlation in favour of the alternative hypothesis of DCC.

The DCC between the SGX and CME is shown in Figure 6.6. This is very similar to the DCC between the OSE and CME in Figure 6.5, because of the close and stable relationship between the OSE and SGX. The average level of the SGX-CME DCC is 0.7843 (sample A) and 0.7207 (sample B). In the pre-crisis sample, noticeable is a sharp spike within a short period after the 9/11 event, which loosens the link between the SGX and CME and makes their correlations temporarily negative, with the lowest correlation -0.0701 on 17/09/2001. However, the DCC restores its normal dynamics shortly afterwards, and the conditional correlations are generally decreasing over time. Similar to the OSE-CME relationship, the SGX-CME relationship falls in the course of the "Big Bang" and the credit crunch. In the post-crisis sample, the correlations are highly persistent and generally increasing over time. The level of co-movement between the two markets temporarily rises in the aftermath of the Japan earthquake on 11/03/2011, with the highest correlation 0.8685 on 15/03/2011. Note that the earthquake and the following incidents exert different impacts on the bivariate conditional correlations. They weaken the correlations between the OSE and SGX but strengthen the correlations between the OSE (SGX) and CME. This implies that the Nikkei investors tend to transfer to the CME to hedge and/or diversify in the face of domestic shocks.

For all of the Nikkei pairs, the average conditional correlations are larger than their counterpart unconditional correlations (compared with Table 5.2 in Chapter 5), which means that the unconditional correlations are liable to underestimate the true co-movements of these markets. The high degree of co-movements indicates that, by and large, news is absorbed and transmitted in the Nikkei markets jointly. The stability of the market co-movements can be seen as the correlations evolving inside their two-standard-error bands most of the time in Figures 6.1 through 6.6. The persistence in the correlations decreases for the spot-futures pairs and increases for the bilateral futures pairs from sample A to sample B.

6.4.5 Effect of different trading hours on the conditional correlations

I examine the effect of different trading hours of the CME futures on the conditional correlations by applying an alternative time sequence and re-estimating the bivariate DCC models. On a typical trading day, the OSE opens 9.00-15.15, with an overnight session 16.30-3.00 (Japan Standard Time, JST); the SGX opens 7.45-14.25, with an overnight session 15.15-2.00 (Singapore Time, SGT). Given that SGT is 1 hour behind JST, the trading hours of the two markets are almost overlapping. For this reason, I only consider the time differences between the OSE and CME. Figure 6.7 illustrates the OSE and CME trading hours. Although the Central Standard Time (CST) used by the CME is 15 hours behind the JST used by the OSE, with the aid of the CME Globex and the OSE overnight trading, there are fairly long periods during a day when both markets are open. Moreover, the futures settlement prices in the OSE and the CME are generated on the same day.[93] The former application of the default time sequence is hence justified from two aspects: a) arbitrage activities across the markets can be quite active due to the common trading hours in the default time sequence; b) the CME returns on day *t* reflects the information on day *t*; from the perspective of the OSE investors, the OSE returns on day *t* also reflects the information on day *t* (although it is actually day *t*-1 from the perspective of the CME investors) - matching the CME returns on day *t* with the OSE, SGX returns on day *t* captures information on the same "nominal" day.

Alternatively, the CME returns on day *t*-1 can be matched with any other market returns on day *t*, so that the CME becomes the earliest trading market in the sequence and all the returns are able to reveal information within the same 24-hour time intervals (Booth et al., 1996). Due to the high level of integration between the OSE and SGX which is not affected by the timing issues, the conditional correlation structure of the SGX and CME will not be dissimilar to that of the OSE and CME with the alternative time sequence, and thus I will re-estimate the conditional correlations between the OSE and CME only. I again follow the

[93] This also holds when the Central Daylight Time (CDT) is observed by the CME during summer. The CDT reduces the time differences between the OSE and the CME to 14 hours, so that the settlement prices OSE_t are generated at 1.15 in Chicago on day *t* under the CDT.

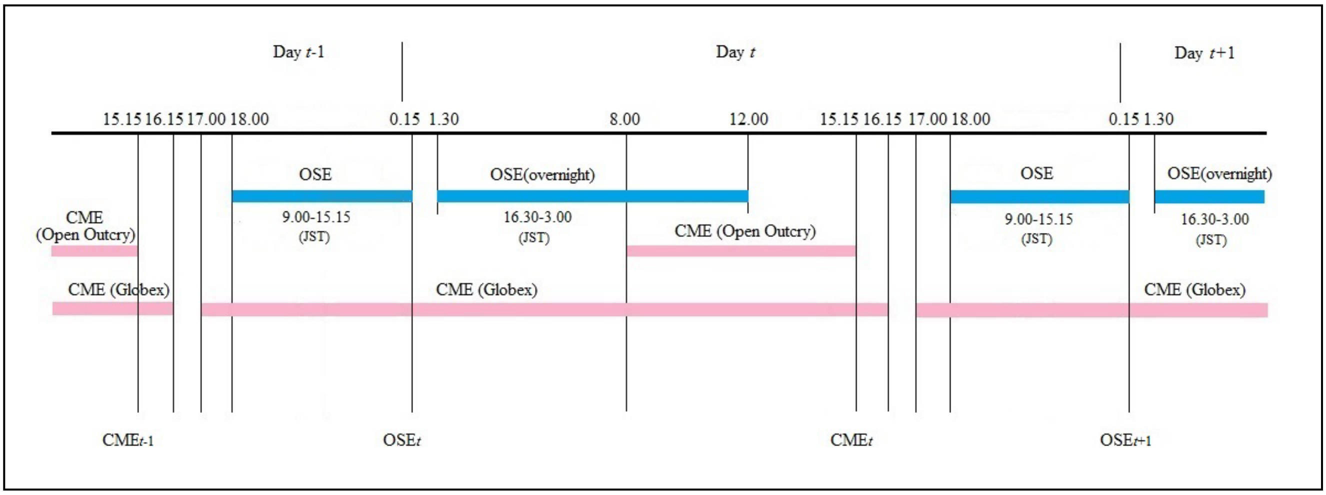


Figure 6.7 Trading hours of the OSE and the CME Nikkei futures markets

Notes: This figure illustrates the trading hours of the OSE (including the overnight session) and the CME (Globex and open outcry) as of 31/12/2014. The time is CST unless otherwise marked. The bottom shows the time when the OSE, CME settlement prices are generated; the subscripts *t*-1, *t* and *t*+1 indicate the timing differences.

two-stage approach of Engle (2002) and Engle and Sheppard (2001). The conditional mean model is the linear ECM, equations (6.10a) (6.10b). The sequential modified likelihood ratio test suggests the model lag p=6 (sample A) and p=4 (sample B).[94] For the univariate GARCH-class models, I use the AIC and SBC to select from univariate GARCH, GJR-GARCH and EGARCH models, all at the order (1, 1). The finding is that the GJR-GARCH shows smaller values of the AIC and SBC than the GARCH, and the EGARCH is difficult to converge.[95] Hence, the conditional variance model is the GJR-GARCH, equations (6.3) and (6.12). I first estimate the univariate GJR-GARCH and then estimate the conditional correlation parameters using the univariate residuals transformed by their standard deviations estimated from the first stage. As before, the estimation of the DCC-GJR-GARCH (1, 1) is by (quasi-)maximum likelihood; the optimisation algorithm is BHHH. I check the model adequacy by the ARCH-LM test of

[94] It is noticed that the AIC and SBC select too short model lags with which the model residuals are autocorrelated. I use the sequential modified likelihood ratio test as the lag length criterion to ensure that the model residuals are white. However, the CME still shows remaining autocorrelations which cannot be removed by increasing the number of lags, especially in sample B. As illustrated in Figure 6.7, on a typical trading day *t*, there is a non-trading interval after the OSE overnight session closes and before the OSE normal session opens, lasting about 6 hours. News that arrives during the non-trading interval can only manifest itself via the CME as it is the only open market during the interval. This may explain the remaining autocorrelations observed in the re-timed univariate model in the CME. Therefore, my results with the alternative time sequence should be interpreted with caution.

[95] The univariate results are not reported but available upon request.

Engle (1982), and test the null hypothesis of constant correlation against the alternative hypothesis of DCC by likelihood ratio test.

Table 6.11 presents the estimation results of the DCC-GJR-GARCH (1, 1) specification for the OSE and CME with the alternative time sequence. In the conditional mean, the OSE with negative and smaller α in magnitude now reflects price information more quickly, whereas the CME with positive and larger α mainly makes adjustments to spreads between the markets. In other words, the CME lags behind the OSE in the cross-border price discovery process. Before the crisis, there is feedback causality-in-mean in the short run and the causality running from the OSE to the CME is slightly stronger than the reverse. After the crisis, the short-run causality is one-way from the OSE to the CME, and yet the long-run causality is bidirectional. Combining the previous results of the SGX leading the OSE which is not affected by the timing issues, I find that the SGX is the quickest market in transmitting price information across the border, followed by the OSE and the CME. With the alternative time sequence, the information leadership of the CME seems to be transferred to the SGX. This is consistent with the findings of the univariate CCF test, and still consistent with the bivariate DCC results obtained when the default time sequence is used, in the sense that the foreign markets (the CME and SGX) lead the domestic market (the OSE) in the cross-border information transmission. The conditional variance results are similar to those in Table 6.9. The asymmetry coefficient λ is significantly positive, lending support to the presence of the leverage effect in the two markets.

The OSE-CME correlation pattern exhibits strong persistence, for the news parameter m is small and the persistence parameter n is large. The sum (m+n) is over 0.99, and it increases slightly from sample A to sample B, implying an even higher level of persistence in the post-crisis period. The estimated models do not suffer from excessive ARCH effects. The null hypothesis of constant correlation is rejected in sample A. Nevertheless, it is not rejected in sample B because the log-likelihood of the DCC-GJR-GARCH (1, 1) is smaller than that of the corresponding CCC model, giving rise to a negative χ^2 statistic and thus the likelihood ratio test cannot be performed. Recall that the same OSE-CME relationship rejects the null hypothesis of constant correlation when the default time sequence is applied (Table 6.9). The non-rejection here suggests insufficient time variation in the correlations, which probably arises from an inactive trading period entailed in the alternative time sequence. From Figure 6.7, on a typical trading day *t*, there is a non-trading interval after the OSE overnight session closes and before the OSE normal session opens, lasting about 6 hours. Although the CME is still open during the interval, spread arbitrage and index arbitrage activities are not available for Nikkei investors as the OSE, SGX and the underlying spot market are all closed.[96] As a consequence, news that arrives during the non-trading interval can only manifest itself via the CME as it is the only open market during the interval, and trading volumes in the Nikkei markets are expected to be low in those hours. The lack of active transactions may lead to the little time variation in the correlations and hence the non-rejection of the null hypothesis of constant correlation.

Figure 6.8 shows the estimated conditional correlations between the OSE and CME with the alternative time sequence. The average level of the DCC is 0.4900 (sample A) and 0.6069 (sample B), which are smaller than the average level of the DCC, 0.7806 (sample A) and 0.7186 (sample B), obtained with the default time sequence. The relatively low correlations may not reflect the true relationship between the two markets; instead, they may simply reflect the inactive trading period which the alternative time sequence inevitably includes.

To see this from another perspective, in Figure 6.8 the OSE-CME correlations drop during 1997-2001 and in March 2011 which can be related to the Japanese “Big Bang” and the massive earthquake on 11/03/2011, respectively. However, worldwide incidents such as the terrorist attacks on 11/09/2001 do not seem to have an obvious effect on the DCC series. The conditional correlations show a generally rising trend in sample A, which contradicts the overall decreasing trend of the OSE-CME correlations over the same period in Figure 6.5. The different correlation pattern obtained from the re-timed DCC models is not likely to reflect the real impact of the information shocks due to thin trading in these markets.

