The Time Series Momentum Effect: The Impact of Information Diffusion and Time-varying Risk

By

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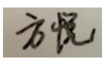
Author's signature  Date 31 March 2021

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Abstract

The time-series momentum effect is the phenomenon that past positive (negative) return assets tend to generate positive (negative) returns in subsequent periods. This thesis first analyses the relationship between the time-series momentum effect and information environment at the global asset class level. It then focuses on the US market and studies the time-series industry momentum effect and its interaction with information environment. Finally, the risk factors (macroeconomic environment, value premium, market volatility, as well as market liquidity) that influences asset performance are included as conditional variables to explain time-series industry momentum returns.

In the first empirical chapter, the impact of information diffusion on the time-series momentum effect is studied to test the Moskowitz et al. (2012) conjecture that time-series momentum return patterns are linked to information diffusion and show what specific information diffusion elements that influence time-series momentum returns. In the second empirical chapter, the existence of the time-series industry momentum effect is examined. This work is the first to study the time-series industry momentum effect. In the third empirical chapter, value premium, market volatility, and market liquidity, as conditional time-varying risks, are linked to time-series industry momentum returns. It is novel to introduce the three time-varying risk factors as conditional variables to examine the relationship between time-series industry momentum and time-varying risk.

The information diffusion measure grouped time-series momentum returns are calculated and multivariate regression analysis are conducted to decompose the influence of information diffusion on the long and short positions of time-series momentum returns. To study the relationship between time-varying risk and time-series industry momentum, Jordan (2012) style conditional CAPM macroeconomic models and factor analyses are utilised.

The main findings include: 1) negative information discreteness significantly influences time-series momentum returns and time-series industry momentum returns, whereas the influence of abnormal return volatility and abnormal turnover are insignificant; 2) time-series industry momentum returns are enhanced in up markets and weakened in down markets; and 3) the time-series industry momentum effect could be compensating for market liquidity risk rather than an anomaly.

Key words: Time-Series Momentum, Time-Series Industry Momentum, Anomaly, Value Premium, Market Volatility, Market Liquidity, Information Discreteness, Conditional Asset Pricing Models

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List of abbreviations

ARD/ARV	Abnormal Return Dispersion/ Abnormal Return Volatility
AT	Abnormal Turnover
BHS	Barberis et al. (1998) theory
CAPM	Capital Asset Pricing Model
CS	Cross Sectional
CSM	Cross-sectional Momentum
DHS	Daniel et al. (1998) theory
HML	Value premium
HS	Hong and Stein (1999) theory
ID	Information Discreteness
ID_{MAG}	Modified Information Discreteness
JT	Jegadeesh and Titman
LIQ	Market liquidity
TH	Long portfolio of standard time-series momentum strategy
TH (AH)	Long portfolio with positive/high abnormal return volatility
TH (AL)	Long portfolio with negative/low abnormal return volatility
TH (A_TH)	Long portfolio with positive/high abnormal turnover
TH (A_TL)	Long portfolio with negative/low abnormal turnover
TH (IH)	Long portfolio with positive/high information discreteness
TH (IL)	Long portfolio with negative/low information discreteness (continuous information)
TH (IH_{MAG})	Long portfolio with positive/high modified information discreteness
TH (IL_{MAG})	Long portfolio with negative/low modified information discreteness (continuous information)
TL	Short portfolio of standard time-series momentum strategy
TL (AH)	Short portfolio with positive/high abnormal return volatility
TL (AL)	Short portfolio with negative/low abnormal return volatility
TL (A_TH)	Short portfolio with positive/high abnormal turnover
TL (A_TL)	Short portfolio with negative/low abnormal turnover
TL (IH)	Short portfolio with positive/high information discreteness

TL (IL)	Short portfolio with negative/low information discreteness
TL (IH_{MAG})	Short portfolio with positive/high modified information discreteness
TL (IL_{MAG})	Short portfolio with negative/low modified information discreteness
TH (AH)-TL (AH)	Return difference between TH (AH) and TL (AH)
TH (AL)-TL (AL)	Return difference between TH (AL) and TL (AL)
TH (A_TH)-TL (A_TH)	Return difference between TH (A_TH) and TL (A_TH)
TH (A_TL)-TL (A_TL)	Return difference between TH (A_TL) and TL (A_TL)
TH (IH)-TL (IH)	Return difference between TH (IH) and TL (IH)
TH (IL)-TL (IL)	Return difference between TH (IL) and TL (IL)
TS	Time Series
TSM	Time-series Momentum
VOL	Market volatility

Chapter 1 Introduction

This introductory chapter demonstrates the motivation for conducting this study on the influence of three different elements of information diffusion and time-varying risk on time-series momentum effect. The three elements are: information discreteness, which captures whether information arrives in small pieces or large chunks; abnormal return volatility, which captures noise level in the prior asset information; and abnormal turnover, which captures the investor attention shocks. Next, this chapter shows the objective and contribution of this study via answering three key research questions. These questions are: 1) Is the time-series momentum effect influenced by information diffusion?; 2) Does the time-series industry momentum effect exist?, and if it exists, is it also influenced by information diffusion?; and 3) What is the role of time-varying risk in the time-series industry momentum effect? Finally, a thesis outline is shown as a roadmap for this study.

1.1 Motivation

1.1.1 First empirical chapter

Andrei and Cujean (2017) construct behavioural theories to explain the relationship between information percolation and time-series momentum return. They demonstrate that time-series momentum is induced by rumours that deviating prices from fundamentals, and then the increasing speed of information flow leads to more precise information, and therefore moving price back to its fundamental. Moskowitz et al. (2012) conjecture a potential relationship between time-series momentum and information diffusion. They show that in the futures market, the total return (composed of spot return and roll return) shocks cause cumulative total return increase in the first 12 months, with the pattern dissipating thereafter. A similar pattern is observed in spot return, but not in roll return, indicating that shocks in spot return alone induce the initial momentum, and later reversal, in cumulative total return. Since information diffusion is conjected to induce spot return changes, a potential link between information diffusion and the time-series momentum effect is established. However, which elements of information diffusion impact time-series momentum performance remains a question.

The relationship between information diffusion and cross-sectional momentum is established by the mainstream behavioural theories (i.e., Barberis et al., 1998; Daniel et al., 1998; Hong and Stein, 1999). However, the time-series momentum effect is a more direct application of the theories, as is argued by Moskowitz et al. (2012). The mainstream behavioural theories demonstrate that investors' slow responses to prior asset price information is due to slow information diffusion induce momentum returns. Unlike the cross-sectional momentum effect, which predicts that the assets outperforming (underperforming) other assets in the previous periods tend to continue to outperform (underperform) other assets in the following periods, the time-series momentum effect predicts that assets that generate positive (negative) returns in the previous periods tend to continue to generate positive (negative) returns in the following periods. Since these theories focus on the explanation on absolute asset return continuation of single asset rather than relative asset performance continuation across multiple assets, Moskowitz et al. (2012) argue that time-series momentum effect is a more direct application of these behavioural theories.

Motivated by the theoretical and empirical literature which shows the potential relationship between time-series momentum and information diffusion, the impact of three different elements of information diffusion on the time-series momentum effect is examined in the first empirical chapter, to specify which information diffusion elements have a significant effect on time-series momentum. The elements are information discreteness, which captures whether information arrives in small pieces or large chunks, abnormal return volatility, which captures noise level in the prior asset information, and abnormal turnover which captures investor attention level.

1.1.2 Second empirical chapter

Moskowitz and Grinblatt (1999) demonstrates the existence of the cross-sectional industry momentum effect, and attempts to use mainstream behavioural theories to explain cross-sectional industry momentum return patterns. The major difference between the cross-sectional and the time-series momentum effect is that the former is on the relative performance continuation, whereas the latter is on the absolute performance continuation. If behavioural explanations on momentum returns hold at the industry level, time-series industry momentum strategies are a more direct application of behavioural theories in comparison with cross-sectional industry momentum strategies. This is because these theories demonstrate investor reaction to prior absolute industry price changes rather than relative industry price changes.

Time-series momentum literature is initially focused on the broad asset class level, but has recently been extended to the individual stock level. To the best of the authors knowledge, this chapter is the first study on the existence of time-series industry momentum. The study of the existence of time-series industry momentum may contribute to cross-sectional industry momentum studies, time-series individual stock momentum studies, corporate finance studies, and asset allocation studies.

Firstly, it may contribute to cross-sectional industry momentum literature by providing evidence for future cross-sectional industry momentum studies on whether it is meaningful to study to the extent to which cross-sectional industry momentum returns are influenced by time-series industry momentum components.

Secondly, since individual firms are influenced by the corresponding industry performance as is shown in prior literature, the study of time-series industry momentum may provide time-series individual stock momentum researchers evidence as to whether to include the time-series industry effect in their study. This will help to identify whether it is individual firms, or the industry impact, that leads to time-series individual stock momentum.

Thirdly, industry performance is important in corporate finance literature (e.g., IPOs, M&As, SEOs, etc.) and the industry effect is adjusted when studying the stock performance around IPOs, M&As, and SEOs. The study of the time-series industry momentum effect may provide evidence for the researchers as to whether disentangling time-series industry momentum effect is required in future studies.

Finally, industry as a unit of analysis provides empirical evidence for tactical asset allocation recommendations for fund managers, or individual investors, who utilise sector rotation strategies. They may construct industry-neutral funds to eliminate the extra risk induced by time-series industry momentum and increase alpha by improving their sector rotation strategies.

1.2.3 Third empirical chapter

The study of the relationship between the time-series industry momentum effect and time-varying risk are motivated by the reasons below:

1) The industry return co-movement and time-series industry momentum return co-movement makes it natural to ask whether there is any common processes that drive the co-movements.

2) Time-series industry momentum returns are significantly positive in all horizons reported. It is enhanced in up markets and weakened in down markets. To find a possible explanation for time-series industry momentum returns (i.e., whether it is simple compensation for risk), the influence of time-varying risk on time-series industry momentum returns needs to be examined.

Since value premium, market volatility, and market liquidity are the risk factors in asset pricing models, and are related to market equity risk premium as well as economic growth, they are good candidates for the common processes that drives the industry return correlations. As is shown in asset price anomalies literature (e.g., Ferson et al. 1987; Hansen and Richard, 1987; Harvey, 1989), the CAPM model alone cannot explain asset price anomalies (e.g., size, value and momentum) due to the existence of risks other than market risk, and the model's static nature. Literature on conditional models (e.g., Avramove and Chordia, 2006; Ho and Hung, 2009; Jordan, 2012; Cooper and Maio, 2019) demonstrate that via allowing the variation of the factor loadings with conditional variables, conditional models have better explanatory power compared to static beta models. For example, Jordan (2012) demonstrates that the models conditioning on market factors increase the explanatory ratio of standard macroeconomic models in terms of explaining cross-sectional reversal. Therefore, the three risk factors outlined above are introduced to Jordan (2012) CAPM style macroeconomic model as conditional factors to study the relationship between time-series industry momentum effect and time-varying risk.

1.3 Objective and Contribution

This study focuses on understanding the impact of information diffusion and time-varying risk on the time-series momentum effect. The objective of this study is to answer the following research questions:

1) Is time series momentum effect enhanced under greater information diffusion (measured by three different elements of information diffusion: information continuity; abnormal return volatility; and abnormal turnover)?
2) Does the time-series industry momentum effect exist?
3) Is the time-series industry momentum effect influenced by information diffusion?
4) What is the impact of macroeconomic risk on the time-series industry momentum effect?
5) What is the role do time-varying risks play in the time-series industry momentum effect?

By answering these research questions, the contributions of this study to prior literature are as below.

First, by specifying what specific information diffusion elements significantly influence time-series momentum returns, it complements Moskowitz et al. (2012) by showing supporting evidence that information diffusion influences time-series momentum returns. However, not all elements of information diffusion have the same effect. Investors process information that arrives in small pieces differently from other information that is included in the prior asset price changes, whereas the noise contained in the information is treated in the same way as other information in the asset price changes.

Second, the demonstration of the time-series industry momentum effect, and the influence of negative information discreteness on time-series industry momentum returns, contributes to the literature for practitioners that fund managers may reduce strategy risk by constructing ID-neutral industry-neutral trading strategies. For sector rotation strategy traders, they may increase strategy alpha by adding low ID dimension and high time-series industry momentum dimension to their strategies.

Third, the study of value premium, market volatility, and market liquidity, as conditional time-varying risk factors in understanding the relationship between time-series industry momentum and time-varying risk, are novel. By demonstrating that market liquidity and macroeconomic risk jointly influence time-series industry momentum returns, the present study contributes to industry momentum literature by showing that time-series industry momentum may be compensating for market liquidity risk rather than an anomaly.

1.4 Thesis outline

Chapter 2 summarises the literature on cross-sectional individual momentum, cross-sectional industry momentum, and time-series momentum, and shows the research gaps in prior literature. Chapter 3 then demonstrates the construction of information diffusion measures, time-series momentum strategies, the application of Jordan 7 models, the models conditioning on time-varying factors, and the factor analysis.

Chapter 4 is the first empirical chapter which examines the impact of information diffusion on time-series momentum in global equity indices and commodity indices. The three elements of information diffusion are included: information discreteness; abnormal return volatility; and abnormal turnover.

Chapter 5 is the second empirical chapter, and examines time-series industry momentum effect and the impact of information diffusion on time-series industry momentum returns. Here, only two elements of information diffusion are included; information discreteness, and abnormal return volatility, due to industry data availability.

Chapter 6 is the third empirical chapter examining the relationship between time-series industry momentum and time-varying risk. Finally, Chapter 7 summarises the key findings, conclusions, and implications for the three empirical chapters. Limitations and recommendations for future research are also discussed.

Chapter 2 Literature review

Momentum is the phenomenon that firms/assets with previous good (bad) performance continue to perform well (badly). Reversal is the opposite, whereby a firm's performance changes in contrary to previous performance. Prior to the study on time-series momentum by Moskowitz, Ooi, and Pedersen (2012), momentum and reversal are studied in a cross-sectional context (i.e., cross-sectional momentum is the tendency that previous winner firms continue to be winners and previous loser firms continue to be losers). Unlike cross-sectional momentum and reversal, which are constructed based on relative performance among all firms/assets, time-series momentum and reversal only focus on individual firm/asset performance history. Accordingly, time-series momentum is the phenomenon that firms/assets with previous positive (negative) returns continue to generate positive (negative) returns.

This section presents the literature examining the empirical and theoretical development of cross-sectional momentum, cross-sectional industry momentum, momentum profit channels, and time-series momentum, as well as the conditional asset pricing approach that is adopted in momentum studies.

2.1 Cross-sectional momentum

Momentum was first documented in a seminal paper by Jegadeesh and Titman (1993). Through constructing portfolios that purchase previous winner stocks and short sell previous loser stocks, they find that momentum strategy generates average annual excess returns of 12.01% (Jegadeesh and Titman's (1993) momentum strategy is dubbed JT thereafter). After Jegadeesh and Titman's (1993) seminal study, researchers such as Rouwenhorst (1998) and Jegadeesh and Titman (2001) provide evidence for the global existence and persistence of momentum profits. The momentum effect spurred a flurry of research on its profit sources spanning the multiple decades.

Jegadeesh and Titman (1993) constructed momentum strategies based on practitioners' relative strength rules, proposing the acquisition (sale) of stocks with strong (weak) performance 3- to 12-month previous. To take into consideration the impact of price pressure on strategy returns, they include strategies that skip one week between the portfolio formation period and the portfolio holding period. They find the returns with one-week lag are slightly higher than the returns without one-week lag. They find significant returns of 12.01% per year from 1965 to 1989 for the strategy that acquires (short sells) winners (losers) based on past 6-month stock performance, and hold the portfolio for 6 months (without one-week gap). Similar significant returns are found in the remaining strategies that are based on different portfolio ranking and holding horizons. The strategy with the best performance is the 12-month formation period and 3-month holding period strategy, with on average 1.31%, and 1.49%, per month returns for the strategies without one-week gap, and with one-week gap, respectively. According to efficient market hypothesis, all future information has been contained promptly in the current stock prices and therefore stocks cannot be over- or under-priced. If the stocks are traded at its intrinsic value, it is impossible for investors to consistently outperform the market. However, the inclusion of 9 more years data in Jegadeesh and Titman (2001) still demonstrate the significant momentum returns. The existence of such lucrative trading strategies, based on the past relative price information challenges the efficient market hypothesis, indicating that investors underreact to price information.

To identify what induces momentum profits, Jegadeesh and Titman (1993) decompose the strategy profits to two systematic risk components (i.e., cross-sectional variation in stock returns and factor timing) and one firm specific component (i.e., serial correlation among firm returns). In addition, at the end of their paper, they propose two potential behavioural explanations; the first is positive feedback trading, and the second is short term investor underreaction and long-term investor overreaction. The authors argue that the firm specific component is the most potential momentum profit driver. However, the source of momentum effect is still debated. The next section presents the literature on source of momentum effect, according to the direction that is pointed out by Jegadeesh and Titman (1993).

2.1.1 Cross-sectional variation in stock returns

Cross-sectional variation in expected stock returns is one of the two systematic risk components decomposed by Jegadeesh and Titman (1993). The rationale is that due to the continuation of unconditional expected returns, past winners typically continue to outperform past losers. Conrad and Kaul (1998) supports that cross-sectional variation in expected stock returns is the main source of momentum profits. They assume that the mean stock returns are constant over the momentum strategy implementation period. They explain that, since expected returns are part of realised returns, expected returns in the next period are higher than average if the current realised returns are higher than average. Accordingly, past winners continue to outperform past losers in subsequent periods. The authors decompose returns into time-series components and cross-sectional variation in stock returns. They conduct bootstrap and Monte Carlo simulations of momentum strategy returns to exclude the influence of time-series components on momentum strategy returns while keeping the cross-sectional properties.

However, Jegadeesh and Titman (1993) did not find cross-sectional variation in expected stock returns as an important momentum profit driver. The authors use the average size and post-ranking betas of the 6-month/6-month relative strength portfolios to proxy for systematic risk. Results show that the post-ranking beta is higher than average for both winner and loser portfolios, with losers' beta higher than winners' beta, leading to a negative momentum portfolio beta. In addition, the market capitalisation of winners and losers are lower compared to average stocks, with losers' market capitalisation lower than that of the winners. These indicate that the profit of momentum strategies is not a result of the higher systematic risk stocks that tend to be picked by the strategies. The authors conclude that momentum profits are not due to the cross-sectional variation of stock returns.

Jegadeesh and Titman (2001) find further evidence that cross-sectional variation in stock returns is not likely to be main driver of momentum. Here, it is demonstrated that momentum losers perform significantly better than momentum winners in 13-60 months after the portfolio formation periods. If Conrad and Kaul (1998) argument that cross-sectional variation in stock returns is the cause of momentum profits is correct, the momentum profits should not disappear after months, let alone the existence of reversal.

Grundy and Martin (2001) directly test Conrad and Kaul's (1998) conjecture by controlling for stock own risk, which is to proxy stock expected return by stock ranking period mean return. They find that the non-January momentum return is still significant after adjusting for stock own risk, indicating that cross-sectional mean variation may not be the source of momentum profits.

2.1.2 Factor timing

Factor timing is the other systematic risk component decomposed in Jegadeesh and Titman (1993). Under the assumption that positive serial correlation exists in the factor portfolio returns, stocks with high factor sensitivity will be more likely to be chosen under the high conditional expectation of the factor portfolio returns. However, Jegadeesh and Titman (1993) find evidence that negative serial covariance for 6-month returns of equally weighted index, reducing momentum profits, eliminating factor timing as a candidate for momentum driver. By demonstrating the failure of the Fama French three factors in explaining momentum returns, Fama and French (1996) and Grundy and Martin (2001) support the view that risk-based models cannot explain cross sectional momentum effect.

Other researchers examine whether pricing factors such as macroeconomic risk, value premium, market volatility, and market liquidity can explain the momentum effect. The following subsections show the literature on macroeconomic risk, value premium, market volatility, and market liquidity as pricing factors, and the influence of macroeconomic risk on these three factors. Additionally, the role of macroeconomic risk, value premium, market volatility, and market liquidity in cross-sectional momentum literature will be explored.