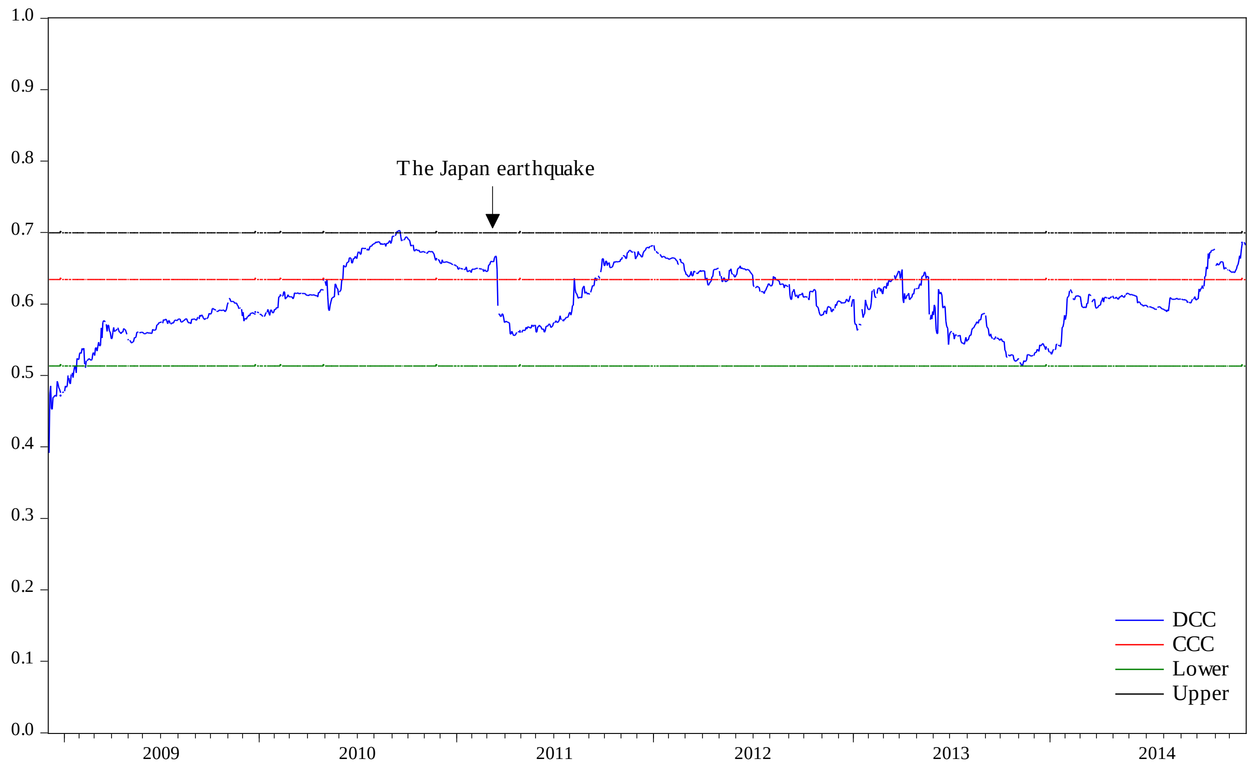
[96] The trading hours of the Nikkei spot market are 9.00-11.30, 12.30-15.00 (JST), corresponding to 18.00-20.30, 21.30-0.00 (CST).

Table 6.11 Estimation results of the DCC models: OSE and CME with the alternative time sequence

Sample A	OSE		CME		Sample B	OSE		CME	
	Estimate	*t*-stat	Estimate	*t*-stat		Estimate	*t*-stat	Estimate	*t*-stat
ECM coefficients					ECM coefficients				
k	-0.0001	-0.2367	-0.0009	-5.2779	k	0.0003	0.9375	0.0011	4.3360
OSE lags					OSE lags				
π_1	0.0037	0.0574	-0.0337	-0.9172	π_1	0.1160	1.4233	0.1650	4.0069
π_2	0.0019	0.0331	-0.0578	-1.7598	π_2	0.1027	1.4312	0.1030	2.4082
π_3	0.0164	0.3154	-0.0290	-0.9732	π_3	0.0841	1.5233	0.0574	1.5142
π_4	-0.0056	-0.1177	-0.0323	-1.1828	π_4	0.0078	0.1793	-0.0071	-0.2345
π_5	0.0225	0.5284	-0.0394	-1.6215					
π_6	0.0157	0.4620	-0.0409	-2.0981					
CME lags					CME lags				
π_1	-0.0306	-0.5190	0.0530	1.5712	π_1	-0.0885	-1.1574	-0.0762	-1.6570
π_2	-0.0265	-0.4956	0.0497	1.6273	π_2	-0.1020	-1.5941	-0.0409	-1.0307
π_3	-0.0189	-0.3879	0.0438	1.5700	π_3	-0.0691	-1.4675	-0.0029	-0.0918
π_4	-0.0079	-0.1803	0.0520	2.0812	π_4	-0.0257	-0.8607	0.0059	0.3195
π_5	-0.0375	-1.0225	0.0381	1.8133					
π_6	-0.0610	-2.9358	0.0016	0.1311					
α	-0.0890	-1.3361	0.9934	26.0807	α	-0.2173	-2.6155	0.8070	17.3188
GJR-GARCH coefficients					GJR-GARCH coefficients				
ω	0.0000	3.5787	0.0000	3.9540	ω	0.0000	4.1688	0.0000	4.6998
a	0.0312	3.2329	0.0228	2.4843	a	0.0454	4.2971	0.0693	3.8723
b	0.9329	101.6893	0.9298	94.7647	b	0.9042	63.1935	0.8506	42.0420
λ	0.0474	3.9296	0.0626	5.2476	λ	0.0360	4.0208	0.0811	4.7389
DCC-GJR-GARCH coefficients					DCC-GJR-GARCH coefficients				
m	0.0066	2.3291			m	0.0081	3.2423		
n	0.9932	241.2071			n	0.9917	375.0335		
$m+n$	0.99981				$m+n$	0.99984			
ARCH-LM(10)	[0.8829]		[0.6818]		ARCH-LM(10)	[0.6632]		[0.5161]	
Testing for CCC	LR stat		*p*-value		Testing for CCC	LR stat		*p*-value	
	23.2836		0.0000			-11.8395		NA	

Notes: This table contains the DCC estimation results for the pair (OSE, CME), with the CME returns on day *t*-1 aligned with the OSE returns on day *t* to make the alternative time sequence by which the CME is the earliest trading market. The conditional mean is the linear ECM, equations (6.10a) (6.10b): $\Delta f_{1,t} = k_1 + \sum_{j=1}^{p} \pi_{11,j}\Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{12,j}\Delta f_{2,t-j} + \alpha_1 z_{t-1} + u_{1,t}$, $\Delta f_{2,t} = k_2 + \sum_{j=1}^{p} \pi_{21,j}\Delta f_{1,t-j} + \sum_{j=1}^{p} \pi_{22,j}\Delta f_{2,t-j} + \alpha_2 z_{t-1} + u_{2,t}$. The subscripts of the ECM parameters are omitted for brevity except that the model lags *j* of the autoregressive coefficients are retained in the table presentation. The conditional variance is the GJR-GARCH (1, 1), equations (6.3) and (6.12): $u_t = \sigma_t \eta_t$, $\sigma_t^2 = \omega + a u_{t-1}^2 + \lambda I_{t-1} u_{t-1}^2 + b\sigma_{t-1}^2$, where the dummy variable I_{t-1}=1 if u_t<0 and 0 otherwise. The conditional correlation is equation (6.8): $\mathbf{R_t} = \mathbf{Q_t^{*-1} Q_t Q_t^{*-1}}$, where $\mathbf{Q_t} = (1-m-n)\bar{\mathbf{Q}} + m u_{t-1} u'_{t-1} + n\mathbf{Q_{t-1}}$. The DCC model adequacy is checked by the ARCH-LM test of Engle (1982) up to order 10, and the significance levels are in square brackets. The bottom line reports the likelihood ratio (LR) test statistics and the associated *p*-values of testing the null hypothesis of constant correlation (CCC) against the alternative hypothesis of DCC.

Sample A



Sample B

Figure 6.8 Conditional correlations between the OSE and CME (alternative time sequence)

Notes: This figure shows the conditional correlations between the OSE and CME, with the CME returns on day *t*-1 aligned with the OSE returns on day *t* to make the alternative time sequence by which the CME is the earliest trading market. "DCC" denotes the conditional correlations estimated from the re-timed DCC-GJR-GARCH (1, 1) model. "CCC" denotes the constant correlations estimated from the re-timed CCC-GJR-GARCH (1, 1) model. "Lower" and "Upper" denote the two-standard-error lower and upper bands of the estimated DCC, respectively. The mean of the estimated DCC is 0.4900 (sample A) and 0.6069 (sample B). The estimated CCC is 0.4807 (sample A) and 0.6344 (sample B).

The low trading volume involved in the alternative time sequence also affects the persistence in the DCC series in Figure 6.8. In sample A, the conditional correlations are much more persistent than the conditional correlations estimated by default in Figure 6.5. Because of thin trading, news cannot contribute much to the evolution of the conditional correlations over time. The DCC is mainly driven by its past correlations and exhibits less dynamics than the DCC of the default time sequence. The conditional correlations estimated with the different time sequences look similar in terms of persistence in sample B. Nevertheless, the estimated persistence parameter n in Table 6.11 is always larger than that in Table 6.9.

To sum up the effect of the different trading hours, the conditional mean results estimated from the re-timed DCC models are consistent with those estimated when the timing issues are ignored, suggesting the leading role of the foreign Nikkei futures exchanges in the information dissemination process across the border. The different dynamics of the conditional correlations obtained with the alternative time sequence may result from the thinly traded period in the time sequence; they do not represent the true co-movements of the Nikkei markets. The different trading hours do not affect the underestimation of the unconditional pair-wise correlations (Table 5.2 in Chapter 5) which are still smaller than the corresponding re-timed DCC on average, nor affect the stability of the conditional correlations as they evolve within their two-standard-error bands most of the time in Figure 6.8. The increased persistence in the correlations observed for the bilateral futures pairs in the post-crisis period is also robust to the time differences among the Nikkei markets.

6.5 Discussion and conclusion

The chapter investigates the international volatility transmission process in the Nikkei 225 stock index futures markets from two perspectives: a) the volatility interactions between the Nikkei stock index and index futures markets, and across the Nikkei futures markets; b) the time-varying behaviour of the dynamic conditional correlations of the Nikkei markets. With a 19-year sample covering a pre-crisis period and a post-crisis period, the Nikkei spot and futures markets are found to be cointegrated, in the sense that the spot and futures returns are cointegrated with the cointegrating vector [1, -1] in individual Nikkei markets, and that the three Nikkei futures returns are cointegrated with one common stochastic trend. Error correction mechanism is thus employed to describe the conditional mean for both perspectives.

The volatility interactions or spillovers of the Nikkei markets are examined by the CCF test based on the ESTECM-EGARCH specification. Using the CCF test, I find the critical importance of the contemporaneous relationships between the Nikkei spot and futures markets, and across the Nikkei futures markets. This means that the majority of information is transmitted in and across the Nikkei markets in a simultaneous manner. In individual Nikkei markets, I document bidirectional causality-in-variance between spot and futures, with some evidence that the information flows from the futures market to the spot market are stronger than the reverse. Across the Nikkei futures markets, the CME causes the other markets in variance the most strongly and thus takes the information leadership in the cross-border second-moment information dissemination. More generally, it is the foreign Nikkei futures markets (the CME and SGX) that play a major part in the international volatility transmission process. This is in agreement with the price dominance of the foreign futures markets in the international price discovery process in Chapter 5. Therefore, my results corroborate the international centre hypothesis that global financial centres are more likely to dominate cross-border information transmission; in the Nikkei markets, the information leadership of the foreign futures markets exists in both the first-moment and the second-moment information transmission mechanisms across the border.