Macroeconomic risk

Macroeconomic news is believed to systematically influence asset returns and thus macroeconomic variables are intuitive proxies for business cycle. However, the state variables are unidentified until Chen, Roll and Ross (1986) identify economic forces influencing stock returns to explain the co-movement among different assets. Influencing variables include unexpected inflation, expected inflation changes, term spread, and industrial production changes. This model is later utilised by researchers such as Griffin, Ji, and Martin (2003) in cross-sectional momentum studies. Additionally, motivated by the studies (e.g., Fama, 1981; Fama and Schwert, 1977; Keim and Stambaugh, 1986; Campbell and Shiller, 1988; Fama and French, 1988) establishing a relationship between macroeconomic variables and future stock market returns, Chordia et al. (2002) established a macroeconomic model which is composed of dividend yield, term spread, default spread, and the yield on the three-month T-bill to examine the relationship between momentum returns and macroeconomic risk. They term the macroeconomic factors in their model the ‘standard macroeconomic variables’, and their model is utilised by researchers such as Cooper, Gutierrez, and Hameed (2004) and Jordan (2012) in cross-sectional momentum and reversal studies.

To mitigate the problem of “missing predictor” problem, Maio and Philip (2015) derive six common processes (from 124 macroeconomic variables) via factor analysis to study the relationship between macroeconomic environment and stock returns. Maio and Philip (2018) argue that the macroeconomic variables that are purely linked to economic activities should be primary candidates for capturing systematic risk. Accordingly, in Maio and Philip’s (2018) study on economic activities and momentum returns, growth rate of industrial production index, capacity utilization rate changes, retail sales growth, and the growth in Conference Board Coincident Economic Index are chosen to be the components of the multifactor asset pricing model. These economic activity proxies are chosen because these risk factors have predictive power over stock market volatility and future economic activity. The variables are related to the business cycle and are not contingent on asset prices, and therefore the model contains more economic contents compared to other macroeconomic asset pricing models.

Researchers have long studied the cross-sectional momentum effect via asset pricing models. These models include macroeconomic variables as risk factors. However, the role of macroeconomic risk factors in cross-sectional momentum remains controversial. The lack of consensus on which macroeconomic asset pricing model specification to apply may partially lead to the controversial results. Chordia and Shivakumar (2002) demonstrate that momentum profits can be captured by lagged macroeconomic variables (dividend yield, term spread, default spread, and the yield on the 3-month T-bill), finding momentum profits to be positive (insignificantly negative) in the expansionary (recession) stages. However, Cooper, Gutierrez, and Hameed (2004) find that after microstructure adjustment, Chordia and Shivakumar's (2002) macroeconomic variables do not have explanatory power. Instead, they find that lagged market returns can explain the momentum effect, and that the relationship is non-linear. Here, momentum profits summit around the median level of market returns, starting to dissipate after the median. Jordan (2012) examines the relationship between macroeconomic risk (as one source of time-varying risk) and long-term cross-sectional contrarian effect from 1925 to 2005 in international markets (at country index level). Jordan includes January effect, market return and standard macroeconomic variables in his conditional models, finding that macroeconomic factors to be important in understanding contrarian profits whether or not trading costs are considered.

Griffin, Ji, and Martin (2003) use Chen, Roll, and Ross's (1986) macroeconomic factors (unexpected inflation, expected inflation changes, term spread, and industrial production changes), finding these macroeconomic factors not to explain momentum profits. Connolly and Stivers (2003) study cross-sectional momentum and reversals at equity indices, index futures and individual stock level, finding that abnormal turnover and abnormal return dispersion tend to coincide with macroeconomic news, playing an important role in understanding momentum and reversals. The cross-sectional momentum studied in Asness et al. (2013) is expanded to broader asset classes (stock market, currency market, government bonds, and commodity futures), demonstrating the negative relationship between default spread and momentum returns in all asset classes.

Though Maio and Philip (2015) find no significant influence of macroeconomic common processes on stock returns, a recent study on the impact of macroeconomic risk factors on cross-sectional price momentum and industry momentum by Maio and Philip (2018) shows macroeconomic risk factors to be related to economic activities (growth rate of industrial production index, capacity utilization rate changes, retail sales growth, and the growth in Conference Board Coincident Economic Index), capturing a significant part of cross-sectional individual momentum and industry momentum returns. They conclude that the reason that momentum winners outperform momentum losers is because the winners bear higher macroeconomic risk, and thus, need to be compensated via higher returns.

Value premium

Value premium is found to be negatively related to cross-sectional momentum returns (Asness et al. 2013). It is hypothesised as one of the risk factors by Fama and French (1992, 1993) and empirical evidence supports this hypothesis by showing that it can predict future market returns and economic growth. For example, economic growth (proxied by GDP growth) is found to be predicted by value premium (HML) and size effect (SMB), with the predictability still significant after controlling for market factor (Liew and Vassalou, 2000). Value spread (i.e., the difference between high and low book to market ratios), which strongly predicts HML returns, is found to be positively correlated with default spread (Cohen et al., 2003). Furthermore, value premium and dividend yield are found to predict market return from 1926 to 1991 (Kothari and Shanken, 1997). Finally, macroeconomic risk (i.e., innovations in economic growth expectations, inflation, the aggregate survival probability, the term structure of interest rates, and the exchange rate) can be partially captured by SMB and HML (Aretz et al., 2010). Vassalou (2003) model shows that HML and SMB are related to GDP growth.

Market liquidity

Prior literature shows that liquidity comoves across assets (Chordia et al., 2000; Huberman and Halka, 2001; Hasbrouck and Seppi, 2001; Brunnermeier and Pedersen, 2009), with market liquidity is studied as a systematic risk factor and introduced to asset pricing models. Amihud (2002) also proposes market liquidity as systematic risk and demonstrates the positive relationship between expected stock returns and expected market illiquidity, indicating illiquidity premium. The illiquidity in Amihud (2002) is the average of absolute stock daily return over the corresponding dollar volume of individual stocks, reflecting the daily absolute price changes per unit of dollar volume changes. Acharya and Pedersen (2005) introduces liquidity risk (proxied by Amihud 2002 illiquidity measure) to the capital asset pricing model, demonstrating a positive relationship between security return and liquidity risk, consistent with Amihud (2002). Pastor and Stambaugh (2003) adopt an alternative measure of market liquidity (equally weighted individual stock liquidity measures in a given month), finding abnormal returns in liquidity beta strategy, which is not explained by market, size, value or momentum factor. Thus, their findings also support market liquidity to be a priced factor, inducing around 50% of momentum profits. 40%-80% variation of cross-sectional momentum expected returns can be explained by market wide liquidity risk (Sadka, 2006).

Studies show strong links between market liquidity and the macroeconomic environment. Investor investment choices are influenced by business cycle and their participation is impacted by market liquidity (Naes et al., 2011). Chordia et al. (2001) demonstrates that market liquidity is influenced by interest rate and decreases in down markets. Naes et al. (2011) finds that market liquidity (LIQ) and macroeconomic environment (proxied by real GDP, unemployment rate, real consumption, and real investment) are strongly associated. Bernile et al. (2015) demonstrates the relationship between liquidity and business cycle at US state level.

Asness et al. (2013) on value and momentum strategies demonstrates the co-movement among value and cross-sectional momentum strategy returns in different asset classes across globe, showing a significantly positive relationship between cross-sectional momentum returns and market liquidity. A modest relationship between macroeconomic risk (measured in the aspect of business cycle, consumption, and default risk) and the co-movement is also found.

Market volatility

Market volatility, a proxy for market risk induced by market innovation, leads to changes in investment strategies and expected returns. Ang et al. (2006) and Adrian and Rosenberg (2008) model market volatility as an asset pricing factor and demonstrate that investors require higher returns to compensate the increase in risk induced by higher market uncertainty. This is consistent with Kim et al.'s (2004) finding that market volatility and equity premium are positively related.

Literature such as Schwert (1989) and Adrian and Rosenberg (2008) show the co-movement between market volatility and economic activity measures. Choudhry et al. (2016) demonstrates that stock market volatility predicts business cycle, which is proxied by industrial production growth. Market volatility is found to influence cross-sectional momentum returns and market volatility-controlled momentum strategies generate greater performance. Managing market volatility via reducing (increasing) position when market volatility is high (low) can generate higher abnormal returns (Moreira and Muir, 2017). This is similar to the influence of momentum strategy-specific volatility on momentum returns (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) find that momentum strategy-specific volatility-controlled strategies generate twice the Sharpe ratio of the uncontrolled counterparts.

2.1.3 Serial correlation among firm returns

The serial correlation among firm specific returns is the third potential momentum driver that is decomposed in Jegadeesh and Titman (1993). The first two components are systematic risk components, whereas the third is firm specific component. If this leads to momentum profits, it will challenge the efficient market hypothesis. Though prior literature shows evidence that firm specific returns may explain cross-sectional momentum returns, the definition of firm specific returns varies in different literature.

Jegadeesh and Titman (1993) find positive individual stock residuals in serial covariance of the market model, and argues that these residuals may be from stock underreaction to firm-specific information. In addition, they find a negative relationship between the lagged squared market portfolios returns and momentum profits, eliminating the chance that the lead-lag effect is an important driver of momentum returns. Therefore, they conclude that market underreaction to firm specific information is a potential source of momentum profitability.

Grundy and Martin (2001) also support that firm specific information is a main source of momentum returns. They disentangle returns related to Fama-French risk factors and define the remaining returns as stock-specific returns. Based upon stock specific returns, they construct the momentum strategy, finding this strategy to generate significantly more returns than traditional momentum strategies, which are based on total returns. Consequently, they conclude that momentum returns are driven by stock-specific returns.

Moskowitz and Grinblatt (1999) utilise the industry components to represent the source of correlation between stocks other than Fama French 3 risk factors, finding industry components to be the main drivers of momentum returns; this will be discussed in more detail in Section 2.2.

George and Hwang (2004) construct a 52-week high strategy built upon investor anchoring bias and cross-sectional momentum. The rationale is that the prices that are close to, or at a 52-week high, usually coincide with good news and slow investor reaction to the news. In addition, compared to previous returns (e.g., six months) utilised in JT, the 52-week high is more readily available and popular among investors. Their strategy generates 1.06% outside January abnormal returns per month (0.46% for JT) from July 1963 to December 2001.

2.1.4 Information diffusion: mainstream behavioural models

There are three mainstream behavioural explanations of momentum and reversal. Firstly, Daniel, Hirshleifer and Subrahmayam's (1998) overreaction theory (hereafter dubbed DHS), which is based on investor overconfidence and biased self-attribution, whereas Barberis et al.'s (1998) underreaction and overreaction theory (hereafter dubbed BSV) is based on investor conservatism and representativeness bias. Finally, Hong and Stein's (1999) united underreaction and overreaction theory (hereafter dubbed HS) is based on the interaction between two groups of investors with heterogeneous beliefs.

Daniel, Hirshleifer and Subrahmayam (1998) construct their model based on the two psychological findings. First, investors tend to be overconfident on their ability to access and process private information (investor overreaction). Second, investors update their level of confidence asymmetrically. That is, the increase in confidence caused by confirming information is larger than the decrease in confidence caused by disconfirming information (biased self-attribution). This occurs when the new information is consistent with private information, with investors ascribing it to their advanced skill. However, when the new information arrived is against their private information, they ascribe it to external noise. Therefore, given an unbiased starting point of investor ability belief, when the newly arrived public information is in the same direction as they predicted based on their private information, their confidence levels increase. On the contrary, if the direction is different from their judgement, the confidence levels decrease on a much smaller scale compared to the scale of increase. Thus, the arrival of public information leads to short term overreaction. When more disconfirming information comes and prices gradually reverse to fundamentals, reversal follows in the long run.

Barberis et al.'s (1998) model is motivated by investor conservatism and representativeness bias. In this model, it is assumed that there is only one risk neutral investor, which represents the aggregate expectation of all investors and one asset with earnings following random walk process. They also assume that the investor does not know that firm earnings follow random walk process and their belief on firm earnings shifts between two different states; mean reverting, and trending. When the investor believes that the firm is in a certain state, it is more likely that the next period the investor will stick to the same state. However, when new information arrives, the judgement will be updated. Here, if the new information is in the same direction as the previous information, the investor considers the firm in the trending state, whereas if the new information arrives in the opposite direction to the previous information, the investor regards the firm in the mean reverting state.

Psychology literature on conservatism demonstrates that investors tend to be slow to update their beliefs with the new information. This insufficient (not prompt enough) update in beliefs leads to an underreaction to information. Psychology literature on representativeness bias shows that investors tend to underweight the weight and overweigh the strength of the information. That is, investors underreact to information that appears with a higher probability, but with moderate scale, and overreact to information with an extreme scale but with low probability of occurrence. For example, they may believe that future firm performance will follow the trend of the most recent extreme earnings performance, even if the most recent extreme performance is only a small portion of the longer-term past firm performance; this belief leads to investor overreaction. Investors may also not react adequately to the new information with moderate scale, even though such information occurs with a much higher probability compared to the extreme information; this leads to investor underreaction. The model attributes short-term price continuation to initial underreaction to earnings news, due to investor conservatism and representativeness bias, and the later reversal due to firms' failure to meet the expected earnings targets.

Unlike Daniel, Hirshleifer and Subrahmayam's (1998) and Barberis et al.'s (1998) models which focus on investor cognitive bias, Hong and Stein's (1999) model only demonstrates the interaction of two different groups of boundedly rational investors, termed "news-watchers" and "momentum traders". Their model is based on three assumptions. First, they assume that news-watchers only utilise a fundamental analysis based on private information, and do not utilise current or past price information. Second, they assume that momentum traders stick to simple strategies which only utilise past price information without considering other factors. Third, they assume that news watchers react slowly to information, as private information diffuses slowly amongst them. Under these assumptions, they first analyse the scenario that there are only news watchers, and demonstrate that new information travels slowly among news watchers. Consequently, underreaction to information occurs all the time. Next, they add momentum traders to form a second scenario, and demonstrate that since momentum traders make investment decisions according to past price, they initially cancel out the underreaction caused by slow information diffusion among news watchers. At later stage, when underreaction has been completely negated, overreaction follows, since momentum traders only condition on past price and stick to a univariate strategy. Thus, Hong and Stein's model demonstrates that "momentum traders" gain profit from initial price underreaction due to a slow response to new information by "news-watchers". Following momentum, an overreaction created by the univariate strategy implementation of "momentum traders", leading to future price corrections, and thus, reversals.

Problems of behavioural theories

Though mainstream behavioural theories seem to fit the pattern of medium-term momentum (i.e., 3 to 12 months) and long-term reversal, Jegadeesh and Titman (2001) demonstrate that the reversals are weak in large firms, and weak in certain years (i.e., subperiod 1965-1981 and subperiod 1982-1998). Here, momentum profit magnitude did not witness a significant difference compared to other periods. By demonstrating the evidence that 52-week high strategies can generate significant momentum profits that are not subject to reversals, George and Hwang (2004) challenge the behavioural explanations that are based on the presumption that momentum and reversal are based on the same underlying process. They argue that cross-sectional momentum and reversals are induced by different underlying drivers. Coval and Stafford (2007) document that involuntary transactions are followed by reversals, while voluntary transactions by unconstrained funds are not. George and Hwang (2007) find that locked-in capital gains can capture long-term return reversal in the US stock market, and that reversals do not occur in the Hong Kong stock market where tax is not imposed on investment income. Lou (2012) finds that the timing and magnitude of reversals are induced by the net return effect of momentum and reversal; the two are offsetting and separate process. Da et al. (2014) find a strong return continuation following continuous information with no evidence of long-horizon reversal.

In addition, Moskowitz et al. (2012) outlines that behavioural theories fit more in momentum strategies in a time-series context compared to a cross-sectional context. This is because the theories focus on explaining the return continuation of single asset rather than the relative performance continuation among multiple assets. By purchasing previous positive return assets and short selling previous negative return assets, Moskowitz et al. (2012) find a time-series momentum effect in bond futures, currency, equity index, and commodity market across different countries, both within and across, each asset classes.

Finally, mainstream models fail to point out the source of information that induces investor underreaction or overreaction. Though a large body of empirical literature in cross-sectional momentum attempts to figure out the source, no current literature examines this in time-series context. The relevant empirical studies on information diffusion and cross-sectional momentum will be shown in the following subsection.

Empirical findings on information diffusion

Empirical studies on the relationship between information diffusion and cross-sectional momentum returns are motivated by psychology literature. Investors are found to be overconfident, self-attributed, over conservative and are subject to representativeness bias (Barberis et al., 1998; Daniel et al., 1998; Hong and Stein, 1999). The theoretical influence of these attributes on investment decision making, as well as on asset prices, is discussed in the previous section. The theoretical frameworks suggest a positive relationship between asset returns and information diffusion (e.g., Hong and Stein, 1999). Accordingly, this section is focused on the empirical findings regarding information diffusion and momentum returns.

A bountiful of proxies for information diffusion are established in the extant literature. Earnings surprises (Chan, Jegadeesh, and Lakonishok, 1996), abnormal turnover (Connolly and Stivers, 2003), abnormal return dispersion (Connolly and Stivers, 2003), order imbalance (Chordia, Roll, and Subrahmanyam, 2002; Andrade, Chang, and Seasholes, 2008; Lou, 2012), consumption growth shocks (Li and Zhang, 2016), price jumps (Jiang and Zhu, 2017) are examples of these proxies.

There is a well-established link between information diffusion and cross-sectional momentum and reversal. Chan et al. (1996) establishes three earnings surprises measures, and document that the slow reaction to previous stock returns and earnings news are jointly responsible for momentum returns. Chordia et al. (2002) show that investors tend to be contrarian traders by demonstrating an increase (decrease) in order imbalance after down (up) market. Market reversals occur following days with high negative order imbalance and significant negative returns. Based on Taiwan Stock Exchange data, Andrade et al. (2008) find that institutional trading imbalance can be used to predict short-term stock returns and return reversals. Their portfolios, constructed on weekly trading imbalances, produce average weekly returns of 242 basis points. These returns are via short selling top-trading-imbalance-quintile stocks, and purchasing bottom-trading-imbalance-quintile stocks and reversals (125 basis points) toward pre-formation level are found 10-weeks following the portfolio formation period.

Investors are found to underreact to price signals more under more information diffusion. Zhang (2006) finds that under greater information uncertainty, positive (negative) news is accompanied by greater positive (negative) returns. Da et al. (2014) construct information discreteness, motivated by psychology literature (Gino and Bazerman, 2009). In Gino and Bazerman (2009), human beings are found to underreact to negative information (moral degradation) with the same direction consistently in small scales, and react properly to negative information that comes in large scale abruptly. Based on this phenomenon, Da et al. (2014) propose that investors tend to underreact to price information that arrives in small pieces. Here, the cross-sectional momentum effect is enhanced under continuous information (5.94% monthly return), and is weakened under discrete information (-2.07% monthly returns). Furthermore, they demonstrate that following continuous information, prominent momentum returns occur without reversals.

Connolly and Stivers (2003) study cross-sectional momentum and reversals at equity indices, index futures and individual stock level. To better understand investors' unanticipated portfolio reallocation behaviour, they choose abnormal turnover and abnormal return dispersion as proxies. The reason they want to have more in depth understanding of investor reallocation behaviour is because it is vital to understand the relationship between return and volume. They define abnormal turnover as the turnover residuals after adjusting for autoregressive components and movements with the market in terms of the signs and magnitude of portfolio returns. Connolly and Stivers (2003) define abnormal return dispersion as the return dispersion residuals after adjusting for autoregressive components and the part of the return dispersion that comoves with the market in terms of portfolio return sign and magnitude. They choose weekly horizons to increase sample size, and eliminate irrelevant daily return and trading volume fluctuations. They find that abnormal turnover and abnormal return dispersion tends to coincide with macroeconomic news, and this plays an important role in understanding momentum and reversals.

2.1.5 Trading cost

Lesmond et al. (2004) defend market efficiency by demonstrating the high trading costs incurred in the momentum trading and demonstrate that after accounting for trading costs, the momentum effect disappears. They argue that the trading costs that are estimated in Jegadeesh and Titman (1993) are based on NYSE trades as far back as early 1985, and that Jegadeesh and Titman (1993) only calculate trade weighted mean commission and market impact. However, this does not apply to other non-NYSE stocks, and the trading costs are not time invariant. In addition, bid-ask spread, taxes, short-sale costs and holding period risk are not taken into consideration. Among these factors, the missing of short-sale costs in momentum return calculations may heavily influence momentum returns, since the momentum returns from the short positions are the main components of momentum returns. Furthermore, they argue that the trading intensive feature of momentum trading deteriorates the influence of trading costs on portfolio returns. Since momentum strategies only trade extreme performers, the less liquid feature of these stocks pushes the trading costs further up. Lesmond et al. (2004) estimate over 1.5% per trade as appropriate trading costs after taking into account all the factors they propose for Jegadeesh and Titman (1993) 6-month strategies.

The role of trading cost is also discussed in currency market momentum studies. Menkhoff et al. (2012) studied cross-sectional momentum in the currency market and find that the momentum profits deteriorate after taking into consideration trading costs, although trading costs cannot completely explain momentum profits. By demonstrating a negative relationship between portfolio size and abnormal returns via the construction of liquidity-weighted and hybrid liquidity/value-weighted strategies, Korajczyk and Sadka (2004) argue that though trading cost cannot explain the existence of the momentum effect, it can explain the persistence of it.

2.2 Cross-sectional Industry momentum

Cross-sectional momentum literature mostly focuses on individual stock performance. Industry performance plays an important role in corporate finance literature in terms of IPO and SEO markets, Merges and Acquisitions (M&A), investment, and financial policy decisions, arousing the interest of studying cross-sectional momentum effect at industry level; this is termed industry momentum (Moskowitz and Grinblatt, 1999). To differentiate industry momentum from time-series industry, the term ‘cross-sectional industry momentum’ will be utilised. Cross-sectional industry momentum is the phenomenon that prior winner industries tend to outperform prior loser industries in the near future. Cross-sectional industry momentum strategies generate statistically significant monthly returns and are found to drive a significant portion of cross-sectional individual stock momentum returns in prior literature (e.g., Moskowitz and Grinblatt, 1999; Scowcroft and Sefton, 2005).

Moskowitz and Grinblatt (1999) find that industry momentum is more significant than individual stock momentum returns, but lower in return scale. Contrary to momentum returns which are mainly driven by short portfolio returns, industry momentum is mainly induced by long portfolio returns. Though long-term (over 12-month holding period) return dissipation and reversal are observed in industry momentum, short-term (one month horizon) positive returns are observed in cross-sectional industry momentum, as opposed to the short-term reversal that is demonstrated in individual stock momentum literature. Industry momentum still exists after taking into consideration Fama French factors, individual stock momentum effect, cross-sectional variation in unconditional mean returns, and microstructure.

Moskowitz and Grinblatt (1999) decompose momentum return into 4 components. These are cross-sectional stock expected return variation, serial correlation among stocks induced by Fama French 3 factors, industry components, and firm specific components. Cross-sectional stock expected return variation is conjectured in Conrad and Kaul (1998) to be the main source of individual stock momentum returns. However, this is rejected by other authors (see Jegadeesh and Titman, 1993; Jegadeesh and Titman, 2001; Grundy and Martin, 2001).

Industry components are chosen by Moskowitz and Grinblatt (1999) to represent the source of correlation between stocks. Serial correlation among stocks caused by factors other than Fama French 3 factors, and/or firm specific factors, are potential sources of momentum returns (Jegadeesh and Titman, 1993). Moskowitz and Grinblatt (1999) test the profit source of 6-month ranking period and 6-month holding period momentum returns. They use NYSE, Amex, and Nasdaq stocks, and define the top and bottom 30% performers in the past 6 months as ‘winners’ and ‘losers’, respectively. Their data is based on 20 monthly-formed value weighted US industry portfolios from 1963 to 1995, with the number of stocks in each industry varying from 25 to 230. They demonstrate that after deducting the average returns of the industry that the stock belongs to from the stock returns, momentum strategy returns decrease significantly. They further demonstrate that random industry momentum replaces stocks in industry i with the stocks that are located above and below the given stock, after ranking the performance of all stocks. In this means, the random industry portfolios contain similar stocks to industry portfolios, but the components are from different industries. Therefore, the random industry momentum strategy is supposed to generate insignificant returns if the industry component is the driver of momentum returns. They find that this strategy generates insignificant returns, indicating that momentum is mainly driven by the industry component. They further construct three other industry neutral portfolios, generating consistent result that the industry component primarily drives momentum effects.

However, Grundy and Martin (2001) argue that industry momentum per se is not sufficient to explain momentum profits. They find that the month following the portfolio formation period influences the significance of portfolio returns. For example, for the 6-6 strategy (i.e., 6-month ranking period and 6-month holding period), value weighted real industry momentum returns are insignificant with one-month intervals between portfolio formation period and portfolio holding period, yet this is significant when there is no interval. They further show that skipping one month (or not) between the portfolio formation period and holding period may influence the significance of random industry returns. For example, the value-weighted random industry strategy with an 11-month ranking period, without skipping one month, generates insignificant returns. However, random industry returns can be significantly positive in a strategy with the same ranking period with a one-month interval. The random industry momentum strategies are expected to generate insignificant returns if industry momentum is the main driver of momentum returns. Therefore, this finding is not consistent with Moskowitz and Grinblatt's (1999) conclusion that the industry component mainly drives momentum returns. Thus, Grundy and Martin (2001) conclude that industry momentum per se is not sufficient to explain momentum returns. This is supported by evidence provided by Chordia and Shivakumar (2002), who follows Grundy and Martin (2001) in terms of data selection and portfolio formation. They show that after controlling for industry components, individual stock momentum is still significantly positive.

The noticeable differences between the Moskowitz and Grinblatt's (1999) study, and Grundy and Martin (2001) and Chordia and Shivakumar's (2002) are that: 1) the former use broader dataset (NYSE, Amex and Nasdaq), with the latter two only using NYSE and Amex stocks, and 2) The former defines the top and bottom 30% as momentum winners and losers, whereas the latter two define top and bottom 10% as momentum winners and losers. Among these differences, the different momentum winner and loser definitions may influence whether industry momentum explains the individual momentum effect. According to prior cross-sectional momentum literature, extreme performers generate more extreme returns than average performers, and winner minus loser returns, utilising the top and bottom 10% performers to generate higher and more significant returns, than winner minus loser returns, utilising less extreme performer groups, such as the top and bottom 30% performers.

Hou (2007) shows that slow information diffusion, induced by investor underreaction to information contained in prior industry returns, is a potential explanation of the industry lead-lag effect. The author shows that information is incorporated slower in small firm stock prices than in large firm stock prices in the same industry, and that this intra-industry lead-lag effect, in terms of firm size, is more prominent under negative information. In addition, other information uncertainty proxies, such as analyst forecast coverage, institutional ownership, trading volume, firm market share in industry, and analyst dispersion, also play a role in the intra-industry lead-lag effect. This is consistent with the findings in information diffusion literature that investors tend to underreact to price changes in uncertain and dispersed information environments (Zhang, 2006; Da et al., 2014).

The relationship between industry momentum and time-varying risk are explored in prior literature. Chordia and Shivakumar (2002) show that both individual stock momentum and industry momentum can be subsumed by common risk, proxied by standard macroeconomic risk factors that are related to the business cycle. The relationship between individual stock momentum and macroeconomic risk are not induced by the industry component in individual stocks, as is shown by insignificant negative mean unexplained returns after regressing industry adjusted momentum returns on lagged standard macroeconomic risk factors. Maio and Philip (2018) find that the exposure to time-varying risks, such as macroeconomic risk, increases monotonically with industry returns. Maio and Philip (2018) argue that the reason that cross-sectional individual, as well as industry momentum winners, outperform momentum losers, is because the winners bear higher macroeconomic risk. Thus, this needs to be compensated via higher returns.

2.3 Time-series momentum

Among the literature on momentum effects, time-series momentum strategy (Moskowitz et al., 2012) points in a completely different direction. Unlike JT cross-sectional momentum strategy, based on the rationale that winners (losers) will continue to be winners (losers), and the later studies on cross-sectional momentum profit drivers, time-series momentum strategies are based on the prediction that positive (negative) returns are followed by positive (negative) returns. This is based on the argument that the behavioural explanations of momentum profits fit better to a time-series context. Behavioural models focus on explaining the return continuation of a single asset rather than the relative performance continuation among multiple assets. By purchasing previous positive return assets, and short selling previous negative return assets, and scale the portfolios to meet the target of 40% ex ante annual volatility, Moskowitz et al. (2012) find a time-series momentum effect in bond futures, currency, equity index, and commodity market across different countries, within and across each asset classes. The reason they scale the portfolio is to eliminate the influence of the difference in volatility in different asset classes on portfolio returns. Their study arouses the interest of many researchers who later contribute to the study on time-series momentum phenomenon. Before moving on to the development of time-series momentum, I will demonstrate the difference between time-series momentum and cross-sectional momentum in the next section.

2.3.1 The similarities and differences between TSM and CSM

Cross-sectional and time-series momentum strategy are similar in terms of two aspects. First, they are both trend-following strategies. The former is constructed based upon the prediction that cross-sectional winners (losers) tend to be cross-sectional winners (losers) in the near future, and the latter is constructed based on the prediction that time-series winners (losers) tend to be time-series winners (losers) in the near future. Second, the return of both strategies follows the pattern of medium-term (3- to 12-month holding period) momentum and long-term (over one year holding period) reversal. Moskowitz et al. (2012) document that, like cross-sectional momentum, which suffers from reversal, time-series reversals also occur 12 months after the portfolio formation period in their time-series momentum strategy. They argue that the information dissemination effect and hedging pressure are jointly responsible for the time-series momentum effect in the futures market. In addition, they demonstrate that spot price changes, that are mainly due to information shocks, are subject to overreaction, whereas hedging pressure are not.

Cross-sectional and time-series momentum are associated, but not the same. Cross-sectional winners (losers) are more likely to be overlapping with time-series winners (losers), since they are more likely to be located in positive (negative) return groups. Therefore, the two strategy returns are highly correlated, as is demonstrated in Moskowitz et al. (2012). However, Moskowitz et al. (2012) regress time-series momentum returns on cross-sectional momentum returns, finding that cross-sectional momentum returns cannot fully explain time-series momentum returns. In addition, Goyal and Jegadeesh (2017) compare the dissimilarities between cross-sectional and time-series strategies by scaling both strategies. They find that scaled cross-sectional strategies significantly outperform scaled time-series strategies.

The dissimilarities of the two strategies are determined by the nature of the strategy constructions. First, cross-sectional momentum is based on the relative performance among all the firms/assets, whereas time-series momentum only focuses on the absolute performance of an individual firm/asset. Second, cross-sectional momentum strategies are zero net strategies, which means that the long positions can be fully financed by the proceeds from the short positions. However, there are differences between long and short position value in time-series strategies. Goyal and Jegadeesh (2017) find that time-series strategies are subject to time-varying net long positions, whereas cross-sectional strategies are zero-financing strategies.

2.3.2 The Development of Time-series Momentum

Moskowitz et al. (2012) find that TSM outperforms CSM and may help to understand CSM profitability and fully explain CSM. Thus, they recommend TSM as a risk factor in multifactor asset pricing models to explain asset pricing anomalies. Later literature extends time-series momentum studies in many ways, for example, into broader asset classes and longer sample periods; comparing the profitability of time-series momentum strategies and cross-sectional momentum strategies; exploring the profit driver of time-series momentum strategies; analysing the relationship between the different strategy constructions and the performance differences; examining the influence of time-varying risk such as macroeconomic environment. Therefore, later literature extends the discussion on time-series momentum effect in more depth in terms of whether it is eligible to be a risk factor.

The time-series momentum effect is first studied in Moskowitz et al. (2012) in the bond, commodities, and currency market from January 1965 to December 2009. Later, TSM is examined in broader asset classes and over longer time horizon by researchers. Hurst et al. (2017) find TSM in 29 commodities, 11 equity indices, 15 bond markets, and 12 currency pairs from January 1880 to December 2013. Georgopoulou and Wang (2017) demonstrate the existence of TSM in 45 emerging and developed market equity indices, and 22 commodity indices, from December 1969 to August 2015. Bird et al. (2017) studies the performance of TSM across 24 equity markets. Georgopoulou and Wang (2017) demonstrate the relationship between the time-series momentum effect and mutual fund performance using global equity indices, commodity indices, and monthly mutual fund returns, from 1969 to 2015. They find that, without taking into consideration currency effect, TSM is stronger, but shorter, in emerging markets, and weaker, but longer, in developed markets. Time-series momentum studies are later extended into individual stock level by Goyal and Jegadeesh (2018) and Lim et al. (2018). Goyal and Jegadeesh (2018) utilise US individual stock data from 1946 to

2013 and Lim et al. (2018) utilise data from 1927 to 2017 in US, and data from 12 other countries. They find that TSM is also persistent at the individual stock level.

TSM strategy design and return

Though some researchers (e.g., Koijen et al., 2018) use TSM as a risk factor to carry their studies, taking a further look at the detailed findings on TSM reveals that whether TSM is a risk factor is still under debate. Some researchers argue that it is the targeted volatility in Moskowitz et al.'s (2012) time-series momentum design that leads to the improved performance of time-series momentum compared to cross-sectional momentum returns, and others add that the net long position led by the strategy design is the main cause of the greater performance.

Prior literature demonstrates the role of the time-series momentum strategy volatility control in leading to the better performance of TSM compared to CSM. To mitigate the natural volatility difference across different assets, Moskowitz et al. (2012) set 40% ex ante annual volatility which is the average annual volatility of individual stocks as strategy volatility target. The studies that follow Moskowitz et al.'s (2012) volatility control tend to demonstrate favourable TSM performance and similar TSM outperformance, whereas the studies that compare unscaled TSM with CSM generate opposing results. For example, Menkhoff et al. (2012) find that cross-sectional momentum in the currency market outperforms its time-series counterparts. The time-series strategies they adopted are currency market technical analysis trading strategies, such as filter rule and moving average, which have long been studied in currency market literature. These strategies are known as trend following, which is similar in nature as time-series momentum (Moskowitz et al., 2012). As is pointed out by Kim et al. (2016), Menkhoff et al. (2012) utilises an unscaled time-series momentum strategy and generates unfavourable TSM results.

Kim et al. (2016) study the influence of volatility control of TSM returns, demonstrating a positive relationship between strategy volatility and return. They also show that without volatility control, TSM fails to outperform CSM. Kim et al. (2016) find that volatility scaled strategies generate better returns compared to unscaled strategies for both time-series momentum and buy and hold strategies; the larger the controlled volatility, the better the returns. They ascribe this phenomenon to risk parity approach, where the risk is proxied by ex-ante volatility in Moskowitz et al. (2012) rather than the dollar value invested, arguing that it is the volatility scale rather than time-series momentum that generates the profit for Moskowitz et al. (2012) strategies. They show that unscaled time-series momentum strategies generate similar returns to buy and hold strategies in futures market. Cross-sectional momentum generates better returns than unscaled time-series momentum strategies, and generates similar returns to scaled time-series momentum strategies.

Except for the scaled volatility contained in the strategy design, Goyal and Jegadeesh (2018) add that the net long position of TSM also plays an important role in TSM performance. For CSM, the positions of long-side and short-side are equal, making it zero net investment strategies. This means that the proceeds from the short legs can be used to fund the investment in the long side. However, TSM is time-varying net long investment strategy. In a 12-1 TSM strategy, the average long position is $1.24, and the average short position is $0.76. The volatility scale enlarges the net long position, with the average long position $3.28, and the average short position is $1.73. The net long position occurs in TSM because the strategy dynamically adjusts to the market condition and the overall market witnesses more positive returns than negative returns, making the overall TSM position net long. This makes the overall active position $5 for scaled TSM and $2 for unscaled CSM in Moskowitz et al. (2012). A higher active position is like a leverage effect which generates higher returns. To equalize the positions so that CSM and TSM returns are comparable when considering leverage effect, Goyal and Jegadeesh (2018) add time-varying investment in the market (TVM) to scaled CSM to compare against scaled TSM performance. They find that the individual stock level performance for the two strategies is similar, which leads to the conclusion that it is the net long position of TSM that leads to its outperforming CSM, and therefore CSM cannot be subsumed by TSM.

Goyal and Jegadeesh (2018) further demonstrate that scaled TSM underperforms against scaled CSM. The TSM strategy picks more bonds that generate low excess returns compared to other asset classes than CSM strategy, which indicates that TSM is not good for picking undervalued or overvalued bonds. At the individual stock level, the TSM consists of CSM and time-varying investments in the market. Thus, TSM is not a better candidate than CSM for being a risk factor in a multiple asset pricing model. In an international asset market, scaled TSM underperforms against scaled CSM, reinforcing this proposition.

Lim et al. (2018) regress TSM returns on Fama French Carhart four factor model where CSM factor is included, finding an insignificant TSM alpha. They then follow Goyal and Jegadeesh's (2018) method and use dollar neutral TSM returns and regress on the same model, and the alphas then become significantly positive. Thus, they conclude that though the CSM seems to be able to explain TSM, this is not the case when both strategies are dollar neutral. This finding is consistent with the argument by Goyal and Jegadeesh (2018) that the different weighting scheme between TSM and CSM (i.e., net long position of TSM and zero net position of CSM) contribute to the difference in returns.

Georgopoulou and Wang (2017) find that 12-1 time-series long only strategies can better explain fund returns compared to time-series 12-1 strategies. They ascribe this phenomenon to the fund managers who tend to systematically purchase TSM winners, but not short selling TSM losers. Though their argument is focused on fund manager trend-following behaviour, it is consistent with Goyal and Jegadeesh (2018) that the net long position of TSM plays an important role in driving TSM returns.

TSM and information diffusion

The relationship between cross-sectional momentum and information diffusion is long established in prior literature. Recently, researchers have begun to study the influence of information diffusion on time-series momentum. Lim et al. (2018) find that Da et al.'s (2014) information discreteness influences TSM in the same way as it does CSM. They demonstrate that TSM profits increase monotonically from the most discrete information group (monthly return equals to 0.5%) to the most continuous information group (monthly return equals to 1.15%). This implies that investors tend to underreact to price information that comes persistently in small scales. This is the same as the pattern shown in Da et al. (2014), where cross-sectional momentum effect is enhanced under continuous information (5.94% monthly return), and is weakened under discrete information (-2.07% monthly returns). Furthermore, they find that TSM performance is positively related to investor sentiment. The Huang et al. (2015) investment sentiment index they utilise is composed of the close-end fund discount rate, stock turnover, IPO number, first-day average returns of IPOs, dividend premium, and equity share in total new issues, developed by Baker and Wurgler (2006).

TSM, market state, and macroeconomic environment

Moskowitz et al. (2012) show that time-series momentum returns are correlated with cross-sectional momentum returns, both within and across each asset classes. This implies the potential existence of a common factor that leads to the across asset co-movement. Though time-series momentum returns cannot be explained by risk factors such as CAPM, Fama French factors, and firm size, the relationship between macroeconomic environment and TSM is still under debate. The relationship between market states and TSM is explored by researchers. Bird et al. (2017) compares the performance between TSM and CSM across 24 markets. They find that time-series momentum performs better than cross-sectional momentum in down markets, leading to its overall greater performance. They ascribe this to the time component in time-series momentum, because TSM adjusts its portfolio composition with the market state. That is, unlike CSM, which selects constant number of winners and losers in all market states, TSM selects more winners in its long portfolios in up market and more losers in its short portfolios in down market.

Goyal and Jegadeesh (2018) added time-varying investment in the market (TVM) to CSM to equalise the position compared to TSM and compare the strategy returns. They find that individual stock level performance for the two strategies is similar, which leads to the conclusion that it is the net long position of TSM that leads to TSM outperforming CSM; this supports the influence of market state on TSM performance. Lim et al. (2018) utilise ex post market risk premium as a proxy for market state and they also demonstrate supporting evidence that TSM returns are significantly positive in down markets, moderate in normal markets, and significantly negative in up markets.