The bivariate DCC model is used to study the time-varying dynamics of the Nikkei conditional correlations. With the linear ECM as the conditional mean, there is widespread evidence of error correction dynamics in the Nikkei markets. Between Nikkei spot and futures markets, the futures market acts as the main price discovery vehicle, with two exceptions that the spot leads the OSE, SGX futures in the post-crisis period. Across the Nikkei futures markets, the CME is the most dominant market in transmitting information, followed by the SGX and OSE. If the alternative time sequence is applied whereby the CME returns on day *t*-1 is matched with any other market returns on day *t*, the information leadership of the CME seems to be transferred to the SGX. In any case, my results point to the information advantage of the foreign Nikkei futures markets (the CME and SGX) and thus repeatedly support the international centre hypothesis. Taking together the volatility spillover results of the CCF test, I confirm the primary role of the foreign futures markets in spreading first-moment and second-moment information. This can be explained by the fact that foreign futures exchanges are usually global financial centres which are more efficient in processing and sharing information, and provide more lenient trading environment for investors - for example, lower and more heterogeneous transaction costs, longer trading hours, fewer trading restrictions and more risk management opportunities. My findings are consistent with Fung et al. (2001), Covrig et al. (2004) in revealing the contribution of offshore futures exchanges to information dissemination across the border. My findings are also consistent with Rochet and Tirole (2003) in suggesting that information tends to gravitate to the most ubiquitous international platform. The key functions of the foreign futures markets in the cross-border information dissemination imply that small offshore exchanges are able to compete with a large home exchange,[97] and that it is a valuable task to understand and take advantage of the information role of global financial centres when trading futures contracts listed on multiple venues.

Turning to the second-moment dynamics, with the DCC-GJR-GARCH (1, 1) model I find prevalent evidence of the leverage effect in the Nikkei markets. The Nikkei volatility behaviour is asymmetric: negative information increases market volatility to a larger extent than positive information of the same magnitude. Exceptions are for the pairs (spot, OSE) and (OSE, SGX) in the post-crisis sample, where a simple GARCH (1, 1) model acts as the conditional variance, implying the absence of volatility asymmetry. On the other hand, the Nikkei markets are highly integrated, and the majority of information is absorbed jointly on a daily basis. The highest level of integration occurs between the OSE and SGX futures markets; or in the wider sense, among the Nikkei spot, OSE and SGX futures. The OSE and

[97] The SGX and CME are small while the OSE is large in terms of trading volume. See section 3.3, Chapter 3 for more discussions.

SGX futures are based on the same underlying spot market and thus information originating from one market should be quickly transmitted to the other. The common characteristics shared by the OSE and SGX, such as operating at almost the same time and using the same currency, make their relationship even closer. The CME futures is based on the same index, but its extra issues such as exchange rate risk and low trading volume may have reduced its degree of co-movement with the other Nikkei markets. This is in relative terms, however. Overall, the Nikkei markets are all closely related, and the Nikkei conditional correlations are always larger than their corresponding unconditional correlations. In this respect, I show different result from Koutmos (1996) who records the overestimation of unconditional correlations and the underestimation of the potential for diversification among major European stock returns. I argue that the generally high conditional correlations may make further diversification difficult, because the high level of co-movements implies that investors are already well diversified among the Nikkei markets. For regulators, the high level of Nikkei market co-movements implies that effective measures should be taken to maintain the stability of the financial system in each market.

The Nikkei conditional correlations are time-dependent, strongly persistent and stable. Except for major events, news has a small impact on the Nikkei market relationships, which are mainly driven by their history. This may reject the argument that news drives volatility, as the volatility of the Nikkei correlations is mainly in-built. However, in relative terms, it is still found that the level of persistence in the correlations decreases for the spot-futures pairs and increases for the bilateral futures pairs from the pre-crisis period to the post-crisis period. The persistence decline in the spot-futures correlations implies that index arbitrageurs may wish to pay more attention to the impact of news on the market relationships in recent years, when news has a *relatively* more immediate effect and the correlations exhibit more dynamics. The impact of news largely relies on the nature of the events (national or global, temporary or long-lasting, etc.) and the cross-market linkages. For example, the Japanese “Big Bang” causes the Nikkei conditional correlations to fall until its completion. The terrorist attacks on 11/09/2001 leads to a dramatic, temporary drop of the correlations. The credit crunch starting from 2007 also decreases the CME co-movement with the other markets. The Japan earthquake on 11/03/2011 and the following events have mixed effects: they loosen the link between the OSE and SGX while strengthen the link between the OSE (SGX) and CME, implying that the CME acts as an important vehicle for cross-market hedging and/or diversification when confronted with domestic shocks. To consider the effect of different trading hours of the CME futures, the alternative time sequence is applied and a different correlation pattern is obtained which may merely reflect the thinly traded period incorporated in the sequence rather than the true relationships of the Nikkei markets. Robust to the time differences are the main characteristics of the Nikkei conditional correlations such as high level, strong persistence and stability. These characteristics should be emphasised in Nikkei futures trading and regulation to a greater extent than the time differences.

Chapter 7

Concluding remarks

7.1 Summary of main empirical findings

Nikkei 225 stock index futures contracts are a vital investment tool in worldwide trading activities, but little is known about the spot-futures pricing relationship, market dynamics and the level of integration in and across the Nikkei futures exchanges, in the context of rapidly changing market conditions and in the course of futures market globalisation. This dissertation studies the cost of carry relationship and the international dynamics of mispricing, price and volatility in the three Nikkei futures markets - the Osaka Exchange (OSE), the Singapore Exchange (SGX) and the Chicago Mercantile Exchange (CME), over a comprehensive new 19-year sample period covering a series of important historical events such as the 2008 global financial crisis. The dissertation contains three empirical chapters, each with a distinctive focus. Chapter 4 investigates the cost of carry relationship, static and dynamic mispricing behaviour and index arbitrage activities in the three Nikkei markets. Chapter 5 examines the price discovery process in individual Nikkei markets and across the Nikkei futures markets. Chapter 6 examines the volatility transmission process in individual Nikkei markets and across the Nikkei futures markets.

The most important contribution of the dissertation is that it investigates the cost of carry equilibrium and disequilibrium, price discovery and volatility transmission in and across the three Nikkei futures markets. Previous research does not fully consider the special characteristics of the triple-listed Nikkei futures contracts and the key institutional differences among the Nikkei exchanges, or the price and volatility dynamics in the three Nikkei futures markets at the same time. The dissertation therefore contributes to knowledge in the areas of the Nikkei spot-futures equilibrium and index arbitrage behaviour, international first-moment and second-moment information transmission mechanism, and futures market integration.

The dissertation contributes to the theoretical framework on pricing and modelling the triple-listed Nikkei futures contracts. In terms of pricing, it modifies the standard cost of carry model for each Nikkei futures contract, allowing for the special characteristics of the Nikkei futures contracts such as the dividend and currency risks, and the key institutional differences such as the different trading hours and transaction costs. No previous research on the Nikkei futures pricing has considered the unique features of the Nikkei futures and the institutional differences as comprehensively as this work. In terms of modelling, it describes the nonlinear adjustment processes of the Nikkei futures mispricing and price with smooth transition models, and shows that the level of heterogeneity in investor structure and transaction costs is closely related to the information role of the Nikkei markets. The level of heterogeneity as a futures market characteristic was not emphasised in the literature until the 2000s but never in an international setting. In this way, the dissertation contributes to the literature by demonstrating the importance of market heterogeneity in price discovery and informational efficiency in individual Nikkei markets and across the border.

Moreover, the dissertation provides substantial empirical evidence on the spot-futures pricing relationship, market dynamics and the level of integration for the three Nikkei futures markets. First, almost all studies on the Nikkei markets were published in the early 1990s-early 2000s. Using a comprehensive new 19-year dataset, the dissertation significantly updates the empirical studies on the Nikkei markets by encompassing the quickly changing market conditions in research and comparing the cross-border mispricing, price and volatility dynamics before and after the 2008 global financial crisis. Second, smooth transition models have been studied in a few markets but never in the triple-listed Nikkei markets. The dissertation applies the smooth transition models to the Nikkei futures mispricing and price, and hence it extends the smooth transition literature by showing the suitability of the smooth transition models for the triple-listed Nikkei futures contracts. Third, studies on the Nikkei market dynamics tend to focus on the OSE and SGX, and circumvent the CME due to its currency and time complexities. Two exceptions are Booth et al. (1996) who study the price dynamics across the three Nikkei markets without allowing for the effect of transaction costs, and Bacha and Vila (1994) who study the potential destabilising effects of the inception of a new Nikkei futures market (as it then was) on the existing Nikkei volatilities. The systematic evidence that this work presents on the international dynamics of Nikkei futures mispricing, price and volatility is not available in past research. Fourth, this work studies the dynamic Nikkei market linkages and the effect of the time differences on the Nikkei market linkages, issues previously ignored in the literature. The dissertation therefore fills in this research space and sheds light on the dramatic integration process of the Nikkei markets in the context of globalisation.

The main empirical findings of the dissertation can be summarised as follows.

7.1.1 Cost of carry, mispricing and index arbitrage activities

Chapter 4 first studies the cost of carry relationship in the Nikkei markets. The standard cost of carry model cannot be directly applied to the triple-listed Nikkei futures contracts, as it lacks the considerations of dividend lumpiness, exchange rate fluctuations and time differences. It is found that the dividend and currency risks have a significant impact on the pricing of the Nikkei contracts, while the impact of the time differences among the exchanges is trivial. As such, the standard cost of carry formula is modified for each Nikkei contract: the cost of carry model adjusted for lumpy dividends (COC2) is adopted for the OSE, SGX contracts; the cost of carry model adjusted for lumpy dividends and exchange rate fluctuations (COC3) in the original view is adopted for the CME contracts. The formula of the no-arbitrage bounds are also modified to take into account the effect of transaction costs to estimate the Nikkei futures mispricing.

The static behaviour of Nikkei futures mispricing is examined in a systematic way over the 19-year sample period, by parametric and non-parametric methods. The economic significance of the Nikkei futures mispricing, or whether the mispricings represent profitable arbitrage opportunities, is of particular interest. The evidence suggests that only brokers with a lower level of transaction costs may have been able to profit from short arbitrage in the OSE and SGX. It is relatively difficult for institutional investors to make a profit in the two markets, in that the mispricings are substantially less under a higher level of transaction costs. In contrast, the CME mispricings are much larger in size and quantity, most of which survive and cluster even with a stricter level of transaction costs. This may suggest profitable opportunities for arbitrage; nonetheless, in fact most of the CME mispricings arise from the currency risk and arbitrage in the CME is not strictly risk-free. The general properties of the Nikkei futures mispricing include the dominance of underpricing, persistence, path dependence, positive relationship with time to maturity, and positive relationship with underlying stock volatility.