The macroeconomic environment plays a mixed role in TSM. Georgopoulou and Wang (2017) show the influence of central bank intervention on TSM performance, demonstrating the negative influence of quantitative easing policies on the performance of TSM. Lim et al. (2018) proxy macroeconomic risk by standard macroeconomic factors (DIV, YLD, TERM and DEF) and GDP growth, and find a weak relationship between macroeconomic risk and TSM. The most recent time-series momentum literature (Hutchinson and O'Brien, 2020) extends Moskowitz et al. (2012) by analysing the relationship between time-series momentum returns and macroeconomic conditions in futures market from 1950 to 2014. They choose 8 macroeconomic factors that are regarded most important for hedge fund managers and traditional portfolio managers. These are default spread (DEF), dividend yield (DIV), monthly GDP change (GDP), monthly inflation (INF), market returns (MKT), short term interest rate (RREL), term spread (TERM), and unemployment rate (UNEMP). They use the sign of GDP change and the National Bureau of Economic Research (NBER) definition of economic expansion and recession. Utilising a linear regression including these factors, they find that time-series momentum returns are related to macroeconomic risk, and the return is better in expansion periods. Following Bali et al. (2014), they construct economic uncertainty based on the time-varying conditional volatility of the 8 macroeconomic factors. They find that better time-series momentum performance is observed when macroeconomic uncertainty is low.

2.3.3 Behavioural models

He and Li (2015) establish a model that utilises the participation of fundamental, momentum, and contrarian traders to explain the short term underreaction and long-term overreaction pattern of the time-series momentum returns. They show that markets are destabilised by momentum traders and stabilised by contrarian traders. They demonstrate a positive relationship between momentum trader activity and momentum returns, and a negative relationship between the ranking time horizon and momentum returns. In addition, they show that more active momentum trading induces short-term underreaction and long run overreaction in market price, giving rise to momentum positive returns in the short run and negative returns in the long run.

Andrei and Cujean (2017) construct a model to rationalise time-series momentum and time-series reversal. They argue that information percolation is the driver of time-series momentum and reversal. In their model, there are two groups of traders who trade against each other: contrarian traders, who are better informed, and momentum traders, who are less informed. They release the constraint of fixed trader type, which means that contrarian traders can shift to momentum traders if they wish to do so. When new information arrives, the initial spread of rumours makes prices deviate from fundamentals, leading to momentum. The increasing speed of information flows leads to more precise information, which pushes prices back to their fundamentals, inducing reversals.

2.4 Conditional Multifactor Asset Pricing Models

Sharpe (1964) demonstrates in their capital asset pricing model that the expected return of an asset is the sum of the risk-free rate and compensation for bearing additional relative risk with the market (asset beta), which is standard deviation of the asset over the standard deviation of the market multiplied by market returns over the same period. The two parts are named ‘price of time’ and ‘price of risk’, respectively. Lintner (1965) presents his capital asset pricing model that is similar in nature. Their work lays a solid foundation for modern capital asset pricing studies by pointing to the direction of decomposing the overall risk of assets. Following this route, scholars find other risk factors that determine the cross-sectional variations in mean returns.

However, the CAPM model cannot explain asset price anomalies (e.g., size, value and momentum) due to the existence of risks other than market risk and its static nature according to asset price anomalies literature (Ferson et al., 1987; Hansen and Richard, 1987; Harvey, 1989). Conditional models allow the variation of the factor loading with condition variables, which improves the explanatory power of model compared to the static beta model (Avramove and Chordia, 2006; Ho and Hung, 2009; Jordan, 2012; Cooper and Maio, 2019).

Avramove and Chordia (2006) show that under the constant beta model, asset pricing models cannot explain size effect, value effect, and momentum effect. However, under a model where beta is allowed to change, the size and value effect can be explained in most cases. When the model mispricing is allowed to vary with macroeconomic variables, momentum effect can be explained. Jordan (2012) demonstrates that the models conditioned on market factors increases the explanatory ratio of standard macroeconomic models in terms of explaining cross-sectional reversal. In addition, it is shown that standard macroeconomic factors (default spread, term spread, T-bill yield and dividend yield), together with trading cost play an important role in cross-sectional contrarian returns.

Jordan (2012) analyses the relationship between macroeconomic risk as one source of time-varying risk and long-term cross-sectional contrarian effect in international markets at country index level (from 1925 to 2005). Via full conditional models which contain the January effect, time-varying beta and time-varying alphas, they find macroeconomic factors are important in understanding contrarian profits no matter whether trading costs are considered. The time-varying beta refers to market return and time-varying alpha refers to lagged standard macroeconomic factors that are found to be able to explain stock and bond returns (i.e., default spread, term spread, T-bill yield and dividend yield).

Ho and Hung (2009) introduce investor sentiment proxied by the principal component of the Conference Board Consumer Confidence Index (CCI), the Investors' Intelligence Survey Index (II) and the University of Michigan Consumer Sentiment Index (MS) as conditional variables. They find improved model performance in capturing anomalies compared to unconditional models. They further find that the cross-sectional momentum effect can be captured by conditional liquidity adjusted FF models, where investor sentiment and default spread are introduced as conditioning variables.

To better understand the impact of conditioning information that are related to profitability and investment on the explanatory power of models on cross-sectional stock returns, Cooper and Maio (2019) introduce conditioning information for HXZ and FF multifactor models. They find that the conditioning information for multifactor models are under-researched in most literature on conditional CAPM, and they show evidence that the conditional multifactor model performs better than Hou et al. (2015) and Fama and French (2015; 2016) models via testing 25 CAPM anomalies. Momentum, investment, and intangibles-related anomalies witness the biggest improvement. The conditional variables are chosen according to the predictive power for profitability and investment factors, for these are the two major elements in HXZ and FF models. After applying the conditioning variables, the explanatory ratios are increased by 22% and 20% for HXZ and FF models, respectively. In addition, they introduce NBER business cycle dummy variables and find countercyclical time variation feature of profitability and investment factor.

Bird et al. (2017) utilises multivariate regression model by setting CSM long position returns, CSM short position returns, TSM long position returns, and TSM short position returns as dummy variables. They regress individual stock returns on size effect, and the dummies to show the incremental impact of the strategies on stock returns, showing the superiority of TSM over CSM. Therefore, I will introduce conditional variables to this multivariate regression model in my robustness check.

2.5 Literature Summary and gaps

To sum up, this chapter first reviews the persistence and existence of cross-sectional momentum and the debates on cross-sectional momentum drivers (cross-sectional mean variation, factor timing, serial correlation among firm returns, information diffusion, and trading cost). Next, it shows the existence of cross-sectional industry momentum and its relationship with information diffusion and time-varying risk. Then, the existence of time-series momentum and a comparison between time-series momentum and cross-sectional momentum is demonstrated. Finally, the conditional asset pricing models are reviewed. From the literature review, three gaps can be spotted in the prior literature.

From the literature review, three gaps are apparent. First, the impact of the information environment has received little attention in time-series momentum literature. The literature that is related to this topic includes Lim et al. (2018), which finds that Da et al.'s (2014) information discreteness influences TSM in the same way as the influence on CSM at the individual stock level. However, studies are yet to examine this at broader asset class level or at industry level.

Second, though TSM literature has extended Moskowitz et al. (2012) to a broader asset class level and over longer time horizons, there are no industry level studies.

Also, there are no studies examining the relationship between information diffusion and time-series industry momentum.

Third, among the potential momentum profit drivers, factors such as value premium, market liquidity and market volatility are hypothesized as time-varying risk factors in the extant literature (Fama and French, 1992; 1993; Kothari and Shanken 1997; Pontiff and Schall 1998; Chordia et al. 2000; Liew and Vassalou, 2000; Amihud 2002; Vassalou, 2003; Acharya and Pedersen, 2005; Brunnermeier and Pedersen, 2009; Aretz et al., 2010). These factors are related to market equity risk premium and GDP growth. However, the linkage between time-series industry momentum and time-varying risk is yet to be established to understand whether time-series industry momentum is simply compensation for risk or not.

To address these gaps, this thesis will answer three research questions in my three empirical chapters. These are: 1) Is the time-series momentum effect more prominent under greater information continuity, information uncertainty, and information dispersion? By answering this question, this work contributes to the momentum literature by specifying information diffusion measures, linking them to the time-series momentum effect, and testing the relationship at the broader asset class level (i.e., global equity indices and commodity futures).

2) Does time-series momentum exist in US industries? If it does exist, is the time-series industry momentum effect enhanced under greater absolute information continuity, information uncertainty, and information dispersion? This research question is motivated by time-series momentum, cross-sectional industry momentum and information diffusion literature. Time-series momentum effects are found at the broad asset class level (Moskowitz et al., 2012) and the individual stock level (Goyal and Jegadeesh, 2018; Lim et al., 2018). Though in corporate finance literature, industry level is important in terms of IPO and SEO markets, M&A, investment and financial policy decisions (Moskowitz and Grinblatt, 1999), it is unexplored in time-series momentum literature. By answering this question, this work contributes to the prior literature by demonstrating the existence of the time-series industry momentum effect, which implies that time-series momentum effect is not confined to across asset level and individual stock level. In addition, this work demonstrates the linkage between the

time-series industry momentum effect and information environment. The time-series industry momentum effect is stronger when information arrival is continuous and information uncertainty has insignificant impact on the time-series industry effect (Information discreteness matters not just in relative industry performance as is shown in Da et al. (2014), but also for absolute industry performance in our study).

3) What is the relationship between time-series industry momentum and time-varying risk? This research question is motivated by the impact of time-varying risk on cross-sectional industry momentum returns. Cross-sectional industry momentum literature shows that the exposure to time-varying risk such as macroeconomic risk increases monotonically with industry returns (Maio and Philip, 2018), and industry momentum disappears after controlling for macroeconomic variables (Chordia and Shivakumar, 2002). The most recent time-series momentum literature (Hutchinson and O'Brien, 2020) finds that time-series momentum returns are related to macroeconomic risk and the return is better in expansion periods. Better time-series momentum performance is observed when macroeconomic uncertainty is low. Value premium (HML), market liquidity (LIQ), and market volatility (VOL) are risk factors that are related to market equity premium and macroeconomic environment. Thus, the variation of factor loadings with macroeconomic risk should be contained in the model, which cannot be realised via a static beta model. By answering this research question, this work complements the time-series momentum literature by examining the relationship between time-varying risk and the performance of our time-series industry momentum by adopting a broader set of conditional variables in comparison to prior literature.

Chapter 3 Methodology

This chapter discusses the shared methods that are utilised in the following three empirical chapters. The unique methods that are used in the different empirical chapters will be introduced separately in the corresponding chapters. The structure of this chapter is as follows. Section 3.1 introduces the proxies for information diffusion. These are information discreteness, modified information discreteness, abnormal return volatility, and abnormal turnover. Section 3.2 demonstrates the construction details of time-series momentum, information discreteness grouped TSM, abnormal return volatility grouped TSM, abnormal turnover grouped TSM, as well as the strategy constructions at industry level, respectively. Section 3.3 shows the application of Jordan 7 models to this work. Section 3.4 demonstrates the models conditioning on time-varying factors other than macroeconomic factors. Finally, Section 3.5 discusses the factor analysis.

3.1 Information Diffusion Proxies

The major difference between cross-sectional and time-series momentum strategies is that cross-sectional momentum strategies form portfolios according to relative firm performance, whereas time-series momentum strategies form portfolios according to absolute firm performance. Thus, when studying the role of information environment in time-series momentum, measures are selected with valid meaning under both positive and negative signs so that the information environment dimension can be added to time-series momentum portfolios by adopting the sign of the measures, rather than the relative performance of these measures. To meet this criterion, among the measures previously mentioned in the empirical findings on information diffusion in the Chapter 2 literature review, information discreteness from Da et al. (2014) and abnormal return volatility and abnormal turnover from Connolly and Stivers (2003) are chosen to be proxies for information diffusion.

3.1.1 Information discreteness

To study the impact of information discreteness on cross-sectional momentum, Da et al. (2014) double sort firms according to five momentum quintiles and five information discreteness quintiles, and observe the performance pattern of the portfolios. Lim et al. (2018) investigates the influence of information discreteness on time-series momentum by following Da et al.’s (2014) construction of information discreteness. They conduct their double-sort based on two TSM groups and information discreteness quintiles. The two TSM groups are TSM winners (positive ranking period return stocks) and TSM losers (negative ranking period return stocks). They conduct their analysis using both independent double sort and sequential double sort. Their overall results are consistent with Da et al.’s (2014) return pattern. That is, time-series momentum returns increase monotonically with information continuity, identifying that trend-following time-series momentum investors also underreact to information that arrives continuously in small pieces.

In this study, instead of utilising information discreteness quintiles, the sign of information discreteness is the chosen double sort. This is the major difference between the current work and Lim et al. (2018). As is mentioned before, what differentiates time-series momentum and cross-sectional momentum is that the former uses absolute asset performance as investment criterion, whereas the latter uses relative performance. Therefore, it is natural to introduce absolute performance measures when doing the double-sort in this time-series momentum study. To differentiate from Da et al.’s (2014) measure, these are termed absolute information discreteness and their relative information discreteness, for they divide information discreteness into five quintiles whereas the present study only takes into consideration the sign of information discreteness. The difference can only be observed in the portfolio holding periods. Thus, the present study still follows Da et al.’s (2014) information discreteness measure construction, and uses the same name as theirs.

By adapting Da et al. (2014), the information discreteness measures (ID) is constructed as follows:

$$ID_{i,t-1}^{s} = sign(PRET)_{i,t-2}^{s} * (\%neg_{i,t-2}^{s} - \%pos_{i,t-2}^{s}) \quad (1)$$

where $sign(PRET)_{i,t-2}^{s}$ is the sign of the cumulative previous month return of asset i in asset class s, $\%neg_{i,t-2}^{s}$ is the percentage of negative return days in the previous month for asset i, and $\%pos_{i,t-2}^{s}$ is the percentage of positive return days in the previous month for asset i. $ID \in [-1,1)$. According to Da et al. (2014), if $ID_{i,t-1}^{s}$ >0, the previous price information of asset i is discrete; if $ID_{i,t-1}^{s}$ <0, it is continuous. The rationale is that if the positive (negative) sign of the previous overall performance is induced by more frequent positive (negative) daily returns, then the continuously daily positive (negative) returns induce the overall positive (negative) performance; thus, the information is continuous. However, if the positive (negative) sign of the previous performance is induced by the less frequent but large in absolute value daily positive (negative) returns, the information is discrete. The lower limit of ID is -1 when the formation period daily returns are all negative (positive), and the cumulative return is also negative (positive). The upper limit is 1 when almost all the formation period daily returns are negative (positive), and the cumulative return is positive (negative). The shorter the distance between ID and 1, the more discrete the information is. The shorter the distance between ID and -1, the more continuous the information is.

3.1.2 Modified information discreteness

To smooth the influence of the magnitude of daily returns on the measure of information discreteness, Da et al. (2014) also construct a daily return magnitude adjusted information discreteness measure ID_{MAG} . The modified information discreteness measure is calculated as follows:

$$ID_{MAG}{}_{i,t-1}^{s} = -\frac{1}{N} sign(PRET)_{i,t-2}^{s} * \sum_{i=1}^{N} sign\left(Return_{i,t-2}^{s}\right) * w_{i,t-2}^{s} \quad (2)$$

where N is defined as the number of days in the looking back period (also known as the portfolio formation period); $sign(PRET)_{i,t-2}^{s}$ is denoted as the sign of the cumulative previous months' return of asset i in asset class s, $ID \in [-1,1)$. According to Da et al. (2014), each return quintile $|Return|_i$ is allocated corresponding consistently decreasing weight w_i ($\frac{5}{15}, \frac{4}{15}, \frac{3}{15}, \frac{2}{15}, and \frac{1}{15}$). The weights are summed to one. It can be observed from the formula that more (less) weight is allocated to small (large) daily returns. In this way, the influence of the magnitude of daily returns on the measure of information shock is smoothed. For example, if the daily returns in month t-2 are in the bottom return quintile (lowest absolute return quintile), the weight $\frac{5}{15}$ will be assigned to these returns.

3.1.3 Abnormal return volatility

There are a couple of other information diffusion measures used in prior literature (e.g., Zhang, 2006), for example, firm age, firm size, analyst coverage, forecast dispersion, and cash flow volatility. The advantages of return volatility are that: 1) compared to firm age, firm size, analyst coverage and forecast dispersion, it is more suitable to be adopted at asset index and industry level; and 2) compared to cash flow volatility, which is a pure fundamental measure that may be influenced by information quality, return volatility is a measure calculated from the asset/industry index directly, which is a signal that incorporates both fundamental and behavioural information.

However, return volatility itself does not satisfy the selection criterion[1] that the sign of the measure must have valid meanings. Thus, instead of utilising return volatility, Connolly and Stivers (2003) abnormal return volatility is utilised. The remaining part of the asset/industry return volatility that is not explained by the autoregressive behaviour of return volatility and the changes induced by the sign and scale of previous period returns is defined as abnormal volatility by Connolly and Stivers (2003). Abnormal return volatility does not involve cross asset/industry comparison when it comes to forming time-series momentum portfolios (or time-series industry momentum portfolios) under different information environment. Positive abnormal return volatility is classified as high information uncertainty and negative abnormal return volatility is classified as low information uncertainty. In Connolly and Stivers (2003), they use large firm returns to calculate the standard deviation to proxy for return volatility. Since the first and the second empirical chapter is at asset and industry level, respectively,

[1] The selection criteria and the rationale behind these criteria are discussed in Section 3.1 Information diffusion proxies.

I use the monthly standard deviation converted from daily standard deviation of asset/industry returns proxies for asset/industry return volatility.

By adapting Connolly and Stivers (2003), abnormal return volatility is the residual gained from the time-series regression model below:

$$RV_{i,t} = \gamma_0 + \sum_{m=1}^{6} \gamma_m RV_{i,t-m} + \gamma_7 |R_{i,t}| + \gamma_8 D_{i,t}^{-} |R_{i,t}| + \gamma_9 |R_{i,t-1}| + \gamma_{10} D_{i,t-1}^{-} |R_{i,t-1}| + \mu_{i,t} \tag{2}$$

where $RV_{i,t}$ is the time t return volatility of asset/industry i, $|R_{i,t}|$ is the absolute value of time t return of asset/industry i, $D_{i,t}^{-} = 1$ if $R_{i,t} < 0$ and $D_{i,t}^{-} = 0$ otherwise, and $\mu_{i,t}$ is the residual, which is our abnormal return volatility.

3.1.4 Abnormal turnover

Similar to the criteria[2] that is adopted when using Connolly and Stivers (2003) abnormal return volatility as proxies for information diffusion, the reason that I borrow abnormal turnover from Connolly and Stivers is used as another element of information diffusion measure is because, compared to other information diffusion measures such as firm age, firm size, analyst coverage, and forecast dispersion, it is more feasible to adopt turnover at asset class and industry level. In addition, turnover can be directly retrieved from asset/industry level data. Thus, it incorporates both fundamental and behavioural information, and is not influenced by information quality.

Since turnover does not satisfy the selection criterion that the sign of the measure must bear valid meanings, Connolly and Stivers's (2003) abnormal turnover is utilised. The remaining part of the asset/industry turnover that is not explained by the autoregressive behaviour of turnover and the changes induced by the sign and scale of previous period returns, is abnormal turnover. It does not involve cross asset/industry comparison when it comes to forming time-series momentum portfolios

[2] The selection criteria and the rationale behind these criteria are discussed in Section 3.1 Information diffusion proxies.

under different information environments. Positive abnormal turnover is classified as high information diffusion, and negative abnormal turnover is classified as low information diffusion. However, due to data availability, this measure is only adopted at equity indices level in the first empirical chapter.

By adapting Connolly and Stivers (2003), abnormal turnover is the residual gained from the time-series regression model below:

$$TO_{i,t}^{s} = \gamma_0^s + \sum_{k=1}^{6} \gamma_k^s TO_{i,t-k}^{s} + \gamma_7^s \left|R_{i,t}^{s}\right| + \gamma_8^s D^{-}{}_{i,t}^{s} \left|R_{i,t}^{s}\right| + \gamma_9^s \left|R_{i,t-1}^{s}\right| + \gamma_{10}^s D^{-}{}_{i,t-1}^{s} \left|R_{i,t-1}^{s}\right| + \mu_{i,t}^{s} \qquad (3)$$

where $TO_{i,t}^{s}$ is the time t turnover of asset i in asset class s, $|R_t^s|$ is the absolute value of time t return of asset i in asset class s, $D^{-}{}_t^s = 1$ if R_t^s <0 and $D^{-}{}_t^s = 0$, otherwise, and $\mu_{i,t}$ is the residual.

3.2 Strategy constructions

Strategy specific volatility controls are shown to positively influence the strategy performance in cross-sectional momentum studies such as Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016). A similar phenomenon is observed in time-series momentum literature, for example Kim et al. (2016) and Goyal and Jegadeesh (2018), where TSM strategy specific volatilities are positively related to TSM returns, improving the TSM performance. In this study, to eliminate the influence of external controls in terms of strategy volatility management, and volatility targets for strategy-specific volatility control, as is in Moskowitz et al. (2012), these are not set in the construction of the time-series momentum portfolios. The present study's strategy construction is similar to that of Huang et al.'s (2020) and Kim et al.'s (2016) simple time-series momentum strategies.

3.2.1 Time-series momentum strategies

Standard time-series momentum strategy

Prior to Moskowitz et al. (2012), momentum literature focuses on the cross-sectional context. Moskowitz et al. (2012) studies time-series momentum at the international asset class level, whereas Goyal and Jegadeesh (2017) and Lim et al. (2018) generalise it to individual stocks. In this work, I use the proxies for information diffusion to modify the standard time-series momentum strategy, and conduct across and within asset class analysis.

The general formula of standard time-series momentum strategy returns for across and within asset class returns are:

$$r_t^s = \frac{1}{n_t^s}\left(\sum\nolimits_{PRET_{i,t-1}^s<0} r_{i,t}^s - \sum\nolimits_{PRET_{i,t-1}^s>0} r_{i,t}^s\right) \tag{4}$$

where n_t^s is the total number of individual assets within asset class s, $PRET_{i,t-1}^s$ is the time t-1 period cumulative return of asset i in asset class s (the cumulative return is the looking back period returns. Depending on the strategy, it can be chosen from 1, 3, 6, or 12 month returns), and the coefficient 1 makes sure that the total position equals to $1.

The current study extends time-series momentum strategies by adding an information diffusion dimension to form new portfolios. The notion of the two-dimension portfolios can be shown in the 2-by-2 matrix below.

		Time-series momentum	
		L	H
Information diffusion	L	LL	LH
	H	HL	HH

Information discreteness grouped time-series momentum strategy

Da et al. (2014) find the prominent influence of information discreteness in a cross-sectional momentum context. The current study will introduce information discreteness to the time-series context to examine whether standard time-series momentum returns can be improved. I further divide the assets in the long portfolio and the short portfolio of the standard time-series momentum strategy into positive information discreteness assets and negative information discreteness assets, so that four portfolios will be constructed: positive PRET with positive ID, positive PRET with negative ID, negative PRET with positive ID, and negative PRET with negative ID.

The general formula of the information adjusted strategy returns for across and within asset class returns in the standard time-series momentum long and short portfolio are:

$$r_t^s = \frac{1}{n_t^s}\left(\sum_{PRET_{i,t-j}^s>0\ \&\ ID_{i,t-j}<0} r_{i,t}^s - \sum_{PRET_{i,t-j}^s<0\ \&ID_{i,t-1}<0} r_{i,t}^s\right) \tag{5}$$

$$r_t^s = \frac{1}{n_t^s}\left(\sum_{PRET_{i,t-j}^s>0\ \&\ ID_{i,t-1}>0} r_{i,t}^s - \sum_{PRET_{i,t-j}^s<0\ \&ID_{i,t-1}>0} r_{i,t}^s\right) \tag{6}$$

where n_t^s is the total number of individual assets within asset class s; $PRET_{i,t-j}^s$ is the month t-j to month t cumulative returns; the coefficient 1 makes sure that the total position equals to \$1. The two formulas for return calculation indicate that the long portfolio contains assets with previous positive returns and previous continuous (discrete) information, whereas the short portfolio contains assets with previous negative returns and continuous (discrete) information. Asset class s distinguishes across and within asset class returns.

Take equity market index as an example. Following formula (5), the market indices with previous positive returns and continuous information ($ID_{i,t-j}^s$ <0) will be in the long portfolio and the market indices with previous negative returns and continuous information will be in the short portfolio. Following formula (6), the long portfolio contains the market indices with previous positive returns and discrete information ($ID_{i,t-j}^s$ >0), and the short portfolio contains the market indices with previous negative returns and discrete information. The strategy returns are:

$$r_t = \frac{1}{n_t}\left(\sum_{PRET_{i,t-j}>0\ \&\ ID_{i,t-j}<0} r_{i,t} - \sum_{PRET_{i,t-j}<0\ \&\ ID_{i,t-j}<0} r_{i,t}\right) \tag{7}$$

$$r_t = \frac{1}{n_t}\left(\sum_{PRET_{i,t-j}>0\ \&\ ID_{i,t-j}>0} r_{i,t} - \sum_{PRET_{i,t-j}<0\ \&\ ID_{i,t-j}>0} r_{i,t}\right) \tag{8}$$

where n_t is the total number of equity indices at time t, $PRET_{i,t-j}$ is the month t-j to month t equity index returns, $ID_{i,t-j}$ is the month t-j to month t information discreteness of the corresponding equity indices; the coefficient 1 makes sure that the total position equals to $1

Modified information discreteness grouped time-series momentum strategy

The long portfolio contains all individual assets with previous continuous information ($ID_{MAG}{}^{s}_{i,t-1}$ <0), and the short portfolio contain all individual assets with previous discrete information ($ID_{MAG}{}^{s}_{i,t-1}$ >0). The general formula of strategy returns for across and within asset class returns are:

$$r_t^s = \frac{1}{n_t^s}\left(\sum\nolimits_{PRET_{i,t-j}^s>0\ \&\ ID_{MAG}{}^{s}_{i,t-j}<0} r_{i,t}^s - \sum\nolimits_{PRET_{i,t-j}^s<0\ \&\ ID_{MAG}{}^{s}_{i,t-j}<0} r_{i,t}^s\right) \tag{9}$$

$$r_t^s = \frac{1}{n_t^s}\left(\sum\nolimits_{PRET_{i,t-j}^s>0\ \&\ ID_{MAG}{}^{s}_{i,t-j}>0} r_{i,t}^s - \sum\nolimits_{PRET_{i,t-j}^s<0\ \&\ ID_{MAG}{}^{s}_{i,t-j}>0} r_{i,t}^s\right) \tag{10}$$

where n_t^s is the total number assets at time t in asset class s, $PRET_{i,t-j}^s$ is the month t-j to month t returns of asset i in asset class s, $ID_{MAG}{}^{s}_{i,t-j}$is the month t-j to month t modified information discreteness of asset i in asset class s, the coefficient 1 makes sure that the total position equals to $1

Abnormal return volatility grouped time-series momentum strategy

The long portfolio contains all individual assets with previous negative abnormal return volatility and the short portfolio contains all individual assets with previous positive abnormal return volatility. The general formula of strategy returns for across and within asset class returns are:

$$r_t^s = \frac{1}{n_t^s}\left(\sum_{PRET_{i,t-j}^s>0\ \&\ ARV_{i,t-j}^s<0} r_{i,t}^s - \sum_{PRET_{i,t-j}^s<0\ \&\ ARV_{i,t-j}^s<0} r_{i,t}^s\right) \tag{11}$$

$$r_t^s = \frac{1}{n_t^s}\left(\sum_{PRET_{i,t-j}^s>0\ \&\ ARV_{i,t-j}^s>0} r_{i,t}^s - \sum_{PRET_{i,t-j}^s<0\ \&\ ARV_{i,t-j}^s>0} r_{i,t}^s\right) \tag{12}$$

where n_t^s is the total number assets at time t in asset class s, $PRET_{i,t-j}^s$ is the month t-j to month t returnrs of asset i in asset class s, $ARV_{i,t-j}^s$is the month t-j to month t abnormal return volatility of asset i in asset class s, the coefficient 1 makes sure that the total position equals to $1

Abnormal turnover grouped time-series momentum strategy

The long portfolio contains all individual assets with previous negative abnormal turnover and the short portfolio contains all individual assets with previous positive abnormal turnover. The general formula of strategy returns for across and within asset class returns are:

$$r_t^s = \frac{1}{n_t^s}\left(\sum_{PRET_{i,t-j}^s>0\ \&\ AT_{i,t-j}^s<0} r_{i,t}^s - \sum_{PRET_{i,t-j}^s<0\ \&\ AT_{i,t-j}^s<0} r_{i,t}^s\right) \tag{13}$$

$$r_t^s = \frac{1}{n_t^s}\left(\sum_{PRET_{i,t-j}^s>0\ \&\ AT_{i,t-j}^s>0} r_{i,t}^s - \sum_{PRET_{i,t-j}^s<0\ \&\ AT_{i,t-j}^s>0} r_{i,t}^s\right) \tag{14}$$

where n_t^s is the total number assets at time t in asset class s; $PRET_{i,t-j}^s$ is the month t-j to month t returns of asset i in asset class s; $AT_{i,t-j}^s$is the month t-j to month t abnormal turnover of asset i in asset class s; the coefficient 1 makes sure that the total position equals to $1

3.2.2 Time-series industry momentum strategies

Monthly value weighted returns are utilised from Fama French 49 industry portfolios to calculate time-series industry momentum returns. Equation (15)-(17) shows the details of the return calculation.

$$r^{ind}_{t-j\to t,t+1\to t+1+k} \tag{15}$$
$$= 2 * \left(\frac{n_t^{PRET_{t-j\to t}>0}}{n^{t-j\to t}} * \frac{1}{n_t^{PRET_{t-j\to t}>0}} \sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}>0} - \frac{n_t^{PRET_{t-j\to t}<0}}{n^{t-j\to t}} * \frac{1}{n_t^{PRET_{t-j\to t}<0}} \sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}<0}\right)$$

where $r^{ind}_{t-j\to t,t+1\to t+1+k}$ is the monthly industry return for j-month ranking (from month t-j to month t) and k-month (from month t+1 to month t+1+k) holding strategy return, $n^{t-j\to t}$ is the total number of industries in j-month ranking period, $n_t^{PRET_{t-j\to t}>0}$ is the number of industries with positive cumulative returns in j-month ranking period, $n_t^{PRET_{t-j\to t}<0}$ is the number of industries with negative cumulative returns in j-month ranking period, $r_k^{PRET_{t-j\to t}>0}$ is the k-month holding period return for industries with positive j-month ranking period returns, and $r_k^{PRET_{t-j\to t}<0}$ is the k-month holding period return for industries with negative j-month ranking period returns.

From Equation (3), we can see that $\frac{1}{n_t^{PRET_{t-j\to t}>0}} \sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}>0}$ is the weighted average return for the long portfolio and $\frac{1}{n_t^{PRET_{t-j\to t}<0}} \sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}<0}$ is the weighted average return for the short portfolio. $\frac{n_t^{PRET_{t-j\to t}>0}}{n^{t-j\to t}}$ is the number of positive ranking period return industries out of the total number of industries, $\frac{n_t^{PRET_{t-j\to t}<0}}{n^{t-j\to t}}$ is the number of negative ranking period return industries out of the total number of industries; \$2 is the total amount of position.

For example, if 60% of the total amount of industries are positive ranking period return industries, then 40% are negative ranking period return industries. Here, the long position is $\$2 * 60\% = \$1.2$ and the short position is $\$2 * 40\% = \$0.8$. The net position is $\$1.2 - 0.8 = \$0.4$. If the number of positive and negative ranking period return industries are the same, then the long position will be $\$2 * 50\% = \$1$ and the short position will also be $1. Thus, the net position will be $\$2 * 50\% - \$2 * 50\% = \$0$.

Equation (16) is equivalent to equation (15) and is shown as follows.

$$r_{t-j\to t,t+1\to t+1+k}^{ind} = \frac{2}{n^{t-j\to t}} * (n_t^{PRET_{t-j\to t}>0} * \frac{1}{n_t^{PRET_{t-j\to t}>0}} \sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}>0} - n_t^{PRET_{t-j\to t}<0} * \frac{1}{n_t^{PRET_{t-j\to t}<0}} \sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}<0}) \tag{16}$$

After simplification, we have equation (17)

$$r_{t-j\to t,t+1\to t+1+k}^{ind} = \frac{2}{n^{t-j\to t}} (\sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}>0} - \sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}<0}) \tag{17}$$

Thus, our equation (17) is the same as Goyal and Jegadeesh (2018) formula (2) on individual stock time-series momentum returns. The technical details of portfolio formation are shown in the chapter 5 appendices.

Information discreteness grouped time-series industry momentum

$$r_{t-j\to t,t+1\to t+1+k}^{ind,ID_{t-j,t}<0} = \frac{2}{n_t^{ID_{t-j\to t}<0}} (\sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}>0\&ID_{t-j\to t}<0} - \sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}<0\&ID_{t-j\to t}<0}) \tag{18}$$

$$r_{t-j\to t,t+1\to t+1+k}^{ind,ID_{t-j,t}>0} = \frac{2}{n_t^{ID_{t-j\to t}>0}} (\sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}>0\&ID_{t-j\to t}>0} - \sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}<0\&ID_{t-j\to t}>0}) \tag{19}$$

where $r_{t-j\to t,t+1\to t+1+k}^{ind,ID_{t-j,t}<0}$ is the j-month formation and k-month holding negative information discreteness grouped time-series industry momentum strategy return,

$n_t^{ID_{t-j\to t}<0}$ is the number of industries with negative ID in the j-month formation period, $n_t^{ID_{t-j\to t}>0}$ is the number of industries with positive ID in the j-month formation period, $r_{t+1\to t+1+k}^{PRET_{t-j\to t}>0\&ID_{t-j\to t}<0}$ is the k-month holding period return for industries with positive cumulative return and negative ID in the j-month formation period, $r_{t+1\to t+1+k}^{PRET_{t-j\to t}<0\&ID_{t-j\to t}>0}$ is the k-month holding period return for industries with negative cumulative return and positive ID in the j-month ranking period. The two formulas for industry returns indicate that the long portfolio contains industry indices with previous positive returns and previous continuous (discrete) information, and the short portfolio contains industry indices with previous negative returns and continuous (discrete) information. The technical details of portfolio formation are shown in the section 5.7 appendices.

Abnormal return volatility grouped time-series industry momentum

$$r_{t-j\to t,t+1\to t+1+k}^{ind,ARD_{t-j,t}<0} = \frac{2}{n_t^{ARD_{t-j\to t}<0}}\left(\sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}>0\&ARD_{t-j\to t}<0} - \sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}<0\&ARD_{t-j\to t}<0}\right) \tag{20}$$

$$r_{t-j\to t,t+1\to t+1+k}^{ind,ARD_{t-j,t}>0} = \frac{2}{n_t^{ARD_{t-j\to t}>0}}\left(\sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}>0\&ARD_{t-j\to t}>0} - \sum r_{t+1\to t+1+k}^{PRET_{t-j\to t}<0\&ARD_{t-j\to t}>0}\right) \tag{21}$$

where $r_{t-j\to t,t+1\to t+1+k}^{ind,ARD_{t-j,t}<0}$ is the j-month formation and k-month holding low abnormal return volatility grouped time-series industry momentum strategy return, $n_t^{ARD_{t-j\to t}<0}$ is the number of industries with negative ARD in the j-month formation period, $n_t^{ARD_{t-j\to t}>0}$ is the number of industries with positive ARD in the j-month formation period, $r_{t+1\to t+1+k}^{PRET_{t-j\to t}>0\&ARD_{t-j\to t}<0}$ is the k-month holding period return for industries with positive cumulative return and negative ARD in the j-month formation period, $r_{t+1\to t+1+k}^{PRET_{t-j\to t}<0\&ARD_{t-j\to t}>0}$ is the k-month holding period return for industries with negative cumulative return and positive ARD in the j-month formation period. The two formulas for industry returns indicate that the long portfolio contains industry indices with previous positive returns and previous low (high) abnormal return volatility and the short portfolio contains industry indices with previous negative returns and low (high) abnormal return volatility. The technical details of portfolio formation are shown in the section 5.7 appendices.

3.3 Jordan (2012) 7 models

To test the impact of time-varying risk on time-series industry momentum and information environment proxies grouped time-series industry momentum, I use standard macroeconomic models conditioning on MKT, HML, VOL, LIQ, respectively, are used, based on Jordan's (2012) model. In addition, to mitigate the potential model misspecification induced by missing important macroeconomic variable, seven common processes from 128 macroeconomic variables via factor analysis are derived. The Jordan (2012) seven models are as follows.

$$r_t = \beta_0 \tag{1}$$

$$r_t = \beta_0 + \beta_1 MKT_t \tag{2}$$

$$r_t = \beta_0 + \beta_1 JAN_t \tag{3}$$

$$r_t = \beta_0 + \beta_1 MKT_t + \beta_2 JAN_t \tag{4}$$

$$r_t = \beta_0 + \beta_1 MKT_t + \beta_2 TS_{t-1} * MKT_t + \beta_3 DS_{t-1} * MKT_t + \beta_4 TB_{t-1} * MKT_t + \beta_5 DY_{t-1} * MKT_t \tag{5}$$

$$r_t = \beta_0 + \beta_1 MKT_t + \beta_2 TS_{t-1} + \beta_3 DS_{t-1} + \beta_4 TB_{t-1} + \beta_5 DY_{t-1} \tag{6}$$

$$r_t = \beta_0 + \beta_1 MKT_t + \beta_2 JAN_t + \beta_3 TS_{t-1} + \beta_4 DS_{t-1} + \beta_5 TB_{t-1} + \beta_6 DY_{t-1} + \beta_7 TS_{t-1} * MKT_t + \beta_8 DS_{t-1} * MKT_t + \beta_9 TB_{t-1} * MKT_t + \beta_{10} DY_{t-1} * MKT_t \tag{7}$$

where r_t is the month t strategy returns, MKT_t is month t market returns proxied by market return minus 1-month t bill rate, JAN_t is the month t dummy for January effect (JAN_t=1 if month t is January and $JAN_t = 0\ otherwise$), TS_{t-1} is month t-1 term spread, DS_{t-1} is month t-1 default spread, TB_{t-1} is month t-1 3-month T- bill rate, and DY_{t-1} is month t-1 market indices dividend yield. $TS_{t-1,}, DS_{t-1}, DY_{t-1}, TB_{t-1}$ are lagged public information variables, and are constructed by subtracting month 1 to month t-2 average from month t value.

As is explained in Jordan (2012), Model five adjusts for time-varying beta (market beta). Model six adjusts for time-varying alpha, and is a linear macroeconomic model. Model seven contains all independent variables in the previous six models. Models five and seven are conditional models and model seven is the full conditional model.