The dynamic behaviour of Nikkei futures mispricing is examined in terms of market responses to a given mispricing, or propensity-to-arbitrage. An ESTAR-GARCH model is constructed to describe the nonlinear adjustment processes of the Nikkei mispricing. And hereafter the whole sample period is divided into a pre-crisis period (sample A) and a post-crisis period (sample B), separated by the 2008 global financial crisis. Quicker market responses to mispricing are found in the OSE and SGX, yet slower responses are found in the CME in the post-crisis period, which could result from the increased currency risk in arbitraging the CME contracts in more recent years. Moreover, there is evidence of mean reversion and heterogeneous arbitrageurs in the Nikkei markets, but the effect of transaction costs may be stronger than the effect of heterogeneous arbitrageurs, in that larger Nikkei mispricings are removed more quickly than smaller Nikkei mispricings.

7.1.2 Price discovery in and across the Nikkei markets

In Chapter 5, the Nikkei markets are found to be cointegrated, in the sense that the spot and futures prices are cointegrated with the cointegrating vector [1, -1] in individual Nikkei markets, and that the three Nikkei futures prices are cointegrated with one common stochastic trend. This justifies the use of error correction mechanisms for the Nikkei markets. To examine the Nikkei price adjustments towards equilibrium, the linear ECM is first estimated as a base model. The nonlinear ESTECM is further employed to capture the possible smooth transition error correction behaviour in the Nikkei markets. The smooth transition nonlinearity can result from transaction costs, heterogeneity and predictive asymmetry. It is found that the Nikkei prices exhibit the smooth transition dynamics and the nonlinear ESTECM is more appropriate for describing the price interaction mechanisms in the Nikkei markets.

In individual Nikkei markets, the estimated results of the ESTECM generally show that futures lead spot in the pre-crisis period and spot lead futures in the post-crisis period. Given that it is generally believed that the futures market plays a primary role in the price formation process, the spot leadership in the post-crisis period is interesting. This type of price adjustments takes place within a single regime. Going beyond and considering a middle regime of a narrow band around zero which indicates small pricing errors without arbitrage, and an outer regime of areas far away from zero which indicates large pricing errors with active arbitrage, the futures market is found to move more quickly between the regimes before the crisis, while the spot market move more quickly between the regimes after the crisis. The finding that the Nikkei spot market assumes the price discovery function in the post-crisis sample may reflect the relatively low level of heterogeneity in the investors and transaction costs during the period, compared with the futures markets.

Across the Nikkei futures markets, the ESTECM shows that the CME is the most dominant market in the cross-border first-moment information transmission mechanism. The dominance of the CME seems to be transferred to the SGX when an alternative time sequence is applied whereby the CME acts as the earliest trading market in the sequence. Hence, I consistently support the international centre hypothesis that the foreign futures market, which is usually a global information centre, should dominate the international price discovery process. Reasons for the price leadership of the offshore exchanges relate to the better trading conditions they can provide. Following the logic of heterogeneity, the CME and SGX are found to exhibit a more heterogeneous structure of market transaction costs than the OSE. Although all the futures transaction costs have decreased in recent years, the decreasing trend is most notably observed in the CME. Besides, as global information centres, the CME and SGX have higher efficiency in processing and sharing information, and they are able to offer longer trading hours, fewer trading barriers, and more risk management tools for investors. An additional finding is that the last trading market in each time sequence tends to dominate the price discovery process across the border, when different time sequences are applied. This may be because the last trading market in each time sequence has more opportunities to absorb information that already exists in the earlier markets.

7.1.3 Volatility transmission in and across the Nikkei markets

The volatility issues are touched in Chapter 5 but an in-depth study of the Nikkei volatility transmission mechanism is given in Chapter 6. In this chapter, the Nikkei volatility dynamics are studied from the perspectives of volatility interactions and dynamic market linkages. The volatility interactions are examined by the CCF approach based on the ESTECM. In individual Nikkei markets, there is evidence of bidirectional volatility spillover between spot and futures, with some evidence that the information flows from futures to spot are stronger than the other way round. Across the Nikkei futures markets, the CME takes the information leadership in the cross-border volatility transmission process. More generally, it is the foreign Nikkei markets (the CME and SGX) that play a major part in the second-moment information transmission. Combining the results from Chapter 5, I therefore continually support the international centre hypothesis, in that the information advantage of the CME and SGX exists in both the first-moment and the second-moment information transmission mechanisms across the border. The key role of the offshore futures markets is confirmed once more in the subsequent DCC multivariate GARCH analysis.

The CCF results point to the critical importance of the contemporaneous relationships in and across the Nikkei markets. As such, the other perspective of the chapter examines the dynamic Nikkei market linkages through the time-varying behaviour of conditional correlations by the DCC multivariate GARCH specification. Using a bivariate DCC model, I find evidence of the leverage effect in most of the Nikkei markets, i.e. bad news increases market volatility to a larger extent than good news of the same magnitude. Overall, the Nikkei markets are all closely related, and the majority of information is absorbed jointly on a daily basis. The highest level of integration occurs between the OSE and SGX futures markets. This is because the OSE and SGX futures are based on the same underlying spot market and thus information originating from one market should be quickly transmitted to the other. The common characteristics shared by the OSE and SGX, such as operating at almost the same time and using the same currency, make their relationship even closer. Moreover, the bivariate Nikkei conditional correlations exhibit strong persistence and stability. Except for major events, news has a small impact on the dynamic Nikkei market linkages but the news impact on the spot-futures relationships becomes relatively more immediate in recent years. To consider the effect of different trading hours of the CME contracts, the DCC framework is re-estimated with the alternative time sequence. It is found that main characteristics of the Nikkei market relationships are robust to the time differences.

7.2 Theoretical and practical implications of the findings

Although the dissertation is an empirical work, the findings of the dissertation have at least two important theoretical implications. First, the standard cost of carry model is a perfect economy model; modifications of the standard model are necessary for futures contracts listed on more than one trading venue - though based on the same asset, they can be quite different in specifications, costs and risks. For the triple-listed Nikkei futures contracts, in the midst of institutional differences, the dividend payout practices of Japanese firms and the yen-dollar exchange rate fluctuations are shown to be essential in influencing the theoretical (or fair) Nikkei futures prices, while the effect of the time differences among the exchanges is negligible. A growing number of futures contracts, especially those in emerging countries, become listed at home and abroad. As an example, the India Nifty 50 index futures contracts have been traded on the National Stock Exchange of India located in Mumbai as well as the SGX, CME and OSE since 2014.[98] The spot-futures pricing relationship of the multiple-listed futures contracts may be significantly affected by the differences in contract design and regulatory environment in the different exchanges, which should be taken into consideration when pricing these futures contracts in the cost of carry analysis.

Second, much of the research in the dissertation is conducted by smooth transition models, relying on the assumption of heterogeneity. For this reason, I examine aggregate market responses rather than individual reactions. Chapter 4 studies the effect of heterogeneous arbitrageurs on the mean reversion of mispricing, and reports that the effect of heterogeneity may be weaker than the effect of transaction costs in the Nikkei markets. Chapter 5 and 6

[98] The CME Nifty 50 index futures are E-mini futures contracts.

further study the effect of heterogeneity in transaction costs on the error correction dynamics. The level of heterogeneity is the lowest in the Nikkei spot market in the post-crisis period, which may explain the spot leadership in the price formation process during the period. Across the border, the CME and SGX have a more heterogeneous structure of market transaction costs than the OSE, which may contribute to the predominance of the offshore exchanges in the international information dissemination. The level of heterogeneity as a futures market property was not emphasised in the literature until very recently. From the dissertation, it is evident that the level of heterogeneity in investor structure and transaction costs is closely related to the information role of the Nikkei markets. The recognition of financial markets being heterogeneous rather than uniform provides a valuable perspective for studies on price discovery, informational efficiency and market microstructure.

The practical implications of my findings for investors are as follows. Given that the index arbitrage limits in the Nikkei markets are driven by transaction costs to a greater extent than by heterogeneous arbitrageurs, Nikkei investors may need to be more concerned about transaction costs in their arbitrage activities. In terms of portfolio diversification among the Nikkei markets, the high level of Nikkei market co-movements implies that all of the markets respond to information very rapidly and almost simultaneously, and hence, price discrepancies are already adjusted and investors are already well diversified, making further diversification difficult on a daily basis. For index arbitrageurs trading between Nikkei spot and futures markets, they may need to pay more attention to the impact of news on the market relationships, in that news has a relatively more immediate impact on the Nikkei spot-futures conditional correlations in recent years.

For policy makers in the Nikkei markets, importance should be attached to the awareness of heterogeneity in market regulation in separate countries and exchange competition across the border. My findings suggest that the level of heterogeneity in investor structure and transaction costs is closely related to the information role of the Nikkei markets, implying that a change in the level of market heterogeneity may be followed by a change in the market competitiveness in the information transmission process. Regulators may want to increase the diversity of risk management tools and transaction costs available in a market. Moreover, given the high level of Nikkei market co-movements, regulators should take effective measures to maintain the stability of the financial system in each market.

For both investors and policy makers of multiple-listed futures contracts, it would be a valuable task to understand and make use of the information transmission mechanism between the domestic futures market and the equivalent, offshore futures markets. My findings consistently demonstrate the key functions of the offshore Nikkei futures markets in the international price discovery and volatility transmission mechanisms. I also show that the CME acts as an important vehicle for cross-market hedging and/or diversification in the face of Japanese shocks. Therefore, small offshore futures markets are able to compete with a large domestic futures market in practice. In addition, despite time differences among the exchanges, my findings show that the time issue does not exert a significant effect on the pricing of the Nikkei futures contracts, nor affect the information leadership of the offshore exchanges, nor affect the main characteristics of the dynamic Nikkei market linkages such as high level, strong persistence and stability. The message conveyed is that the time issue should not be excessively underlined in Nikkei futures trading and regulation.

7.3 Limitations and directions for future research

Daily data are used throughout this dissertation due to the daily re-settlement procedure in futures markets. Futures contracts are marked to market on a daily basis, and the gains or losses on a particular contract are realised at the end of a trading session each trading day, with reference to the daily settlement price. It follows that the daily settlement price reflects the arbitrage activities and the supply-demand relation in the futures market each trading day. The 19-year daily dataset is sufficiently long to generate reasonable statistical power. However, it is recognised that one limitation of the dissertation is that information contained in the Nikkei mispricings, prices and volatilities at intraday levels cannot be captured. The advances in information technology and the widespread use of computer trading have enhanced the speed and liquidity of higher frequency trading, and the adjustments of disequilibrium towards the steady state may be accomplished within one trading day. Hence, a promising direction for future research is to re-visit some of the research issues in the dissertation using intraday data and compare the relevant results. With intraday data, one can also release some of the restrictions imposed on the smooth transition models. For instance, the constant smoothness parameter (gamma) can be assumed to be time-varying (Taylor, 2007).

The dissertation documents the predictive asymmetry of Nikkei prices and volatilities. In terms of price, bad news triggers a larger aggregate market response than good news of the same magnitude. In terms of volatility, bad news increases market volatility more than equally sized good news. This dissertation uses the CCF test to study the volatility interactions in the Nikkei markets. While the CCF test has many advantages, it is unable to explore the asymmetric volatility spillover effect, i.e. bad news in one market increases volatility in the other market more than equally sized good news. Also, the standard DCC framework of Engle (2002) is unable to model the asymmetry in conditional correlations, which means that conditional correlations may increase after systematic bad news to a larger extent than after systematic good news of the same magnitude. Future research may wish to look into such asymmetries. For example, one can apply the asymmetric DCC (ADCC) model of Cappiello et al. (2006) to the Nikkei conditional correlations to investigate the possible asymmetric correlation dynamics following the 2008 global financial crisis.