3.4 Conditional models

Prior literature (e.g., Avramove and Chordia, 2006; Ho and Hung, 2009; Jordan, 2012; Cooper and Maio, 2019) demonstrates the better performance of conditional models compared to static beta models in terms of better explanatory power via allowing the variation of the factor loading with conditional variables. Jordan (2012) studies the relationship between macroeconomic risk (proxied by standard macroeconomic variables) and long-term cross-sectional contrarian effect, demonstrating that their models conditioning on market factors increases the explanatory ratio of standard macroeconomic models when explaining cross-sectional reversal. Since HML, VOL, and LIQ are shown in prior literature to be related to macroeconomic environment as well as momentum returns, introducing them to the model as conditional variables may help understand the impact of these conditioning information that is related to time-varying risk on the explanatory power of models on time-series momentum returns. The conditional models are constructed as below.

$$\begin{aligned} r_t = \beta_0 + \beta_1 * MKT_t + \beta_2 * HML_t + \beta_3 * TS_{t-1} * HML_t + \beta_4 * DS_{t-1} * HML_t \\ + \beta_5 * TB_{t-1} * HML_t + \beta_6 * DY_{t-1} * HML_t + \beta_7 * TS_{t-1} + \beta_8 \\ * DS_{t-1} + \beta_9 * TB_{t-1} + \beta_{10} * DY_{t-1} \end{aligned} \tag{8}$$

$$\begin{aligned} r_t = \beta_0 * + \beta_1 * MKT_t + \beta_2 * VOL_t + \beta_3 * TS_{t-1} * VOL_t + \beta_4 * DS_{t-1} * VOL_t \\ + \beta_5 * TB_{t-1} * VOL_t + \beta_6 * DY_{t-1} * VOL_t + \beta_7 * TS_{t-1} + \beta_8 \\ * DS_{t-1} + \beta_9 * TB_{t-1} + \beta_{10} * DY_{t-1} \end{aligned} \tag{9}$$

$$\begin{aligned} r_t = \beta_0 * + \beta_1 * MKT_t + \beta_2 * LIQ_t + \beta_3 * TS_{t-1} * LIQ_t + \beta_4 * DS_{t-1} * LIQ_t + \beta_5 \\ * TB_{t-1} * LIQ_t + \beta_6 * DY_{t-1} * LIQ_t + \beta_7 * TS_{t-1} + \beta_8 * DS_{t-1} \\ + \beta_9 * TB_{t-1} + \beta_{10} * DY_{t-1} \end{aligned} \tag{10}$$

where MKT_t is month t market returns proxied by market return minus 1-month t bill rate, HML_t is month t value premium (return of stocks in the top 30 percent market value minus return of stocks in the bottom 30 percent market value from French data library), RV_t is the month t realised Fama French market return volatility, and LIQ_t is month t Amihud (2002) illiquidity of S&P 500 (LIQ_t is calculated as the average of the ratio of the absolute value of market return over the corresponding trading volume in dollar over month t multiplied by 1,000,000,000), TS_{t-1} is the month t-1 term spread, DS_{t-1} is the month t-1 default spread which is the difference between returns of BAA rated firms and the returns of AAA rated firms, TB_{t-1} is the month t-1 3-month T- bill rate, and DY_{t-1} is the month t-1 market indices dividend yield. $TS_{t-1},DS_{t-1}, DY_{t-1},TB_{t-1}$ are lagged public information variables and are constructed by subtracting the month 1 to month t-2 average from the month t value.

3.5 Factor analysis

Jordan's (2012) model incorporates the standard macroeconomic variables, and the present study introduces conditional variables related to time-varying risk, based on Jordan's (2012) models. However, there are hundreds of other macroeconomic variables that may play a role in these models. Missing relevant variables in these models may lead to biased coefficients and invalid t-statistics. Factor analysis is an approach to select common factors from a wide range of possible indicators based on information criteria, which is suitable to minimise the chances of missing relevant macroeconomic variables and correlation among independent variables.

To obtain seven common processes via factor analysis, the MATLAB factor analysis package created by Michael W. McCracken and 128 macroeconomic variables from Research Division of Federal Reserve Bank of St. Louis by Michael W. McCracken is utilised. Monthly coefficients of the seven common processes (C) are derived from the factor analysis and regression analyses based on them are conducted.

$$r_t = \beta_0 + \sum_{i=1}^{7} \beta_i * C_{i,t} \tag{11}$$

where β_0 is constant, $C_{i,t}$ is the ith common process

$$r_t = \beta_0 + \sum_{i=1}^{7} \beta_i * C_{i,t} + \sum_{j=1}^{4}\sum_{i=1}^{7} \beta_{i+7} * C_{i,t} * X_{j,t} \tag{12}$$

where $X\ is\ MKT, HML, VOL, LIQ,$ β_0 is constant, $C_{i,t}$ is the ith principal component, MKT_t is month t market returns proxied by market return minus 1-month t bill rate, HML_t is month t value premium (return of stocks in the top 30 percent market value minus return of stocks in the bottom 30 percent market value from French data library), RV_t is the month t realised Fama French market return volatility, and LIQ_t is month t Amihud (2002) illiquidity of S&P 500 (LIQ_t is calculated as the average of the ratio of the absolute value of market return over the corresponding trading volume in dollar over month t multiplied by 1,000,000,000). MKT, HML, VOL, LIQ are market condition variables.

Chapter 4 Time-series momentum and information diffusion

4.1 Abstract

This chapter focuses on the impact of information diffusion on the time-series momentum effect. Three dimensions of information diffusion, namely information discreteness, information uncertainty, and information dispersion, are incorporated to study their impact. The study finds that time-series momentum conditioning on absolute continuous information generates persistent and significant returns for 3 to 12 months after the portfolio formation period. The returns are significantly improved when information arrives continuously, whereas they disappear when information comes discretely. The difference between the two groups is an annual average of 6.66%, which is economically large. This indicates investors underreact more to previous price information under absolute information continuity. Time-series momentum is not strongly impacted by either information uncertainty (proxied by abnormal return volatility) or information dispersion (proxied by abnormal turnover).

4.2 Introduction

This chapter examines whether the TSM effect is more prominent under greater information diffusion. This is motivated by theoretical and empirical studies on the impact of information diffusion on asset returns and the time-series momentum effect. Three sign-based information diffusion measures are constructed and their impact on TSM returns examined. This work specifies what element of information diffusion is treated differently by investors, and therefore, contributes to TSM literature (e.g., Moskowitz et al., 2012) by demonstrating a clearer relationship between information diffusion and TSM. This study also provides institutional and individual investors with information diffusion signals to enhance strategy returns.

Mainstream behaviour theories (i.e., Barberis, Shleifer, and Vishny,1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999) demonstrate that investors react slowly to news, which gives rise to cross-sectional momentum returns. The strategies gain profit via prompt price adjustment in response to fundamental news. Empirical studies show supporting evidence that investors underreact to price signals more when there is high information diffusion (Connolly and Stivers, 2003; Zhang, 2006; Da et al., 2014). However, Moskowitz et al. (2012) argues that the behavioural explanations of momentum profits fit more in a time-series context, because they focus on explaining the return continuation of a single asset rather than the relative performance continuation among multiple assets. Therefore, they construct time-series momentum strategies, finding the time-series momentum effect to exist in all asset classes.

In addition, Moskowitz et al. (2012) make a contribution of establishing a potential relationship between information diffusion on TSM in futures market. The total futures returns are composed of spot price changes and roll returns. The former is conjected to be linked with information diffusion and the latter with hedging pressure. This is because the roll returns are compensation for liquidity risk for hedgers (incentives for speculators to provide liquidity), and information diffusion is the driver of price changes, according to behavioural theories. They demonstrate that shocks in total returns (measured by one standard deviation shock to total returns) lead to upward trending in cumulative total returns in the first 12 months, with the trend starting to reverse after 12 months. A similar pattern is observed for spot returns, but not for roll returns. The shocks in roll yields induce an increase in cumulative roll returns without reversal. This indicates that the spot returns and roll returns jointly lead to the initial momentum, and it is spot returns alone that lead to the long-term reversal pattern. Thus, a potential link between information diffusion and time-series momentum effect is established.

This work focuses on the relationship between information diffusion and time-series momentum returns, and contributes to the momentum literature by specifying sign-based information diffusion measures, linking them with the time-series momentum effect, and testing the relationship at the broader asset class level (i.e., global equity indices and commodity futures). The findings include: 1) investors tend to underreact to price information more in a continuous information environment; and 2) time-series momentum profits shrink in a discrete information environment. If we assume that continuous information environment is characterised by slower information diffusion, then the finding that TSM in a continuous information environment outperforms TSM in a discrete information environment is consistent with the information diffusion hypothesis.

Hong and Stein's (1999) information diffusion hypothesis suggests that momentum returns are larger when information diffusion is higher. Their model demonstrates initial momentum, then a long-term reversal return pattern via the interaction of two different groups of boundedly rational investors which they name "news-watchers". News-watchers only use fundamental analyses and tend to underreact due to private information diffusion. "Momentum traders", however, exploit past price trend and profit from initial underreaction induced by "news-watchers". Therefore, the increase in the degree of "news-watcher" underreaction, due to increase in information diffusion, may provide more profits for momentum traders. They suggest firm size and stock's residual analyst coverage after controlling for firm size as two information diffusion proxies. Hong et al. (2000) provides supporting evidence by showing the significant influence of firm size and analyst coverage on cross-sectional momentum returns. Since firm size and stock's residual analyst coverage are not appropriate for equity indices and the commodity markets that are studied in this chapter, different measures related to information diffusion are used.

Zhang (2006) argues that the information environment determines whether the cross-sectional momentum anomaly exists or not. A good information environment (i.e., low information uncertainty) has almost no effect on momentum returns, whereas a bad information environment (i.e., high information uncertainty) enhances momentum returns. Zhang (2006) defines the source of information uncertainty to be firm fundamental volatility and poor information, and therefore proxy information uncertainty by firm size, firm age, analyst coverage, dispersion in analyst forecasts, return volatility, and cash flow volatility. Return volatility is a measure calculated from the asset index directly, which is a signal that incorporates both fundamental and behavioural information. Return volatility is more suitable to test at equity indices and commodity indices, and is more ideal proxy for information uncertainty in this chapter.

Da et al. (2014) finds that ID and Zhang's (2006) idiosyncratic return volatility are positively related, with their finding that cross-sectional momentum returns are enhanced following continuous information (low ID), is not consistent with Zhang's (2006) finding that cross-sectional momentum returns are enhanced in high idiosyncratic return volatility stocks. They construct measures to surrogate information discreteness, and test the Frog-in-the-Pan hypothesis that investors tend to underreact to continuous information (small information shocks), and overreact to discrete information (large information shocks). They demonstrate supporting evidence that following continuous information, prominent momentum returns occur without reversals. Lim et al. (2018) observe a similar pattern in individual stock market time-series momentum strategies. The construction of sign-based information discreteness as a proxy for information diffusion is informed by Da et al.'s (2014) information discreteness measure, yet the two are different. They focus on the relative magnitude and consistency of the prior price changes across stocks, whereas the present study only focuses on the assets' own price continuity. The present study argues that sign-based information discreteness is the direct application of the slippery slope effect, shown in the psychology literature (i.e., Gino and Bazerman, 2009) and adopted in Da et al. (2014). In Gino and Bazerman (2009), participants are found to accept gradually added moral degradation whereas they do not accept one-time abrupt moral degradation. The implication of this is that investors would underreact towards price changes that come consistently in small scales, due to their inattentiveness, but react properly to abrupt price changes without comparing the degree of price change discreteness across assets.

Utilising sign-based information diffusion measures instead of using traditional information diffusion measures is important for two reasons: 1) traditional information diffusion measures are created to test the relationship between cross-sectional momentum and information diffusion. However, the major difference between time-series and cross-sectional momentum is that the former focuses on return sign continuation of assets, whereas the latter focuses on the relative return performance continuation of assets. To understand its influence on the time-series momentum effect, information diffusion is added as a second dimension to time-series momentum strategies. It is natural to avoid cross asset comparison by constructing sign-based information diffusion measures; and 2) there are valid meanings of negative ID and positive ID. The former implies a continuous information environment, where the information comes in small pieces continuously. The latter implies a discrete information environment, where the information comes in big chunks.

Information discreteness is only studied at individual stock level in prior literature (e.g., Da et al., 2012; Lim et al., 2018). The reason that the present study extends ID to the broad asset class level is that, compared to individual stock level, asset class level investors are composed of larger proportion of institutional investors. This is because the participation of individual investors is mostly at the individual stock level. If ID is a psychological phenomenon that even the professional investors with more information and better analytical skills cannot avoid, its impact should also occur at the asset class level where institutional investors are clustered.

In addition, sign-based abnormal return volatility and abnormal turnover are constructed to measure information uncertainty and information dispersion, which are two other dimensions of information diffusion. The inclusion of these variables is motivated by Connolly and Stivers' (2003) finding that return continuations are stronger when abnormal return volatility and abnormal turnover are stronger at the equity index level. Return volatility and turnover are used as a proxy for information uncertainty in Zhang (2006), finding that investors underreact more to price changes under information uncertainty at the individual firm level. To meet the criteria that both the positive and negative value of the variables bears valid meanings, abnormal return volatility and abnormal turnover are chosen instead. These are measures of dispersion and turnover shocks, respectively. Since shocks are intuitively accompanied by, and reflected in, discrete price changes, it is predicted that investors also underreact more to price information accompanied with high abnormal return volatility and abnormal turnover.

The present study finds that when prior price changes arrive in an inconspicuous manner, time-series momentum investors tend not to chase these trends. This is reflected in the persistent and significant profit (ranging from annual 6.909 % for 3-6 strategy to 15.596% for 12-1 strategy) of time-series momentum strategies conditioning on absolute information discreteness for 3 to 12 months in 45 global equity indices and 27 commodity indices from 1 January 1973 to 28 September 2018. These findings are robust in each index, asset market, and subsamples.

The behavioural explanation of the finding that investors tend to underreact to price signals only under a continuous information environment could be as follows: if fundamental changes of an asset occur without news released to the market (continuous information environment), investors may fail to react immediately or react fully to the price signal. In a discrete information environment, when news is released to the market, investors absorb information promptly, which is reflected in the insignificant improvement of time-series momentum returns.

The finding that time-series momentum conditioning on absolute information continuity generates persistent and significantly positive returns is consistent with Da et al. (2014) and Lim et al. (2018). Here, cross-sectional momentum and time-series momentum conditioning on relative continuous information generates persistent and significantly positive returns. The finding that time-series momentum conditioning on absolute information discreteness generates insignificant returns is also consistent with Da et al. (2014) and Lim et al. (2018). It challenges to the behavioural theories on the mechanism of momentum effect that investors tend to underreact to price information, which leads to momentum profits (Barberis, et al., 1998; Daniel, et al., 1998; Hong and Stein, 1999), since investors under discrete price information environment do not behave in coherence with these theories.

No significant difference in time-series momentum returns is found following high and low information dispersion in global equity indices and commodity indices. This implies that index level investors are attentive to information dispersion measures. Thus, the price has fully incorporated the information dispersion, making it lack predictive power in future returns. This could be explained by the higher participation level of institutional investors at index level investment compared to individual stock level. This is because institutional investors have a greater capacity to deal with information promptly compared to individual investors.

To mitigate the influence of daily return scales on my absolute information discreteness, as is suggested in Da et al.'s (2014) relative information discreteness, absolute modified information discreteness is constructed, which is independent of the magnitude of daily returns. The results find that daily return scales do make a difference between modified and unmodified information discreteness. After adopting the modified measure, the influence of information discreteness on the time-series momentum effect are weakened significantly, which is not consistent with Da et al.'s (2014) finding on cross-sectional momentum.

Bird et al.'s multivariate regression analysis is utilised as an additional robustness check. The results show that, after controlling for other information diffusion factors, absolute information discreteness is still significant, whereas the impact of abnormal return volatility and abnormal turnover are still insignificant.

This work is relevant to time-series momentum literature on investor underreaction to absolute prior price information (Moskowitz et al, 2012; Lim et al., 2018). The present study complements this literature by showing investor asset reallocation patterns following the period of inconspicuously arriving absolute price information. Investors tend not to react promptly after the small-magnitude changes in asset prices. This provides us a new angle to understand investor trading behaviour after seemingly peaceful times. However, this is not the case following periods of high or low information uncertainty or information dispersion, since index level investors are seemingly attentive to these two measures, incorporating them into new price promptly.

The present findings are also related to the literature on limited investor attention that document investors' relative inattention to relative asset price changes (Zhang, 2006; Hershleifer, et al., 2009; Da et al., 2014). These literature focuses on cross-sectional comparisons among asset performance and invest attention in the stock market. This study complements them by demonstrating what specific elements of information diffusion that significantly influence asset returns, treating this differently from other information contained in asset prior price changes. The results show that investors fail to react promptly to absolute price signals if the signals arrive in consistently small scales at the global equity index and commodity index levels. However, investors treat abnormal return volatility and abnormal turnover similarly to other information that is contained in the prior asset price changes. That is, investors tend to be less attentive to the information arrival scale than the noises contained in the prior asset price changes. For global asset fund managers, the predictability of equity market and commodity market returns makes it unnecessary for them to diversify across these assets. They may construct low ID time-series momentum portfolios to increase portfolio alphas, or construct ID-neutral portfolios to reduce risks that are induced by information arrival scales. For individual investors who are not able to manage portfolios of a large size, they may construct low ID time-series momentum portfolios and invest in Country ETFs and Commodities ETFs.

The structure of this chapter is as follows. Section 4.3 is the development of hypotheses, with Section 4.4 describing the data collection and summary statistics. Section 4.5 then shows time-series momentum performance and demonstrates time-series momentum performance conditioning on information discreteness, abnormal return volatility, and abnormal turnover in all assets, equity indices, and commodity indices, respectively. Section 4.6 then shows multivariate regressions before section 4.7 concludes the chapter.

4.3 Hypothesis development

4.3.1 Time-series momentum and information diffusion

Hong and Stein's (1999) information diffusion hypothesis suggests that more lucrative profits should be generated among larger information diffusion assets, and suggests firm size, and stock's residual analyst coverage (after controlling for firm size) as two information diffusion proxies. Empirical evidence from Hong et al. (2000) supports their hypothesis by showing that: 1) firm size influences cross-sectional momentum returns significantly after removing the smallest stocks; 2) cross-sectional momentum returns are enhanced in low analyst coverage group stocks, after controlling for firm size; and 3) the influence of analyst coverage on cross-sectional momentum returns are more obvious for momentum losers than winners.

Moskowitz et al. (2012) establish a link between time-series momentum and information diffusion in futures market. Total returns future contracts are made up of spot returns from the spot price changes, and roll returns from rolling from short-term to long-term futures contract. They show that the shocks in total returns (measured by one standard deviation shock to total returns) leads to upward trending in cumulative total returns in the first 12 months, with the trend starting to reverse after 12 months. The relationship between shocks in spot returns and cumulative spot returns behaves similarly, however, the shocks in roll yields induce increases in cumulative roll returns without reversal. This indicates that the spot returns and roll returns jointly lead to the initial momentum, and it is spot returns alone that lead to the long-term reversal pattern.

Spot returns are conjectured to be connected to information diffusion by behavioural theories (Moskowitz et al., 2012). In addition, behavioural theories designed specifically to explain time-series momentum returns (e.g., Andrei and Cujean, 2017) also establish links between information diffusion and time-series momentum returns. They show that when new information arrives, the initial spread of rumours makes prices deviate from fundamentals, leading to momentum. The increasing speed of information flows leads to more precise information, which pushes prices back to fundamentals, inducing reversals. Since information diffusion measures are not specified in Moskowitz et al. (2012) and the relevant behavioural theories, different elements of information diffusion are adopted in this chapter to suit time-series momentum, and test the discussed relationship. This contributes to time-series momentum literature by providing more in-depth understanding of the role of information diffusion in the time-series momentum effect.

The relationship between information diffusion and time-series momentum in equity markets and commodity markets by using information discreteness, abnormal return volatility, and abnormal turnover, which are different measures related to information diffusion, will also be tested. The hypothesis development and the reasons for the chosen measures are discussed in the following subsections.

4.3.2 Time-series momentum and information discreteness (Hypothesis 4.1)

Da et al. (2014) test the influence of the slippery slope effect (also named Frog-in-Pan hypothesis in Da et al. (2014)) in the psychology literature (i.e., Gino and Bazerman, 2009) on the cross-sectional momentum effect. They construct information discreteness to capture whether the information generally arrives in big chunks or small pieces. They divide information discreteness into five quintiles and find that cross-sectional momentum effects are enhanced following information that arrives in small pieces.

In Gino and Bazerman (2009), participants are found to accept gradually added moral degradation, whereas they do not accept one-time abrupt moral degradation. The application on investors would be that they underreact towards price changes that come consistently in small scale, and react properly to abrupt price changes. Therefore, if information discreteness is constructed to proxy for the size of information arrival, the measure should not be adopted in a relative manner, because the investor reactions are not supposed to be compared among the degree of price change discreteness across assets. In this sense, to directly apply information discreteness by adopting an asset's own price information arrival scale, instead of using relative information discreteness across assets, is the more natural option for time-series momentum, which only involves the continuation of an assets own price changes. If investors are less attentive to small pieces of price information, the time-series momentum returns should be enhanced when the information continuity is higher (i.e., the information discreteness is lower). Therefore, the following hypothesis is presented.

H4.1 The time series momentum effect is enhanced under greater information continuity (i.e., negative information discreteness).