The scope of the dissertation is confined to the Nikkei yen contracts in the OSE, SGX and the dollar contracts in the CME, for they are the earliest Nikkei futures contracts with sufficiently long time series. New Nikkei futures contracts have emerged to meet various investment demands. The SGX has started to trade Nikkei dollar contracts since 2006 and the CME has started to trade Nikkei yen contracts since 2004. There are also E-mini Nikkei futures contracts denominated in yen in the three exchanges. It is left for future research to study the cost of carry relationship and the price and volatility interactions of these Nikkei products. As more and more futures contracts are on the road of overseas listing, the mispricing, price and volatility dynamics between their equivalent markets will be an interesting research area in the future.

Bibliography

Abhyankar, A.H. 1995, "Return and volatility dynamics in the FTSE-100 stock index and stock index futures markets", *Journal of Futures Markets,* vol. 15, no. 4, pp. 457-488.

Admati, A. and Pfleiderer, P. 1988, "A theory of intraday patterns: Volume and price variability", *Review of Financial Studies,* vol. 1, no. 1, pp. 3-40.

Aggarwal, R. and Dow, S.M. 2012, "Dividends and strength of Japanese business group affiliation", *Journal of Economics and Business,* vol. 64, no. 3, pp. 214-230.

Aielli, G.P. 2013, "Dynamic conditional correlation: On properties and estimation", *Journal of Business and Economic Statistics,* vol. 31, no. 3, pp. 282-299.

Alexander, C. and Chibumba, A. 1997, "Multivariate orthogonal factor GARCH", *University of Sussex, Mimeo*.

Alphonse, P. 2000, "Efficient Price Discovery in Stock Index Cash and Futures Markets", *Annals of Economics and Statistics / Annales d'Économie et de Statistique,* no. 60, pp. 177-188.

Anderson, H.M. 1997, "Transaction costs and non-linear adjustment towards equilibrium in the US treasury bill market", *Oxford Bulletin of Economics and Statistics,* vol. 59, no. 4, pp. 465-484.

Antoniou, A. and Garrett, I. 1993, "To what extent did stock index futures contribute to the October 1987 stock market crash?", *The Economic Journal,* vol. 103, no. 421, pp. 1444-1461.

Asteriou, D. and Hall, S.G. 2007, *Applied Econometrics: A Modern Approach using EViews and Microfit,* Revised edn, Palgrave Macmillan.

Bacha, O. and Vila, A.F. 1994, "Futures markets, regulation and volatility: The case of the Nikkei stock index futures markets", *Pacific-Basin Finance Journal,* vol. 2, no. 2-3, pp. 201-225.

Baillie, R.T., Geoffrey Booth, G., Tse, Y. and Zabotina, T. 2002, "Price discovery and common factor models", *Journal of Financial Markets,* vol. 5, no. 3, pp. 309-321.

Balke, N.S. and Fomby, T.B. 1997, "Threshold cointegration", *International Economic Review,* vol. 38, no. 3, pp. 627-645.

Bauwens, L., Laurent, S. and Rombouts, J.V.K. 2006, "Multivariate GARCH models: A survey", *Journal of Applied Econometrics,* vol. 21, no. 1, pp. 79-109.

Berkman, H., Brailsford, T. and Frino, A. 2005, "A note on execution costs for stock index futures: Information versus liquidity effects", *Journal of Banking and Finance,* vol. 29, no. 3, pp. 565-577.

Bhardwaj, R.K. and Brooks, L.D. 1992, "The January anomaly-effects of low share price, transaction costs, and bid-ask bias", *Journal of Finance*, vol. 47, no. 2, pp. 553-575.

Białkowski, J. and Jakubowski, J. 2008, "Stock index futures arbitrage in emerging markets: Polish evidence", *International Review of Financial Analysis,* vol. 17, no. 2, pp. 363-381.

Board, J. and Sutcliffe, C. 1996, "The dual listing of stock index futures: Arbitrage, spread arbitrage, and currency risk", *Journal of Futures Markets,* vol. 16, no. 1, pp. 29-54.

Board, J., Sutcliffe, C. and Wells, S. 2002, *Transparency and Fragmentation: Financial Market Regulation in a Dynamic Environment,* Palgrave Macmillan, London.

Bohl, M.T., Salm, C.A. and Schuppli, M. 2011, "Price discovery and investor structure in stock index futures", *Journal of Futures Markets*, vol. 31, no. 3, pp. 282-306.

Bollerslev, T. and Wooldridge, J.M. 1992, "Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances", *Econometric reviews,* vol. 11, no. 2, pp. 143-172.

Bollerslev, T. 1986, "Generalized autoregressive conditional heteroskedasticity", *Journal of Econometrics,* vol. 31, no. 3, pp. 307-327.

Bollerslev, T. 1990, "Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH approach", *Review of Economics and Statistics,* vol. 72, no. 3, pp. 498-505.

Bollerslev, T., Chou, R.Y. and Kroner, K.F. 1992, "ARCH modeling in finance. A review of the theory and empirical evidence", *Journal of Econometrics,* vol. 52, no. 1-2, pp. 5-59.

Bollerslev, T., Engle, R.F. and Nelson, D.B. 1994, "ARCH model" in *Handbook of Econometrics Vol. 4*, eds. Engle, R.F. and McFadden, D. Elsevier, Amsterdam;Oxford, pp. 2959-3038.

Bollerslev, T., Engle, R.F. and Wooldridge, J.M. 1988, "A capital asset pricing model with time-varying covariances", *Journal of Political Economy,* vol. 96, no. 1, pp. 116-131.

Booth, G.G., Chowdhury, M., Martikainen, T. and Tse, Y. 1997, "Intraday volatility in international stock index futures markets: Meteor showers or heat waves?", *Management Science,* vol. 43, no. 11, pp. 1564-1576.

Booth, G.G., Lee, T. and Tse, Y. 1996, "International linkages in Nikkei stock index futures markets", *Pacific-Basin Finance Journal,* vol. 4, no. 1, pp. 59-76.

Booth, G.G., So, R.W. and Tse, Y. 1999, "Price discovery in the German equity index derivatives markets", *Journal of Futures Markets,* vol. 19, no. 6, pp. 619-643.

Box, G.E.P. and Jenkins, G.M. 1976, *Time Series Analysis: Forecasting and Control,* Revised edn, Holden-Day, San Francisco.

Brailsford, T.J. and Cusack, A.J. 1997, "A comparison of futures pricing models in a new market: The case of individual share futures", *Journal of Futures Markets,* vol. 17, no. 5, pp. 515-541.

Brennan, M.J. and Schwartz, E.S. 1990, "Arbitrage in stock index futures", *Journal of Business*, vol. 63, no. 1, pp. S7-S31.

Brenner, M., Subrahmanyam, M.G. and Uno, J. 1989a, "Stock index futures arbitrage in the Japanese markets", *Japan and the World Economy*, vol. 1, no. 3, pp. 303-330.

Brenner, M., Subrahmanyam, M.G. and Uno, J. 1989b, "The behavior of prices in the Nikkei spot and futures market", *Journal of Financial Economics*, vol. 23, no. 2, pp. 363-383.

Brenner, M., Subrahmanyam, M.G. and Uno, J. 1990, "Arbitrage opportunities in the Japanese stock and futures markets", *Financial Analysts Journal*, vol. 46, no. 2, pp. 14-24.

Brock, W., Scheinkman, J.A., Dechert, W.D. and LeBaron, B. 1996, "A test for independence based on the correlation dimension", *Econometric Reviews*, vol. 15, no. 3, pp. 197-235.

Brock, W.A. and Kleidon, A.W. 1992, "Periodic market closure and trading volume: A model of intraday bids and asks", *Journal of Economic Dynamics and Control*, vol. 16, no. 3-4, pp. 451-489.

Brooks, C. and Garrett, I. 2002, "Can we explain the dynamics of the UK FTSE 100 stock and stock index futures markets?", *Applied Financial Economics*, vol. 12, no. 1, pp. 25-31.

Brooks, C., Rew, A.G. and Ritson, S. 2001, "A trading strategy based on the lead-lag relationship between the spot index and futures contract for the FTSE 100", *International Journal of Forecasting*, vol. 17, no. 1, pp. 31-44.

Brooks, C. 2014, *Introductory Econometrics for Finance*, 3rd edn, Cambridge University Press, Cambridge.

Buhler, W. and Kempf, A. 1995, "DAX index futures: Mispricing and arbitrage in German markets", *Journal of Futures Markets*, vol. 15, no. 7, pp. 833-859.

Campbell, J.Y. and Hentschel, L. 1992, "No news is good news. An asymmetric model of changing volatility in stock returns", *Journal of Financial Economics*, vol. 31, no. 3, pp. 281-318.

Caporin, M. 2007, "Variance (non)causality in multivariate GARCH", *Econometric Reviews*, vol. 26, no. 1, pp. 1-24.

Cappiello, L., Engle, R.F. and Sheppard, K. 2006, "Asymmetric dynamics in the correlations of global equity and bond returns", *Journal of Financial Econometrics*, vol. 4, no. 4, pp. 537-572.

Chan, F. and McAleer, M. 2002, "Maximum likelihood estimation of STAR and STAR-GARCH models: Theory and Monte Carlo evidence", *Journal of Applied Econometrics*, vol. 17, no. 5, pp. 509-534.

Chan, K. and Chung, Y.P. 1993, "Intraday relationships among index arbitrage, spot and futures price volatility, and spot market volume: A transactions data test", *Journal of Banking and Finance*, vol. 17, no. 4, pp. 663-687.

Chan, K. and Chung, Y.P. 1995, "Vector autoregression or simultaneous equations model? The intraday relationship between index arbitrage and market volatility", *Journal of Banking and Finance*, vol. 19, no. 1, pp. 173-179.

Chan, K. 1992, "A further analysis of the lead-lag relationship between the cash market and stock index futures market", *The Review of Financial Studies,* vol. 5, no. 1, pp. 123-152.

Chan, K., Chan, K.C. and Karolyi, G.A. 1991, "Intraday volatility in the stock index and stock index futures markets", *The Review of Financial Studies,* vol. 4, no. 4, pp. 657-684.

Chang, E.C., Cheng, J.W. and Pinegar, J.M. 1999, "Does futures trading increase stock market volatility? The case of the Nikkei stock index futures markets", *Journal of Banking and Finance,* vol. 23, no. 5, pp. 727-753.

Chang, J., Loo, J. and Chang, C. 1990, "The pricing of futures contracts and the arbitrage pricing theory", *Journal of Financial Research,* vol. 13, no. 4, pp. 297-306.

Chen, N.F., Cuny, C.J. and Haugen, R.A. 1995, "Stock volatility and the levels of the basis and open interest in futures contracts", *Journal of Finance,* vol. 50, no. 1, pp. 281-300.

Chen, Y. and Gau, Y. 2009, "Tick sizes and relative rates of price discovery in stock, futures, and options markets: Evidence from the Taiwan stock exchange", *Journal of Futures Markets,* vol. 29, no. 1, pp. 74-93.

Cheung, Y. and Ng, L.K. 1996, "A causality-in-variance test and its application to financial market prices", *Journal of Econometrics,* vol. 72, no. 1-2, pp. 33-48.

Chou, R.K. and Lee, J. 2002, "The relative efficiencies of price execution between the Singapore Exchange and the Taiwan Futures Exchange", *Journal of Futures Markets,* vol. 22, no. 2, pp. 173-196.

Christie, A.A. 1982, "The stochastic behavior of common stock variances. Value, leverage and interest rate effects", *Journal of Financial Economics,* vol. 10, no. 4, pp. 407-432.

Christodoulakis, G.A. and Satchell, S.E. 2002, "Correlated ARCH (CorrARCH): Modelling the time-varying conditional correlation between financial asset returns", *European Journal of Operational Research,* vol. 139, no. 2, pp. 351-370.

Chung, H., Sheu, H. and Hsu, S. 2010, "Trading platform, market volatility and pricing efficiency in the floor-traded and E-mini index futures markets", *International Review of Economics and Finance,* vol. 19, no. 4, pp. 742-754.

Chung, H.-L., Chan, W.-S. and Batten, J.A. 2011, "Threshold non-linear dynamics between Hang Seng stock index and futures returns", *The European Journal of Finance,* vol. 17, no. 7, pp. 471-486.

Comte, F. and Lieberman, O. 2000, "Second-order noncausality in Multivariate GARCH processes", *Journal of Time Series Analysis,* vol. 21, no. 5, pp. 535-557.

Cornell, B. and French, K.R. 1983a, "The pricing of stock index futures", *Journal of Futures Markets,* vol. 3, pp. 1-14.

Cornell, B. and French, K.R. 1983b, "Taxes and the pricing of stock index futures", *Journal of Finance,* vol. 38, pp. 675-694.

Covrig, V., Ding, D.K. and Low, B.S. 2004, "The contribution of a satellite market to price discovery: Evidence from the Singapore Exchange", *Journal of Futures Markets*, vol. 24, no. 10, pp. 981-1004.

Cox, J.C., Ingersoll, J.E.J. and Ross, S.A. 1981, "The relation between forward prices and futures prices", *Journal of Financial Economics*, vol. 9, pp. 321-346.

Cummings, J.R. and Frino, A. 2011, "Index arbitrage and the pricing relationship between Australian stock index futures and their underlying shares", *Accounting and Finance*, vol. 51, no. 3, pp. 661-683.

Cuthbertson, K., Taylor, M.P. and Hall, S. 1992, *Applied Econometric Techniques*, Harvester Wheatsheaf, New York; London.

Daal, E., Farhat, J. and Wei, P.P. 2006, "Does futures exhibit maturity effect? New evidence from an extensive set of US and foreign futures contracts", *Review of Financial Economics*, vol. 15, no. 2, pp. 113-128.

Darrat, A.F., Rahman, S. and Zhong, M. 2002, "On the role of futures trading in spot market fluctuations: Perpetrator of volatility or victim of regret?", *Journal of Financial Research*, vol. 25, no. 3, pp. 431-444.

de Jong, F. 2002, "Measures of contributions to price discovery: A comparison", *Journal of Financial Markets*, vol. 5, no. 3, pp. 323-327.

Diamond, D.W. and Verrecchia, R.E. 1987, "Constraints on short-selling and asset price adjustment to private information", *Journal of Financial Economics*, vol. 18, no. 2, pp. 277-311.

Dickey, D.A. and Fuller, W.A. 1979, "Distribution of the estimators for autoregressive time series with a unit root", *Journal of the American Statistical Association*, vol. 74, no. 366, pp. 427-431.

Dickey, D.A. and Fuller, W.A. 1981, "Likelihood ratio statistics for autoregressive time series with a unit root", *Econometrica*, vol. 49, no. 4, pp. 1057-1072.

Dolado, J.J. and Lütkepohl, H. 1996, "Making Wald tests work for cointegrated VAR systems", *Econometric Reviews*, vol. 15, no. 4, pp. 369-386.

Dwyer Jr., G.P., Locke, P. and Yu, W. 1996, "Index arbitrage and nonlinear dynamics between the S&P 500 futures and cash", *Review of Financial Studies*, vol. 9, no. 1, pp. 301-332.

Eitrheim, Ø. and Teräsvirta, T. 1996, "Testing the adequacy of smooth transition autoregressive models", *Journal of Econometrics*, vol. 74, no. 1, pp. 59-75.

Enders, W. 2010, *Applied Econometric Time Series*, 3rd edn, Wiley, Hoboken, N.J.

Engle, R.F. and Bollerslev, T. 1986, "Modelling the persistence of conditional variances", *Econometric Reviews*, vol. 5, no. 1, pp. 1-50.

Engle, R.F. and Granger, C.W.J. 1987, "Co-integration and error correction: Representation, estimation, and testing", *Econometrica*, vol. 55, no. 2, pp. 251-276.

Engle, R.F. and Kroner, K.F. 1995, "Multivariate simultaneous generalized ARCH", *Econometric Theory,* vol. 11, no. 1, pp. 122-150.

Engle, R.F. and Ng, V.K. 1993, "Measuring and testing the impact of news on volatility", *Journal of Finance,* vol. 48, no. 5, pp. 1749-1778.

Engle, R.F. and Sheppard, K. 2001, *Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH (Working paper 8554),* National Bureau of Economic Research.

Engle, R.F. and Yoo, B.S. 1987, "Forecasting and testing in co-integrated systems", *Journal of Econometrics,* vol. 35, no. 1, pp. 143-159.

Engle, R.F. 1982, "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation", *Econometrica,* vol. 50, pp. 987-1007.

Engle, R.F. 2002, "Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models", *Journal of Business and Economic Statistics,* vol. 20, no. 3, pp. 339-350.

Engle, R.F., Ito, T. and Lin, W. 1990, "Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market", *Econometrica*, vol. 58, no. 3, pp. 525-542.

Engle, R.F., Lilien, D.M. and Robins, R.P. 1987, "Estimating time varying risk premia in the term structure: The ARCH-M model", *Econometrica,* vol. 55, no. 2, pp. 391-407.

Fama, E.F. 1965, "The behavior of stock-market prices", *Journal of Business,* vol. 38, no. 1, pp. 34-105.

Ferris, S.P., Sen, N. and Yui, H.P. 2006, "Are fewer firms paying more dividends? The international evidence", *Journal of Multinational Financial Management,* vol. 16, no. 4, pp. 333-362.

Figlewski, S. 1984, "Hedging performance and basis risk in stock index futures", *Journal of Finance,* vol. 39, no. 3, pp. 657-669.

Flath, D. 2014, *The Japanese Economy,* 3rd edn, Oxford University Press, Oxford.

Fleming, J., Ostdiek, B. and Whaley, R.E. 1996, "Trading costs and the relative rates of price discovery in stock, futures, and option markets", *Journal of Futures Markets,* vol. 16, no. 4, pp. 353-387.

Forbes, C.S., Kalb, G.R.J. and Kofman, P. 1999, "Bayesian arbitrage threshold analysis", *Journal of Business and Economic Statistics,* vol. 17, no. 3, pp. 364-372.

Franses, P.H. and van Dijk, D. 2000, *Non-linear Time Series Models in Empirical Finance,* Cambridge University Press, Cambridge.

French, K.R. and Roll, R. 1986, "Stock return variances. The arrival of information and the reaction of traders", *Journal of Financial Economics,* vol. 17, no. 1, pp. 5-26.

Frino, A. and West, A. 2003, "The impact of transaction costs on price discovery: Evidence from cross-listed stock index futures contracts", *Pacific-Basin Finance Journal*, vol.11, no.2, pp. 139-151.

Frino, A., Harris, F.H.D., Lepone, A. and Wong, J.B. 2013, "The relationship between satellite and home market volumes: Evidence from cross-listed Singapore futures contracts", *Pacific-Basin Finance Journal*, vol. 24, pp. 301-311.

Fung, H., Leung, W.K. and Xu, X.E. 2001, "Information role of U.S. futures trading in a global financial market", *Journal of Futures Markets*, vol. 21, no. 11, pp. 1071-1090.

Fung, J.K.W. and Draper, P. 1999, "Mispricing of index futures contracts and short sales constraints", *Journal of Futures Markets*, vol. 19, no. 6, pp. 695-715.

Fung, J.K.W. and Yu, P.L.H. 2007, "Order imbalance and the dynamics of index and futures prices", *Journal of Futures Markets*, vol. 27, no. 12, pp. 1129-1157.

Fung, J.K.W. and Jiang, L. 1999, "Restrictions on short-selling and spot-futures dynamics", *Journal of Business Finance and Accounting*, vol. 26, no. 1-2, pp. 227-248.

Garbade, K.D. and Silber, W.L. 1979, "Dominant and satellite markets: A study of dually-traded securities", *The Review of Economics and Statistics*, vol. 61, no. 3, pp. 455-460.

Garman, M.B. and Klass, M.J. 1980, "On the estimation of security price volatilities from historical data", *Journal of Business*, vol. 53, no. 1, pp. 67-78.

Gay, G.D. and Jung, D.Y. 1999, "A further look at transaction costs, short sale restrictions, and futures market efficiency: The case of Korean stock index futures", *Journal of Futures Markets*, vol. 19, no. 2, pp. 153-174.

Ghosh, A. 1993, "Cointegration and error correction models: Intertemporal causality between index and futures prices", *Journal of Futures Markets*, vol. 13, no. 2, pp. 193-198.

Glosten, L.R., Jagannathan, R. and Runkle, D.E. 1993, "On the relation between the expected value and the volatility of the nominal excess return on stocks", *Journal of Finance*, vol. 48, no. 5, pp. 1779-1801.

Gonzalo, J. and Granger, C. 1995, "Estimation of common long-memory components in cointegrated systems", *Journal of Business and Economic Statistics*, vol. 13, no. 1, pp. 27-35.

Grammig, J., Melvin, M. and Schlag, C. 2005, "Internationally cross-listed stock prices during overlapping trading hours: Price discovery and exchange rate effects", *Journal of Empirical Finance*, vol. 12, no. 1, pp. 139-164.

Granger, C.W.J. and Teräsvirta, T. 1993, *Modelling Nonlinear Economic Relationships*, Oxford University Press, Oxford.

Granger, C.W.J. 1969, "Investigating causal relations by econometric models and cross-spectral methods", *Econometrica*, vol. 37, no. 3, pp. 424-438.

Granger, C.W.J. 1981, "Some properties of time series data and their use in econometric model specification", *Journal of Econometrics*, vol. 16, no. 1, pp. 121-130.

Granger, C.W.J. 1983, *Co-integrated Variables and Error-correcting Models*, University of California.

Granger, C.W.J., Robins, R. and Engle, R.F. 1986, "Wholesale and retail prices: Bivariate time series modeling with forecastable error variances", *Model Reliability,* pp. 1-17.

Green, C.J. and Joujon, E. 2000, "Unified tests of causality and cost of carry: The pricing of the French stock index futures contract", *International Journal of Finance and Economics,* vol. 5, no. 2, pp. 121-140.

Grünbichler, A., Longstaff, F.A. and Schwartz, E.S. 1994, "Electronic screen trading and the transmission of information: An empirical examination", *Journal of Financial Intermediation,* vol. 3, no. 2, pp. 166-187.

Guo, B., Han, Q., Liu, M. and Ryu, D. 2013, "A tale of two index futures: The intraday price discovery and volatility transmission processes between the China Financial Futures Exchange and the Singapore Exchange", *Emerging Markets Finance and Trade,* vol. 49, no. 0, pp. 197-212.

Hafner, C.M. and Herwartz, H. 2006, "A Lagrange multiplier test for causality in variance", *Economics Letters,* vol. 93, no. 1, pp. 137-141.

Haggan, V. and Ozaki, T. 1981, "Modelling nonlinear random vibrations using an amplitude-dependent autoregressive time series model", *Biometrika,* vol. 68, no. 1, pp. 189-196.

Hamao, Y., Masulis, R.W. and Ng, V. 1990, "Correlations in price changes and volatility across international stock markets", *The Review of Financial Studies,* vol. 3, no. 2, pp. 281-307.

Hamori, S. 2003, *An Empirical Investigation of Stock Markets: The CCF Approach,* Kluwer Academic Publishers.

Hansen, B.E. and Seo, B. 2002, "Testing for two-regime threshold cointegration in vector error-correction models", *Journal of Econometrics,* vol. 110, no. 2, pp. 293-318.