4.3.3 Time-series momentum and information uncertainty (Hypothesis 4.2)

Motivated by Daniel et al.'s (1998, 2001) behavioural theory prediction that investor over-confidence regarding private information increases with information uncertainty, making the firm return predictability stronger, Zhang (2006) hypothesises that cross-sectional momentum is enhanced under higher information uncertainty. In a good information environment (i.e., low uncertainty), the investors react promptly to new information, whereas in a bad information environment (i.e., high uncertainty), investors fail to react promptly to new information. They find evidence supporting the hypothesis that under greater information uncertainty, positive (negative) news is accompanied by more positive (negative) returns.

Moskowitz et al. (2012) argue that cross-sectional momentum is relative asset performance continuation whereas time-series momentum is absolute asset performance continuation. Therefore, time-series momentum is a more direct application of behavioural theories (i.e., Daniel et al., 1998; Barberis et al., 1998; and Hong and Stein, 1999), since these theories focus on investor reaction to prior absolute price changes of assets, rather than the relative price changes. Following Moskowitz et al.'s (2012) argument, the Zhang (2006) hypothesis should also hold in time-series momentum. Therefore, the time-series momentum effect should also be enhanced under greater information uncertainty.

Zhang (2006) defines the source of information uncertainty to be firm fundamental volatility and poor information, and therefore proxy information uncertainty by firm size, firm age, analyst coverage, dispersion in analyst forecasts, return volatility, and cash flow volatility. However, this chapter focuses on equity indices and commodity indices, therefore, return volatility is more suitable proxy for information uncertainty. In addition, return volatility is a measure calculated from the asset index directly, which is a signal that incorporates both fundamental and behavioural information.

The major difference between time-series momentum and cross-sectional momentum is that the former is the absolute industry performance continuation, and the latter is the relative industry performance continuation. Therefore, when studying the influence of information uncertainty on time-series industry momentum, it is natural to choose the measures that do not require cross-asset comparison. In this sense, the measures with valid meanings under both positive and negative signs may fit the criterion, for they do not involve cross-asset comparison. However, return volatility itself does not satisfy the criterion that the sign of the measure must have valid meanings. Thus, a similar proxy to that from Connolly and Stivers (2003) is utilised, which is abnormal return volatility. Abnormal return volatility is the remaining part of the asset return volatility that is not explained by the autoregressive behaviour of return volatility and the changes induced by the sign and scale of previous period returns. Positive (negative) abnormal return volatility means high (low) information uncertainty.

Another proxy utilised from Connolly and Stivers (2003) is abnormal turnover, which is the remaining part of asset turnover that is not explained by the autoregressive behaviour of asset turnover and the changes induced by the sign and scale of previous period returns. Positive abnormal turnover is classified as high information diffusion and negative abnormal turnover is classified as low information diffusion. The reasons that abnormal turnover from Connolly and Stivers are used as another element of information diffusion are because: 1) compared to other information diffusion measures such as firm age, firm size, analyst coverage and forecast dispersion, it is more feasible to retrieve the data from asset class level; 2) it incorporates both fundamental and behavioural information and will not be influenced by information quality; and 3) abnormal turnover does not involve cross asset comparison when it comes to form time-series momentum portfolios under different information environment. However, due to data availability, this measure is only adopted at equity indices in this chapter. The hypotheses are constructed below.

H4.2 The time series momentum effect is enhanced under more abnormal return volatility.

H4.3 The time series momentum effect is enhanced under more abnormal turnover.

4.4 Data and summary statistics

4.4.1 Sample data

The data is composed of 45 equity indices and 27 commodity indices at a daily frequency. International equity indices and commodity indices are taken from DataStream. Commodity indices are taken from DataStream S&P GSCI Excess Return. It is important to note that GSCI commodity index excess return instead of GSCI commodity index total return, is used. This is because GSCI commodity index excess return is calculated as the sum of contract daily return indexed to a base of 100 whereas GSCI commodity index total return is GSCI commodity index excess return and Treasury bill rates. Thus, the commodity index returns are calculated as the percentage change in excess returns of the current and the previous months. Due to the missing data for some countries and commodities, equity indices are from 1st January 1973 to 28th September 2018 and commodity indices are from 31st December 1969 to 28th September 2018. I use log difference to calculate the compounded monthly returns. The daily frequency indices are used to calculate the information diffusion measures.

The data collection broadly follows Georgopoulou and Wang (2016). The main difference is that the data used in the present study is from DataStream instead of the MSCI World Index due to the database availability. The developed markets are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, and the United States. The emerging markets are Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Malaysia, Mexico, Philippines, Poland, Qatar, South Africa, Taiwan, Thailand, Turkey, United Arab Emirates, Peru, and Korea. For the commodity indices, some minor adjustments were made on their dataset, by excluding Petroleum and including gas oil, lead, orange Juice, platinum, soybean oil, tin and unleaded gasoil. Petroleum is excluded because the current data has included crude oil which is the sub-index of petroleum. Thus, the commodity indices that are included are crude oil, gold, copper, natural gas, corn, silver, zinc, sugar, soybeans, cocoa, heating oil, aluminium, nickel, coffee, lean hogs, palladium, wheat, cotton, live cattle, brent crude, gas oil, lead, orange juice, platinum, soybean oil, tin and unleaded gasoil. Federal funds rates are obtained as a benchmark for excess return calculation. From the list of equity indices and commodity indices, you can note that all major sectors of commodities are covered (energy, metals, grains, industrial raw materials), with all continents are covered, providing a truly global coverage.

4.4.2 Summary statistics

Table 4.1 panel A and B summarise international equity market indices and commodity market indices performance. International equity indices generate moderately positive annual returns (on average 6.49% annual returns, ranging from -2.941% to 26.876%) whereas commodity market generates negative annual returns (-2.091% annual returns on average, ranging from -27.871% to 9.475%). The return volatilities of the two asset classes are high, ranging from 15.021% to 48.613%. The average skewness is -0.332 for equities and -0.211 for commodities. The average kurtosis of the equities is above 4, whereas that of the commodities is around 2. Since the returns are not normally distributed, non-parametric statistics need to be considered.

Table 4.1 panel C and D demonstrates the distribution of the information diffusion measures and their correlations, respectively. It is observed that mean information discreteness is negative for all assets (-0146), equity indices (-0.158), and commodity indices (-0.124). The 25th, 50th, and 75th information discreteness are also negative. This indicates that information comes predominantly in small pieces in the sample. This is reflected in Panel E, where the portfolios with negative ID significantly outnumber the ones with negative ID in all ranking months in all assets, equity indices, and commodity indices. A similar phenomenon can be observed at the individual stock level in Da et al. (2014). They divide ID of individual stocks into five quintiles and calculate the average ID in each quintile, demonstrating that only the top quintile has a positive ID value (defined as discrete in Da et al. 2014), with the remaining quintiles all negative.

The value of modified information discreteness (ID_{MAG}) which is constructed to smooth the influence of the magnitude of daily returns on the measure of information discreteness by Da et al. (2014), is also mainly negative in all assets and equity indices. In commodity indices, mean ID_{MAG} is positive (0.029) and the 50th is slightly negative (-0.002). This is reflected in panel E where the portfolios with negative ID_{MAG} significantly outnumber the ones with positive ID_{MAG} in all ranking months in assets and equity indices. In commodity indices, the difference between the number of portfolios with negative and positive ID_{MAG} decreases. Overall, ID_{MAG} is less negative compared to ID. In Da et al. (2014), the value of ID_{MAG} is also less negative compared to ID. The average values of the most discrete 2 quintiles of ID_{MAG} are 0.02 and 0.00, whereas these values are 0.03 and -0.01, respectively, for ID.

The mean of abnormal return volatility is around 0 in all assets, equity indices and commodity indices and the 50th is slightly negative (-0.002, -0.004, and -0.002 for all assets, equity indices and commodity indices, respectively). This implies that there is very little noise at the asset indices level. This is reflected in panel E where the number of positive abnormal return volatility portfolios are similar to that of negative abnormal return volatility portfolios in all ranking months in all assets, equity indices, and commodity indices.

Panel D shows the Pearson correlation of the information diffusion measures for 1,3,6, and 12 ranking months in all assets, equity indices, and commodity indices. We may find that for all assets, ID and ID_{MAG} are strongly correlated when ranking month is one month, and the correlation decreases with the increase in ranking month. There is no significant correlation between ARV and ID, ARV and ID_{MAG}. For equity indices, the same phenomenon can be observed. In addition, AT also demonstrates no significant correlation with other information diffusion measures. For commodity indices, the correlation between ID and ID_{MAG} is much weaker compared to all assets and equity indices. Overall, the information diffusion measures (i.e., information discreteness, abnormal return volatility, and abnormal turnover) are not highly correlated, indicating that they are different elements of information diffusion.

A slight correlation between ID and time series momentum class (TH and TL) can be observed in panel E. TH is related to more negative ID, indicating that positive previous return assets tend to have more continuous information. Such correlations are trivial in modified ID, ARV, and AT.

Table 4. 1 Summary statistics

Panel A. International equity market indices

	Annualized mean return (%)	Annualised volatility (%)	Skewness	Excess kurtosis
AUSTRALIA	6.679	18.834	-1.678	14.949
AUSTRIA	4.236	18.976	-0.211	7.800
BELGIUM	5.165	16.851	-1.008	6.187
CANADA	5.080	15.264	-0.945	4.261
DENMARK	8.275	17.629	-0.469	1.654
FINLAND	5.877	26.298	-0.310	1.644
FRANCE	6.871	19.580	-0.387	1.629
GERMANY	3.435	17.198	-0.719	2.454
HONG KONG	7.111	30.657	-0.930	7.946
IRELAND	6.480	21.825	-0.637	4.580
ISRAEL	3.342	19.504	-0.495	1.243
ITALY	6.106	22.703	0.195	1.189
JAPAN	4.327	17.373	-0.230	1.435
NETHERLAND	4.351	17.259	-1.220	5.305
NEW ZEALAN	4.192	15.170	0.086	3.527
NORWAY	7.212	23.239	-1.083	3.657
PORTUGAL	0.488	17.995	-0.228	2.234
SINGAPORE	2.131	25.107	-0.355	7.867
SPAIN	3.532	20.025	-0.907	3.783
SWEDEN	8.966	21.436	-0.463	1.878

SWITZ	4.145	15.021	-1.076	4.847
UK	6.402	18.208	0.280	9.623
US	6.352	15.348	-0.760	3.343
BRAZIL	8.709	24.652	-0.743	3.240
CHILE	10.271	17.753	0.138	2.309
CHINA A	10.481	36.608	1.242	7.347
COLOMBIA	9.039	20.580	0.044	1.277
CZECH REP.	3.345	23.564	0.979	12.028
EGYPT	7.197	28.737	-0.236	1.978
GREECE	-2.941	33.361	0.414	3.522
HUNGARY	7.567	28.283	0.268	6.737
INDIA	9.906	30.751	0.174	5.572
INDONESIA	4.541	28.233	-0.981	4.866
MALAYSIA	7.651	23.807	-0.562	6.940
MEXICO	17.786	23.586	0.215	3.402
PHILIPPINE	9.160	24.549	0.005	3.575
POLAND	0.648	28.857	-0.424	4.021
QATAR	5.874	27.997	-0.163	3.019
SOUTH AFRI	12.169	21.603	-0.938	3.930
TAIWAN	1.426	32.282	-0.466	5.628
THAILAND	6.594	30.559	-0.479	3.467
TURKEY	26.876	42.793	0.571	2.810
U.A.E.	4.954	26.092	0.034	2.378
PERU	6.761	20.798	-0.754	5.746
KOREA	3.327	27.270	0.264	3.538

Panel B. Commodity market indices

	Annualized mean return (%)	Annualised volatility (%)	Skewness	Excess kurtosis
Crude Oil	1.812	32.638	-0.547	2.685
Gold	-0.801	18.895	0.107	3.553
Copper	1.484	26.546	-0.571	4.571
Natural Gas	-27.871	48.613	0.042	0.474
Corn	-6.569	24.934	0.632	3.359
Silver	-2.696	32.410	-0.221	6.179
Zinc	-5.622	24.534	-0.470	3.470
Sugar	-4.867	38.149	0.445	1.576
Soybeans	1.250	25.407	0.594	2.717
Cocoa	-7.855	27.336	0.176	1.222
Heating Oil	1.687	30.281	-0.177	2.131
Aluminium	-7.283	18.256	-0.238	0.403
Nickel	-0.600	32.206	-0.254	0.367
Coffee	-6.589	34.663	0.661	2.470
Lean Hogs	-4.524	24.191	-0.204	0.583
Palladium	9.400	25.826	-0.800	0.408
All Wheat	-5.382	26.419	0.199	1.837
Cotton	-2.330	23.151	0.109	0.843

Live Cattle	3.890	16.760	-0.277	2.310
Brent Crude	5.706	33.175	-1.010	3.712
Gas Oil	9.475	30.921	-0.424	1.880
Lead	1.067	28.520	-0.236	1.463
Orange Juice	-4.454	29.470	-0.184	0.479
Platinum	-0.975	21.788	-0.297	3.518
Soybean Oil	-6.380	24.979	-0.665	2.610
Tin	-3.574	33.926	-1.428	6.809
Unleaded Gasoil	6.136	33.969	-0.665	3.976

Panel C. Summary statistics for information diffusion measures

All assets	25th	50th	75th	Mean	Standard deviation
ID	-0.260	-0.140	-0.027	-0.146	0.175
ID_{MAG}	-0.031	-0.004	0.019	-0.006	0.042
ARV	-0.012	-0.002	0.009	0.000	0.021

Equity indices	25th	50th	75th	Mean	Standard deviation
ID	-0.277	-0.151	-0.038	-0.158	0.182
ID_{MAG}	-0.035	-0.006	0.018	-0.008	0.044
ARV	-0.010	-0.002	0.008	0.000	0.019
AT	-0.167	-0.004	0.161	0.000	0.288

Commodity indices	25th	50th	75th	Mean	Standard deviation
ID	-0.232	-0.121	-0.011	-0.124	0.163
ID_{MAG}	-0.024	-0.002	0.019	0.039	0.039
ARV	-0.014	-0.002	0.010	0.000	0.024

Panel D. Pairwise Pearson correlation of information diffusion measures

All assets

Ranking month(s)		ID	ID_{MAG}	ARV
1	ID	1.000	0.517	0.210
	ID_{MAG}	0.517	1.000	0.008
	ARV	0.210	0.008	1.000
3	ID	1.000	0.330	-0.016
	ID_{MAG}	0.330	1.000	-0.023
	ARV	-0.016	-0.023	1.000
6	ID	1.000	0.249	-0.040
	ID_{MAG}	0.249	1.000	-0.022
	ARV	-0.040	-0.022	1.000

12	ID	1.000	0.234	0.051
	ID_{MAG}	0.234	1.000	0.035
	ARV	0.051	0.035	1.000

Equity indices

Ranking month(s)		ID	ID_{MAG}	ARV	AT
	ID	1.000	0.587	0.277	0.072
	ID_{MAG}	0.587	1.000	0.034	0.067
	ARV	0.277	0.034	1.000	0.090
1	AT	0.072	0.067	0.090	1.000
	ID	1.000	0.364	-0.020	0.077
	ID_{MAG}	0.364	1.000	0.036	-0.061
	ARV	-0.020	0.036	1.000	-0.014
3	AT	0.077	-0.061	-0.014	1.000
	ID	1.000	0.327	0.007	0.019
	ID_{MAG}	0.327	1.000	0.020	-0.081
	ARV	0.007	0.020	1.000	0.039
6	AT	0.019	-0.081	0.039	1.000
	ID	1.000	0.299	0.036	0.031
	ID_{MAG}	0.299	1.000	0.071	-0.032
	ARV	0.036	0.071	1.000	0.059
12	AT	0.031	-0.032	0.059	1.000

Commodities

Ranking month(s)		ID	ID_{MAG}	ARV
	ID	1.000	0.279	0.135
	ID_{MAG}	0.279	1.000	0.034
1	ARV	0.135	0.034	1.000
	ID	1.000	0.156	0.004
	ID_{MAG}	0.156	1.000	0.018
3	ARV	0.004	0.018	1.000
	ID	1.000	0.141	-0.029
	ID_{MAG}	0.141	1.000	-0.002
6	ARV	-0.029	-0.002	1.000
	ID	1.000	0.064	0.010
	ID_{MAG}	0.064	1.000	-0.055
12	ARV	0.010	-0.055	1.000

Panel E. Number of assets in each portfolio

All assets

Ranking month(s)	Holding month(s) / Annual Returns (%)	ID		ID_{MAG}		ARV	
		IL	IH	IL_{MAG}	IH_{MAG}	AL	AH
	TH	21	4	14	10	15	12
1	TL	17	4	11	9	13	10
	TH	19	7	15	9	15	12
3	TL	13	7	10	9	12	9
	TH	18	9	16	9	15	13
6	TL	12	8	10	8	12	10
	TH	17	9	17	9	15	14
12	TL	11	8	10	8	11	9

Equity indices

Ranking month(s)	Holding month(s) / Annual Returns (%)	ID		ID_{MAG}		ARV		AT	
		IL	IH	IL_{MAG}	IH_{MAG}	AL	AH	AL_T	AH_T
	TH	15	3	11	7	11	8	8	8
1	TL	11	3	7	6	8	6	6	6
	TH	14	5	12	7	11	9	8	8
3	TL	8	4	7	6	8	6	6	6
	TH	13	6	13	6	11	10	9	9
6	TL	7	5	6	5	7	6	5	5
	TH	13	7	14	6	11	11	9	9
12	TL	6	5	6	5	6	5	5	5

Commodity indices

Ranking month(s)	Holding month(s) / Annual Returns (%)	ID		ID_MAG		ARV	
		IL	IH	IL	IH	AL	AH
	TH	7	2	4	3	5	4
1	TL	7	2	4	4	5	4
	TH	6	2	4	3	5	4
3	TL	6	3	4	4	5	4
	TH	5	3	4	3	4	4
6	TL	5	3	4	3	5	4
	TH	5	3	4	3	4	4
12	TL	5	3	4	3	5	4

Table 4.1. Panel A and B report annualized mean return, annualised volatility (standard deviation), skewness and excess kurtosis of international equity market indices and commodity indices. The international equity market indices range from 1 January 1973 to 28 September 2018, and the commodity indices range 31 December 1969 to 28 September 2018. Panel C reports 25^{th}, 50^{th}, 75^{th}, mean, and standard deviation the information diffusion

measures across 1,3,6, and 12 months' ranking period for all assets, equities, and commodities. ID denotes information discreteness, ID_{MAG} denotes modified information discreteness, ARV denotes abnormal return volatility, and AT denotes abnormal turnover. Due to the unavailability of turnover data for commodity market, the reported statistics of ID, ID_{MAG}, and ARV are for all asset classes while of AT is for equity indices only. The detailed description for the measures is in Section 3.1. Panel D presents pairwise Pearson correlation between the information diffusion measures. Panel E demonstrates the number of assets in each portfolio. IL denotes negative information discreteness (or low information discreteness), IH denotes positive information discreteness (or high information discreteness), IL_{MAG} denotes negative modified information discreteness, IH_{MAG} denotes positive modified information discreteness, AL denotes negative abnormal return volatility (or low abnormal return volatility), AH denotes positive abnormal return volatility (or high abnormal return volatility), AL_T denotes negative abnormal turnover (or low abnormal turnover), AH_T denotes positive abnormal turnover (or high abnormal turnover).

4.5 Empirical results

4.5.1 Standard time-series momentum performance

Table 4.2 panel A presents the annualised raw returns for standard time-series momentum strategies. The strategy returns are shown in the line TH-TL. The returns are prominent across all horizons. The profits are strongly significant in all assets, equity indices, and commodity indices in all ranking month and holding month combinations. For example, the 12-1 strategy (i.e., 12-month ranking period and 1-month holding period), which is the most extensively examined strategy in momentum literature, yields 12.345% annual returns with a t-statistic 5.536 for all assets. The long position (TH) and the short position (TL) generate 8.739% and -3.606% annual returns, respectively. Thus, they all contribute to an overall significant return performance. Among the strategies with a relatively short horizon, 3-1 strategies (i.e., 3-month ranking period and 1-month holding period) yield relatively good annual returns in all assets. Its long position (TH) generates 8.377% annual returns, while its short position (TL) generates -1.114% annual returns. Thus, the overall 3-1 strategy performance is 9.491% (with t-stat=4.851). The time-series momentum strategy returns are economically large and statistically significant in equity indices (9.291% annual return with t-stat 4.172) and commodity indices (9.913% annual return with t-stat 3.039) as well.