Harris, F.H.d., McInish, T.H. and Wood, R.A. 2002, "Common factor components versus information shares: A reply", *Journal of Financial Markets,* vol. 5, no. 3, pp. 341-348.

Harris, L. 1989, "The October 1987 S&P 500 stock-futures basis", *Journal of Finance,* vol. 44, no. 1, pp. 77-99.

Hasbrouck, J. 1995, "One security, many markets: Determining the contributions to price discovery", *Journal of Finance,* vol. 50, no. 4, pp. 1175-1199.

Hasbrouck, J. 2002, "Stalking the ‘efficient price’ in market microstructure specifications: An overview", *Journal of Financial Markets,* vol. 5, no. 3, pp. 329-339.

Hemler, M.L. and Longstaff, F.A. 1991, "General equilibrium stock index futures prices: Theory and empirical evidence", *Journal of Financial and Quantitative Analysis,* vol. 26, no. 3, pp. 287-308.

Ho, H. 2003, "Dividend policies in Australia and Japan", *International Advances in Economic Research,* vol. 9, no. 2, pp. 91-100.

Hong, Y.M. 2001, "A test for volatility spillover with application to exchange rates", *Journal of Econometrics,* vol. 103, no. 1-2, pp. 183-224.

Hsieh, W. 2004, "Regulatory changes and information competition: The case of Taiwan index futures", *Journal of Futures Markets,* vol. 24, no. 4, pp. 399-412.

Hull, J. 2008, *Fundamentals of Futures and Options Markets,* 6th edn, Pearson Prentice Hall, Upper Saddle River, N.J.

Iihara, Y., Kato, K. and Tokunaga, T. 1996, "Intraday return dynamics between the cash and the futures markets in Japan", *Journal of Futures Markets,* vol. 16, no. 2, pp. 147-162.

Jarque, C.M. and Bera, A.K. 1980, "Efficient tests for normality, homoscedasticity and serial independence of regression residuals", *Economics Letters,* vol. 6, no. 3, pp. 255-259.

Jiang, L., Fung, J.K.W. and Cheng, L.T.W. 2001, "The lead-lag relation between spot and futures markets under different short-selling regimes", *Financial Review,* vol. 36, no. 3, pp. 63-88.

Johansen, S. 1988, "Statistical analysis of cointegration vectors", *Journal of Economic Dynamics and Control,* vol. 12, no. 2, pp. 231-254.

Johansen, S. 1991, "Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models", *Econometrica,* vol. 59, no. 6, pp. 1551-1580.

Jonckheere, A.R. 1954, "A distribution free k-sample test against ordered alternatives", *Biometrika,* vol. 41, no. 1, pp. 133-145.

Jones, P.M. and Olson, E. 2013, "The time-varying correlation between uncertainty, output, and inflation: Evidence from a DCC-GARCH model", *Economics Letters,* vol. 118, no. 1, pp. 33-37.

Kang, S.H., Cheong, C. and Yoon, S. 2013, "Intraday volatility spillovers between spot and futures indices: Evidence from the Korean stock market", *Physica A: Statistical Mechanics and Its Applications,* vol. 392, no. 8, pp. 1795-1802.

Kato, K. and Loewenstein, U. 1995, "The ex-dividend-day behavior of stock prices: The case of Japan", *Review of Financial Studies,* vol. 8, no. 3, pp. 817-847.

Kawaller, I.G. 1987, "A note: Debunking the myth of the risk-free return", *Journal of Futures Markets,* vol. 7, no. 3, pp. 327-331.

Kawaller, I.G., Koch, P.D. and Koch, T.W. 1987, "The temporal price relationship between S&P 500 futures and the S&P 500 index", *Journal of Finance,* vol. 42, no. 5, pp. 1309-1329.

Kempf, A. 1998, "Short selling, unwinding, and mispricing", *Journal of Futures Markets,* vol. 18, no. 8, pp. 903-923.

Kendall, M.G. 1938, "A new measure of rank correlation", *Biometrika,* vol. 30, no. 1, pp. 81-93.

Khan, B. and Ireland, J. 1993, *The use of technology for competitive advantage: A study of screen v floor trading,* London Business School.

Kim, B., Chun, S. and Min, H. 2010, "Nonlinear dynamics in arbitrage of the S&P 500 index and futures: A threshold error-correction model", *Economic Modelling,* vol. 27, no. 2, pp. 566-573.

Kim, M., Szakmary, A.C. and Schwarz, T.V. 1999, "Trading costs and price discovery across stock index futures and cash markets", *Journal of Futures Markets,* vol. 19, no. 4, pp. 475-498.

Klimko, L.A. and Nelson, P.I. 1978, "On conditional least squares estimation for stochastic processes", *The Annals of Statistics,* vol. 6, no. 3, pp. 629-642.

Koch, N. 2014, "Dynamic linkages among carbon, energy and financial markets: A smooth transition approach", *Applied Economics,* vol. 46, no. 7, pp. 715-729.

Koch, P. and Yang, S. 1986, "A method for testing the independence of two time series that accounts for a potential pattern in the cross-correlation function", *Journal of the American Statistical Association,* vol. 81, no. 394, pp. 533-544.

Koch, P.D. 1993, "Reexamining intraday simultaneity in stock index futures markets", *Journal of Banking and Finance,* vol. 17, no. 6, pp. 1191-1205.

Koutmos, G. and Booth, G.G. 1995, "Asymmetric volatility transmission in international stock markets", *Journal of International Money and Finance,* vol. 14, no. 6, pp. 747-762.

Koutmos, G. and Tucker, M. 1996, "Temporal relationships and dynamic interactions between spot and futures stock markets", *Journal of Futures Markets,* vol. 16, no. 1, pp. 55-69.

Koutmos, G. 1996, "Modeling the dynamic interdependence of major European stock markets", *Journal of Business Finance and Accounting,* vol. 23, no. 7, pp. 975-988.

Kuserk, G.J. and Locke, P.R. 1993, "Scalper behavior in futures markets: An empirical examination", *Journal of Futures Markets,* vol. 13, no. 4, pp. 409-431.

Kwiatkowski, D., Phillips, P.C.B., Schmidt, P. and Shin, Y. 1992, "Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?", *Journal of Econometrics,* vol. 54, no. 1, pp. 159-178.

Lehmann, B.N. 2002, "Some desiderata for the measurement of price discovery across markets", *Journal of Financial Markets,* vol. 5, no. 3, pp. 259-276.

Lien, D. and Shrestha, K. 2009, "A new information share measure", *Journal of Futures Markets,* vol. 29, no. 4, pp. 377-395.

Lien, D. and Shrestha, K. 2014, "Price discovery in interrelated markets", *Journal of Futures Markets,* vol. 34, no. 3, pp. 203-219.

Lim, K. 1992, "Arbitrage and price behavior of the Nikkei stock index futures", *Journal of Futures Markets,* vol. 12, no. 2, pp. 151-161.

Lin, E., Lee, C. and Wang, K. 2013, "Futures mispricing, order imbalance, and short-selling constraints", *International Review of Economics and Finance,* vol. 25, pp. 408-423.

Ling, S. and McAleer, M. 2002, "Stationarity and the existence of moments of a family of GARCH processes", *Journal of Econometrics,* vol. 106, no. 1, pp. 109-117.

Liu, S. 2010, "Transaction costs and market efficiency: Evidence from commission deregulation", *The Quarterly Review of Economics and Finance,* vol. 50, no. 3, pp. 352-360.

Ljung, G.M. and Box, G.E. 1978, "On a measure of lack of fit in time series models", *Biometrika,* vol. 65, no. 2, pp. 297-303.

Low, A., Muthuswamy, J., Sakar, S. and Terry, E. 2002, "Multiperiod hedging with futures contracts", *Journal of Futures Markets,* vol. 22, no. 12, pp. 1179-1203.

MacKinlay, A.C. and Ramaswamy, K. 1988, "Index-futures arbitrage and the behavior of stock index futures prices", *The Review of Financial Studies,* vol. 1, no. 2, pp. 137-158.

MacKinnon, J.G. 1991, "Critical values for cointegration tests" in *Long-run Economic Relationships: Readings in Cointegration*, eds. Engle, R.F. and Granger, C.W.J. Oxford University Press, Oxford.

Mandelbrot, B. 1963, "The variation of certain speculative prices", *The Journal of Business,* vol. 36, no. 4, pp. 394-419.

Mantalos, P. and Shukur, G. 2010, "The effect of spillover on the Granger causality test", *Journal of Applied Statistics,* vol. 37, no. 9, pp. 1473-1486.

Martens, M., Kofman, P. and Vorst, T.C.F. 1998, "A threshold error-correction model for intraday futures and index returns", *Journal of Applied Econometrics,* vol. 13, no. 3, pp. 245-263.

McMillan, D.G. and Philip, D. 2012, "Short-sale constraints and efficiency of the spot-futures dynamics", *International Review of Financial Analysis,* vol. 24, pp. 129-136.

McMillan, D.G. and Speight, A.E.H. 2003, "Asymmetric volatility dynamics in high frequency FTSE-100 stock index futures", *Applied Financial Economics,* vol. 13, no. 8, pp. 599-607.

McMillan, D.G. and Speight, A.E.H. 2006, "Nonlinear dynamics and competing behavioral interpretations: Evidence from intra-day FTSE-100 index and futures data", *Journal of Futures Markets,* vol. 26, no. 4, pp. 343-368.

McMillan, D.G. 2005, "Smooth-transition error-correction in exchange rates", *North American Journal of Economics and Finance,* vol. 16, no. 2, pp. 217-232.

Michael, P., Nobay, A.R. and Peel, D.A. 1997, "Transactions costs and nonlinear adjustment in real exchange rates: An empirical investigation", *Journal of Political Economy,* vol. 105, no. 4, pp. 862-879.

Miller, M.H., Muthuswamy, J. and Whaley, R.E. 1994, "Mean reversion of Standard & Poor's 500 index basis changes: Arbitrage-induced or statistical illusion?", *Journal of Finance,* vol. 49, no. 2, pp. 479-513.

Neal, R. 1996, "Direct tests of index arbitrage models", *Journal of Financial and Quantitative Analysis,* vol. 31, no. 4, pp. 541-562.

Nelson, D.B. 1990, "Stationarity and Persistence in the GARCH(1,1) Model", *Econometric Theory,* vol. 6, no. 3, pp. 318-334.

Nelson, D.B. 1991, "Conditional heteroskedasticity in asset returns: A new approach", *Econometrica,* vol. 59, no. 2, pp. 347-370.

Osterwald-Lenum, M. 1992, "A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics", *Oxford Bulletin of Economics and Statistics,* vol. 54, no. 3, pp. 461-472.

Pagan, A.R. and Schwert, G.W. 1990, "Alternative models for conditional stock volatility", *Journal of Econometrics,* vol. 45, no. 1-2, pp. 267-290.

Pantelidis, T. and Pittis, N. 2004, "Testing for Granger causality in variance in the presence of causality in mean", *Economics Letters,* vol. 85, no. 2, pp. 201-207.

Phillips, P.C.B. and Perron, P. 1988, "Testing for a unit root in time series regression", *Biometrika,* vol. 75, no. 2, pp. 335-346.

Pope, P.F. and Yadav, P.K. 1994, "The impact of short sales constraints on stock index futures prices: Evidence from FTSE 100 futures", *The Journal of Derivatives,* vol. 1, no. 4, pp. 15-26.

Priestley, M.B. 1980, "State-dependent models: A general approach to non-linear time series analysis", *Journal of Time Series Analysis,* vol. 1, no. 1, pp. 47-71.

Puttonen, V. 1993, "Short sales restrictions and the temporal relationship between stock index cash and derivatives markets", *Journal of Futures Markets,* vol. 13, no. 6, pp. 645-664.

Richie, N., Daigler, R.T. and Gleason, K.C. 2008, "The limits to stock index arbitrage: Examining S&P 500 futures and SPDRS", *Journal of Futures Markets,* vol. 28, no. 12, pp. 1182-1205.

Rochet, J. and Tirole, J. 2003, "Platform competition in two-sided markets", *Journal of the European Economic Association,* vol. 1, no. 4, pp. 990-1029.

Rodrigues, P.M.M. and Rubia, A. 2007, "Testing for causality in variance under nonstationarity in variance", *Economics Letters,* vol. 97, no. 2, pp. 133-137.

Roope, M. and Zurbruegg, R. 2002, "The intra-day price discovery process between the Singapore Exchange and Taiwan Futures Exchange", *Journal of Futures Markets,* vol. 22, no. 3, pp. 221-242.

Ross, S.A. 1989, "Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy", *Journal of Finance,* vol. 44, no. 1, pp. 1-17.

Röthig, A. and Chiarella, C. 2007, "Investigating nonlinear speculation in cattle, corn, and hog futures markets using logistic smooth transition regression models", *Journal of Futures Markets,* vol. 27, no. 8, pp. 719-737.

Saikkonen, P. and Luukkonen, R. 1988, "Lagrange multiplier tests for testing non-linearities in time series models", *Scandinavian Journal of Statistics,* vol. 15, no. 1, pp. 55-68.

Schlusche, B. 2009, "Price formation in spot and futures markets: Exchange traded funds vs. index futures", *Journal of Derivatives,* vol. 17, no. 2, pp. 26-40.

Schwarz, T.V. and Szakmary, A.C. 1994, "Price discovery in petroleum markets: Arbitrage, cointegration, and the time interval of analysis", *Journal of Futures Markets,* vol. 14, no. 2, pp. 147-167.

Sentana, E. and Wadhwani, S. 1992, "Feedback traders and stock return autocorrelations: Evidence from a century of daily data", *The Economic Journal,* vol. 102, no. 411, pp. 415-425.

Sentana, E. 1995, "Quadratic ARCH Models", *The Review of Economic Studies,* vol. 62, no. 4, pp. 639-661.

Shiller, R.J. and Perron, P. 1985, "Testing the random walk hypothesis: Power versus frequency of observation", *Economics Letters,* vol. 18, no. 4, pp. 381-386.

Shleifer, A. and Vishny, R.W. 1997, "The limits of arbitrage", *Journal of Finance,* vol. 52, no. 1, pp. 35-55.

Shleifer, A. 2000, *Inefficient Markets: An Introduction to Behavioral Finance. Clarendon Lectures in Economics,* Oxford University Press, Oxford.

Shyy, G. and Shen, C.H. 1997, "A comparative study on interday market volatility and intraday price transmission of Nikkei/JGB futures markets between Japan and Singapore", *Review of Quantitative Finance and Accounting,* vol. 9, no. 2, pp. 147-163.

Shyy, G., Vijayraghavan, V. and ScottQuinn, B. 1996, "A further investigation of the lead-lag relationship between the cash market and stock index futures market with the use of bid/ask quotes: The case of France", *Journal of Futures Markets,* vol. 16, no. 4, pp. 405-420.

Sim, A.B. and Zurbreugg, R. 1999, "Intertemporal volatility and price interactions between Australian and Japanese spot and futures stock index markets", *Journal of Futures Markets,* vol. 19, no. 5, pp. 523-540.

Sims, C.A. 1972, "Money, income, and causality", *The American Economic Review,* vol. 62, no. 4, pp. 540-552.

Sofianos, G. 1993, "Index arbitrage profitability", *The Journal of Derivatives,* vol. 1, no. 1, pp. 6-20.

Soriano, P. and Climent, F.J. 2005, "Volatility transmission models: A survey"[Online]. Available from: SSRN: https://ssrn.com/abstract=676469.

Stephan, J.A. and Whaley, R.E. 1990, "Intraday price change and trading volume relations in the stock and stock option markets", *Journal of Finance,* vol. 45, no. 1, pp. 191-220.

Stoll, H.R. and Whaley, R.E. 1983, "Transaction costs and the small firm effect", *Journal of Financial Economics,* vol. 12, no. 1, pp. 57-79.

Stoll, H.R. and Whaley, R.E. 1987, *Expiration day effects of index options and futures,* Salomon Brothers Center for the Study of Financial Institutions, Graduate School of Business Administration, New York University.

Stoll, H.R. and Whaley, R.E. 1990, "The dynamics of stock index and stock index futures returns", *Journal of Financial and Quantitative Analysis,* vol. 25, no. 4, pp. 441-468.

Sutcliffe, C.M.S. 2006, *Stock Index Futures,* 3rd edn, Ashgate, Aldershot.

Takagi, S. 1989, "The Japanese equity market: Past and present", *Journal of Banking and Finance,* vol. 13, no. 4, pp. 537-570.

Tamakoshi, G. and Hamori, S. 2013, "Volatility and mean spillovers between sovereign and banking sector CDS markets: A note on the European sovereign debt crisis", *Applied Economics Letters*, vol. 20, no. 3, pp. 262-266.

Tao, J. and Green, C.J. 2012, "Asymmetries, causality and correlation between FTSE100 spot and futures: A DCC-TGARCH-M analysis", *International Review of Financial Analysis,* vol. 24, pp. 26-37.

Tao, J. and Green, C.J. 2013, "Transactions costs, index arbitrage and non-linear dynamics between FTSE100 spot and futures: A threshold cointegration analysis", *International Journal of Finance and Economics,* vol. 18, no. 2, pp. 175-187.

Tao, J. 2008, *A Re-examination of the Relationship between FTSE100 Index and Futures Prices*, PhD Dissertation, Loughborough University.

Taylor, N. 2007, "A new econometric model of index arbitrage", *European Financial Management,* vol. 13, no. 1, pp. 159-183.

Taylor, N., Dijk, D.V., Franses, P.H. and Lucas, A. 2000, "SETS, arbitrage activity, and stock price dynamics", *Journal of Banking and Finance,* vol. 24, no. 8, pp. 1289-1306.

Tchahou, H.N. and Duchesne, P. 2013, "On testing for causality in variance between two multivariate time series", *Journal of Statistical Computation and Simulation,* vol. 83, no. 11, pp. 2064-2092.

Teräsvirta, T. 1994, "Specification, estimation, and evaluation of smooth transition autoregressive models", *Journal of the American Statistical Association,* vol. 89, no. 425, pp. 208-218.

Terpstra, T. 1952, "The asymptotic normality and consistency of Kendall's test against trend, when ties are present in one ranking", *Indagationes Mathematicae,* vol. 14, no. 3, pp. 327-333.

Theissen, E. 2012, "Price discovery in spot and futures markets: A reconsideration", *European Journal of Finance*, vol. 18, no. 10, pp. 969-987.

Theobald, M. and Yallup, P. 1996, "Settlement, tax and non-synchronous effects in the basis of U.K. stock index futures", *Journal of Banking and Finance,* vol. 20, no. 9, pp. 1509-1530.

Toda, H.Y. and Yamamoto, T. 1995, "Statistical inference in vector autoregressions with possibly integrated processes", *Journal of Econometrics*, vol. 66, no. 1, pp. 225-250.

Tong, H. 1990, *Non-linear Time Series: A Dynamical System Approach*, Clarendon, Oxford.

Tsay, R.S. 1989, "Testing and modeling threshold autoregressive processes", *Journal of the American Statistical Association*, vol. 84, no. 405, pp. 231-240.

Tsay, R.S. 2005, *Analysis of Financial Time Series*, 2nd edn, Wiley, New York; Chichester.

Tse, Y. 1999, "Price discovery and volatility spillovers in the DJIA index and futures markets", *Journal of Futures Markets*, vol. 19, no. 8, pp. 911-930.

Tse, Y. 2001, "Index arbitrage with heterogeneous investors: A smooth transition error correction analysis", *Journal of Banking and Finance*, vol. 25, no. 10, pp. 1829-1855.

Tse, Y., Bandyopadhyay, P. and Shen, Y. 2006, "Intraday price discovery in the DJIA index markets", *Journal of Business Finance and Accounting*, vol. 33, no. 9, pp. 1572-1585.

Tse, Y.K. and Chan, W.S. 2010, "The lead-lag relation between the S&P500 spot and futures markets: An intraday-data analysis using a threshold regression model", *Japanese Economic Review*, vol. 61, no. 1, pp. 133-144.

Tse, Y.K. and Tsui, A.K. 2002, "A multivariate GARCH model with time-varying correlations", *Journal of Business, Economics and Statistics*, vol. 20, pp. 351-362.

Tse, Y.K. 1995, "Lead-lag relationship between spot index and futures price of the Nikkei Stock Average", *Journal of Forecasting*, vol. 14, no. 7, pp. 553-563.

Tsuji, C. 2007, "Explaining the dynamics of the Nikkei 225 stock and stock index futures markets by using the SETAR model", *Applied Financial Economics Letters*, vol. 3, no. 2, pp. 77-83.

van Dijk, D. and Franses, P.H. 1997, *Nonlinear error-correction models for interest rates in The Netherlands*, Erasmus University Rotterdam, Erasmus School of Economics, Econometric Institute.

van Dijk, D., Osborn, D.R. and Sensier, M. 2005, "Testing for causality in variance in the presence of breaks", *Economics Letters*, vol. 89, no. 2, pp. 193-199.

van Dijk, D., Teräsvirta, T. and Franses, P.H. 2002, "Smooth transition autoregressive models - A survey of recent developments", *Econometric Reviews*, vol. 21, no. 1, pp. 1-47.

Wahab, M. and Lashgari, M. 1993, "Price dynamics and error correction in stock index and stock index futures markets: A cointegration approach", *Journal of Futures Markets*, vol. 13, no. 7, pp. 711-742.

Wang, J. 2011, "Price behavior of stock index futures: Evidence from the FTSE Xinhua China A50 and H-share index futures markets", *Emerging Markets Finance and Trade*, vol. 47, no. 1, pp. 61-77.

Watanabe, T. 2001, "Price volatility, trading volume, and market depth: Evidence from the Japanese stock index futures market", *Applied Financial Economics*, vol. 11, no. 6, pp. 651-658.

White, H. 1980, "A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity", *Econometrica*, vol. 48, no. 4, pp. 817-838.

Wong, H. and Li, W.K. 1996, "Distribution of the cross-correlations of squared residuals in ARIMA models", *Canadian Journal of Statistics*, vol. 24, no. 4, pp. 489-502.

Yadav, P.K. and Pope, P.F. 1990, "Stock index futures arbitrage: International evidence", *Journal of Futures Markets*, vol. 10, no. 6, pp. 573-603.

Yadav, P.K. and Pope, P.F. 1994, "Stock index futures mispricing: Profit opportunities or risk premia?", *Journal of Banking and Finance*, vol. 18, no. 5, pp. 921-953.

Yang, J., Yang, Z.H. and Zhou, Y.G. 2012, "Intraday price discovery and volatility transmission in stock index and stock index futures markets: Evidence from China", *Journal of Futures Markets*, vol. 32, no. 2, pp. 99-121.

Zhong, M., Darrat, A.F. and Otero, R. 2004, "Price discovery and volatility spillovers in index futures markets: Some evidence from Mexico", *Journal of Banking and Finance*, vol. 28, no. 12, pp. 3037-3054.

Zivot, E. and Andrews, D.W.K. 1992, "Further evidence on the Great Crash, the oil-price shock, and the unit-root hypothesis", *Journal of Business and Economic Statistics*, vol. 10, no. 3, pp. 251-270.