It can be observed that the time-series momentum returns are mainly from the long position in all assets and equity indices, which is consistent with the findings from the prior time-series momentum literature (e.g., Goyal and Jegadeesh, 2018). Goyal and Jegadeesh (2018) find that it is the net long position of TSM that drives TSM returns in asset indices and the individual stock market. Only the short positions of 5 out of 12 strategies (i.e., 3-1, 6-1, 12-1, 12-3, and 12-6 strategy) in all assets, and the short positions of 1 out of 12 strategies (i.e., 12-1 strategy) in equity indices, contribute on a minor scale to the corresponding strategy returns. This suggests that substantial profits can be made without having to short sell[3] in all assets and equity indices. However, in commodity indices, the returns of all 12 strategies are composed of both long and short positions, and in 10 out of 12 strategies, the short positions are the main source of profit.

By demonstrating the significant time-series momentum returns in all assets, equity indices, and commodity indices, the results in this section are consistent with time-series momentum literature (e.g., Moskowitz et al. 2012) findings that positive (negative) return assets in the previous periods tend to generate positive (negative) returns in the next periods. In all assets and equity indices, the main profit sources of TSM are long positions, whereas in commodity indices, the main profit sources are short positions. Since in the real world, not all assets can be short sold and in certain period of times short sell bans can happen. For real world investors, the application of TSM in equity indices or all assets are more feasible, because they do not rely on short position returns.

4.5.2 Is time series momentum effect enhanced under greater information continuity (i.e., negative information discreteness)?

To describe the results concisely, TH is used to denote the long portfolio of standard time-series momentum strategy, TL to denote the short portfolio of standard time-series momentum strategy, TH (IL) to denote the long portfolio with negative information discreteness (continuous information), TH (IH) to denote the long portfolio with positive information discreteness, TL (IL) to denote the short portfolio with negative information discreteness, and TL (IH) to denote the short portfolio with positive information discreteness. TH-TL and IL-IH in the tables are the return difference between the portfolios. TH (IL)-TL (IL) denotes the difference between TH (IL) and TL (IL).

[3] A lot of anomalies are concentrated on short side, which can be difficult to implement.

Table 4.3 panel A reports the annualised raw returns for information discreteness grouped time-series momentum returns in all assets. Comparing with the standard time-series momentum returns in Table 4.2, it can be seen that across all horizons, TH (IL) outperforms TH whereas TH (IH) underperforms TH. This means that the assets with previous positive returns and continuous (discrete) information tend to outperform (underperform) the assets with previous positive returns. In the short portfolios (TL), the reverse occurs: assets with previous negative returns and continuous (discrete) information tend to underperform (outperform) the assets with previous positive returns. This contributes to the dominant performance of time-series momentum portfolios with continuous information over standard time-series momentum strategies. On average, TSM with continuous information generates around 2% more returns than standard time-series momentum strategies in all assets.

For example, for the 12-1 strategy (i.e., 12-month ranking period and 1-month holding period) in all assets, TH (IL)-TL (IL) produces 15.596% annual return (t-stat= 5.326), which is around 3.2% higher than standard 12-1 strategy return (12.345% with t-stat=5.536). TH (IL) generate 10.783% returns, which outperforms TH returns of 8.739% by around 2%. TL (IL) generates -4.183% returns, which induces more negative returns by around 1% compared to the TL returns of -3.606%, inducing an increase in TSM returns by around 3% under information continuity (i.e., negative information discreteness, denoted by IL) compared to standard TSM returns. By contrast, TH (IH)-TL (IH) substantially underperforms against the standard strategy. This is mainly caused by the worse performance of its long position TH (IH), which is almost 4% lower than the standard TSM long position TH.

For a 3-1 strategy (i.e., 3-month ranking period and 1-month holding period) in all assets, it yields annual 11.279% returns (t-stat=4.596), which also outperforms the standard 3-1 TSM strategy (annual 9.491% with t-stat 4.851) in all assets. TH (IL) produces 9.913% returns, which is around 1.5% more than TH (8.377%), and TL (IL) produces -1.365% returns, which is 0.25% more negative return than TL (-1.114%). Therefore, the overall TH (IL)-TL (IL) 3-1 strategy return is around 1.8% higher than the standard time-series momentum 3-1 strategy returns. In contrast, the performance of TH (IH) is much worse than TH and the TL (IH) generates a substantially positive return, inducing the underperformance of TH(IH)-TL (IH) for 3-1 strategy compared to standard 3-1 TSM strategy.

Therefore, the enhanced TSM returns under continuous information environment is induced by more positive long position returns and more negative short position returns of the portfolios. This is also true in equity indices (panel B) and commodity indices (panel C). For example, in equity indices, the 12-1 strategy (i.e., 12-month ranking period and 1-month holding period) TH (IL)-TL (IL) produces 11.673% annual returns (t-stat = 3.252), which is around 2% higher than standard 12-1 strategy returns (9.291% with t-stat = 4.172). TH (IL) generates 10.297% returns, which outperforms TH returns of 8.275% by around 2.3%. TL (IL) generates -1.376% returns, which induces more negative returns by around 0.3% than the TL returns of -1.016%, inducing an increase in TSM returns by around 2.3% under information continuity (i.e., negative information discreteness, denoted by IL) compared to standard TSM returns. Contrarily, TH (IH)-TL (IH) substantially underperforms against the standard strategy. This is jointly caused by the worse performance of its long position TH (IH) (7.707%), which is around 0.5% lower than the standard TSM long position TH (8.275%), and the less negative return generated by its short position TL(IH) (0.572%), which is around 1.5% less negative than the standard TSM short position TL (-1.016%).

In commodity indices, the 12-1 strategy (i.e., 12-month ranking period and 1-month holding period) TH (IL)-TL (IL) produces 17.957% annual returns (t-stat = 4.059), which is around 8% higher than standard 12-1 strategy return (9.913% with t-stat = 3.039). TH (IL) generates 10.286% returns, which outperforms TH returns of 3.771% by around 7%. TL (IL) generates -7.673% returns, which induces more negative returns by around 1% than the TL returns of -6.142%, inducing an increase in TSM returns by around 8% under information continuity (i.e., negative information discreteness, denoted by IL) compared to standard TSM returns. Contrarily, TH (IH)-TL (IH) substantially underperforms against the standard strategy. This is mainly caused by the worse performance of its long position TH (IH) (-3.187%), which is almost 6% lower than the standard TSM long position TH (3.771%).

The above findings support Hypothesis 4.2a that the time series momentum effect is enhanced under greater information continuity (i.e., negative information discreteness).

This finding complements Da et al. (2014) by extending the slippery slope effect (or Frog-in-Pan hypothesis) to the time-series momentum context, and contribute to time-series momentum literature by showing that investors process information that arrives in small pieces differently from other information that is contained in prior asset price changes. That is, they tend to underreact more to prior asset price changes when information arrives in small pieces. For real world investors who are trend chasers, the implication is that they may increase trading strategy alpha by introducing low ID as a second dimension to their trend chasing strategies.

4.5.3 Is time-series momentum effect enhanced under greater modified information continuity (i.e., modified negative information discreteness)?

In this part, I use TH to denote the long portfolio of standard time-series momentum strategy, TL to denote the short portfolio of standard time-series momentum strategy, TH (IL_{MAG}) to denote the long portfolio with negative modified information discreteness (continuous information), TH (IH_{MAG}) to denote the long portfolio with positive modified information discreteness, TL (IL_{MAG}) to denote the short portfolio with negative modified information discreteness, and TL (IH) to denote the short portfolio with positive modified information discreteness. TH-TL and IL-IH in the tables are the return difference between the portfolios. Finally, TH(IL_{MAG})-TL (IL_{MAG}) denotes the difference between TH (IL_{MAG}) and TL (IL_{MAG}).

Table 4.4 panel A (see section 4.8 appendices) demonstrates the performance of modified information discreetness grouped time-series momentum strategies in all assets. The returns of TH (IL_{MAG})-TL(IL_{MAG}) are significantly positive; however, they fail to outperform the standard TSM returns in all cases. This is reflected in the finding that the returns of TH (IH_{MAG}) are as strong as TH (IL_{MAG}), indicating that the introduction of ID_{MAG} does not play a significant role in influencing the performance of the overall modified time-series momentum strategy returns. Thus, in comparison to Table 4.2 and Table 4.3, although the overall performance is significant, modified information discreteness grouped time-series momentum strategy fails to outperform the previous two strategies.

For example, for the 12-1 strategy (i.e., 12-month ranking period and 1-month holding period) in all assets, the annual return for $TH(IL_{MAG})$-$TL(IL_{MAG})$ is 11.690% (t-stat =4.801). This is lower than the TH (IL)-TL (IL) 12-1 strategy (15.596% with t-sat =5.326) and the standard time-series momentum 12-1 strategy (12.345% with t-stat =5.536) in all assets. This is mainly because of the relatively weaker performance of $TH(IL_{MAG})$ (7.756%) compared to TH (8.739%) and TH(IL) (10.783%). In addition, we may find that although $TH(IH_{MAG})$-$TL(IH_{MAG})$ underperforms against $TH(IL_{MAG})$-$TL(IL_{MAG})$ and the returns are of similar scale, with the former annual 11.690% (t-stat = 4.801) and the latter annual 8.545% (t-stat = 3.995).

For 3-1 strategy (i.e., 3-month ranking period and 1-month holding period) in all assets, $TH(IL_{MAG})$-$TL(IL_{MAG})$ is 8.098% (t-stat = 2.713). This is lower than TH (IL)-TL (IL) 3-1 strategy (11.279% with t-stat = 4.596) and the standard time-series momentum 3-1 strategy (9.491% with t-stat =4.851) in all assets. This is induced jointly by the relatively weaker performance of the long position $TH(IL_{MAG})$ (7.536%) compared to TH (8.377%) and TH(IL) (9.913%) and less negative short position returns $TL(IL_{MAG})$ (-0.561%) compared to TL (-1.114%) and TL(IL) (-1.365%). Though $TH(IH_{MAG})$-$TL(IH_{MAG})$ underperform $TH(IL_{MAG})$-$TL(IL_{MAG})$, the returns are of similar scale, with the former annual 8.098% (t-stat = 2.713) and the latter annual 6.716% annual (t-stat = 2.72).

For equity indices, the 12-1 strategy (i.e., 12-month ranking period and 1-month holding period) annual return for $TH(IL_{MAG})$-$TL(IL_{MAG})$ is 9.135% (t-stat=2.687). This is lower than TH (IL)-TL (IL) 12-1 strategy (11.673% with t-stat= 3.252) and is similar to the standard time-series momentum 12-1 strategy returns (9.291% with t-stat=4.172). The weaker performance of TSM under modified negative information discreteness compared to TSM under negative information discreteness is mainly because of the relatively weaker performance of $TH(IL_{MAG})$ (8.304%) compared to and TH(IL) (10.297%). In addition, we may observe that though $TH(IH_{MAG})$-$TL(IH_{MAG})$ underperforms against $TH(IL_{MAG})$-$TL(IL_{MAG})$ and the returns are of similar scale, with the former annual 9.135% (t-stat = 2.687) and the latter annual 7.370% (t-stat = 2.594).

For commodity indices, the 12-1 strategy (i.e., 12-month ranking period and 1-month holding period) annual return for $TH(IL_{MAG})$-$TL(IL_{MAG})$ is an insignificant 7.115% (t-stat

=1.458). This is much lower than TH (IL)-TL (IL) 12-1 strategy (17.959% with t-stat = 4.059) and the standard time-series momentum 12-1 strategy (9.913% with t-stat = 3.039). This is mainly because of the weaker performance of TH (IL_{MAG}) (2.135%) compared to TH (3.771%) and TH(IL) (10.286%). The TH (IH_{MAG})-TL (IH_{MAG}) and TH (IL_{MAG})-TL (IL_{MAG}) returns are of similar scale, with the former annual 7.115% (t-stat = 1.458) and the latter annual 7.112% (t-stat = 1.974).

In Da et al.'s (2014) study on cross-sectional momentum returns, they find that modified information discreteness generates a similar pattern as the original information discreteness, which is not the case in this time-series momentum study. It can be observed that the returns of TH (IL_{MAG})-TL (IL_{MAG}) and TH (IH_{MAG})-TL (IH_{MAG}) are of a similar scale, indicating that ID_{MAG} may not play an important role in influencing time-series momentum returns. The potential reason that leads to the different impact of ID and ID_{MAG} on time-series momentum performance is that the construction of ID_{MAG} smoothens the influence of the magnitude of daily returns by allocating corresponding consistently decreasing weights w_i ($\frac{5}{15}, \frac{4}{15}, \frac{3}{15}, \frac{2}{15}, and\ \frac{1}{15}$). That is, more (less) weight is allocated to small (large) daily returns.

4.5.4 Is time series momentum effect enhanced under more abnormal return volatility?

In this section, I use TH to denote the long portfolio of the standard time-series momentum strategy, TL to denote the short portfolio of the standard time-series momentum strategy, TH (AL) to denote the long portfolio with negative abnormal return volatility, TH (AH) to denote the long portfolio with positive abnormal return volatility, TL (AL) to denote the short portfolio with negative abnormal return volatility, and TL (AH) to denote the short portfolio with positive abnormal return volatility. TH-TL and IL-IH in the tables are the return difference between the portfolios. Finally, TH (AL)-TL (AL) denotes the difference between TH (AL) and TL (AL).

Table 4.5 panel A (see section 4.8 appendices) presents abnormal return volatility grouped time-series momentum performance in all assets. It can be observed that the returns of TH (AH)-TL (AH) and TH (AL)-TL (AL) are of similar scale, indicating that abnormal return volatility fails to make a difference among time-series momentum portfolios. In 9 out of 12 observations, AH leads to significantly more negative returns for the short portfolio compared to their counterparts in standard TSM short portfolios, which is in the favoured direction for overall strategy returns. However, the corresponding long position returns are significantly lower than its standard TSM counterparts. Thus, in most of the observations, abnormal return volatility grouped time-series momentum underperforms against standard time-series long minus short momentum portfolio (TH-TL) returns. In 11 out of 12 observations, long minus short portfolio with positive abnormal return volatility (AH) underperforms against standard time-series long minus short portfolio returns, and all long minus short portfolio with negative abnormal return volatility (AL) underperforming against (TH-TL) portfolio returns. In addition, in 8 out of 12 observations, TH (AH)-TL (AH) outperforms TH (AL)-TL (AL), although most of the outperformances are not statistically significant. Thus, although the overall abnormal volatility grouped time-series momentum is significant, no clear and significant improvement pattern can be observed by introducing the abnormal return volatility.

For example, for 12-1 strategy in all assets, TH(AL)-TL(AL) generates annual returns of 14.563% (t-stat = 5.019), and TH(AH)-TL(AH) generates an annual return of 9.811% (t-stat =3.554). TH-TL generates annual returns of 12.345% (t-stat = 5.536). This indicates that TSM returns are enhanced under low abnormal return volatility. However, in most cases, the TSM returns under low abnormal return volatility and the returns under high abnormal return volatility are of a similar scale. Thus, the strategy returns are similar to or less than standard TSM returns. For example, for 3-1 strategy in all assets, TH(AL)-TL(AL) generates annual returns of 9.275% (t-stat= 3.755) and TH(AH)-TL(AH) generates annual returns of 10.520% (t-stat=3.468). This indicates that the TSM returns are similar under low and high abnormal return volatility. The abnormal return volatility grouped TSM returns are similar to standard TSM returns (9.491% with t-stat = 4.851). The similar phenomenon can be observed strategies such as 3-6, 3-12, 12-3, 12-6 and 12-12 in Table 4.5 panel A.

For equity indices and commodity indices, there is no consistent pattern as to whether TSM performs better in low abnormal return volatility or high abnormal return volatility. Therefore, no significant improvements are found after introducing low or high abnormal return volatility as a second dimension to time-series momentum strategies.

Accordingly, the above findings do not support Hypothesis 4.2b that the time series momentum effect is enhanced under more abnormal return volatility. Connolly and Stivers (2003) show that abnormal return volatility is positively related to cross-sectional momentum in weekly equity indices. The insignificant influence of abnormal return volatility on time-series momentum implies that the abnormal return volatility in the prior index changes is treated in the same way as other information contained in the index changes by investors. Another potential reason could be that the influence of abnormal return volatility is short-lived. In Connolly and Stivers (2003), weekly horizons are used, whereas in this chapter, monthly horizon are adopted. Future research on the relationship between abnormal return volatility and time-series momentum may choose to focus on weekly horizon.

4.5.5 Is time series momentum effect enhanced under more abnormal turnover?

Due to turnover data availability in commodity indices, this section only discusses abnormal turnover grouped TSM returns in equity indices. Table 4.6 (see section 4.8 appendices) demonstrates that time-series momentum returns in equity indices behave similarly in different abnormal turnover environments. This is shown in the cells within column AL-AH and row TH-TL which is the return difference between TH(AL)-TL(AL) and TH(AH)-TL(AH). The scales of the strategy return differences are economically small, and the t-statistics are insignificant. For example, in 12-1 strategy (i.e., 12-month ranking period and 1-month holding period), the difference between low abnormal turnover TSM returns and high abnormal turnover TSM returns is an annual -1.340% (t-stat= -1.188). In 10 out of 12 strategies (i.e., 3-1, 3-6, 3-12, 6-1, 6-3, 6-6, 6-12, 12-1, 12-3, 12-6), TSM with low abnormal return volatility outperforms TSM with high abnormal return volatility, but the outperformances are all economically small and statistically insignificant at 5%. Compared to standard TSM returns in equity indices, there are no significant improvements in returns for both low abnormal return volatility and high abnormal return volatility groups. For example, in 12-1 strategy (i.e., 12-month ranking period and 1-month holding period), TH(AL)-TL(AL) is annual 7.813% (t-stat= 2.160) and TH(AL)-TL(AL) is annual 9.153% (t-stat= 3.812), whereas TH-TL is annual 9.291% (t-stat = 4.172).

Thus, the findings in equity indices does not support Hypothesis 4.2c that time series momentum effect is enhanced under more abnormal turnover, and indicates that abnormal return volatility in the prior equity index changes are treated in the same way as other information contained in the prior index changes by investors. Connolly and Stivers (2003) show that abnormal turnover is related to cross-sectional momentum in weekly equity indices. Here, positive (negative) return autocorrelation is found accompanied with high (low) abnormal turnover. However, no significant influence of abnormal turnover is found on time-series momentum. The potential reason could be that the influence of abnormal turnover is short-lived. In Connolly and Stivers (2003), weekly horizons are used, whereas in this chapter, monthly horizons are adopted. Future research on the relationship between abnormal turnover and time-series momentum may choose to focus on weekly horizons.

Table 4. 2 Standard time-series momentum strategy returns

Panel A. All assets

		Holding month(s)			
Ranking month(s)	Annual Returns (%)	1	3	6	12
3	TH	8.377	7.731	7.589	8.047
	TL	-1.114	0.926	2.020	2.252
	TH-TL	9.491	6.805	5.569	5.796
	t-stat	4.851	5.293	5.828	8.223
6	TH	7.789	8.373	8.336	7.761
	TL	-0.940	0.470	0.231	1.542
	TH-TL	8.729	7.902	8.104	6.220
	t-stat	3.927	4.982	7.467	8.204
12	TH	8.739	8.573	7.861	7.325
	TL	-3.606	-2.020	-0.283	1.764
	TH-TL	12.345	10.594	8.144	5.561
	t-stat	5.536	6.852	7.608	7.423

Panel B. Equity indices

		Holding month(s)			
Ranking month(s)	Annual Returns (%)	1	3	6	12
	TH	8.536	9.026	8.943	9.451
	TL	4.397	5.075	5.866	6.482
	TH-TL	4.139	3.951	3.077	2.969
3	t-stat	1.674	2.901	3.568	4.731
	TH	8.221	9.322	9.332	9.182
	TL	2.493	4.179	4.628	6.184
	TH-TL	5.728	5.143	4.704	2.997
6	t-stat	2.777	4.732	6.419	4.927
	TH	8.275	8.724	8.757	9.232
	TL	-1.016	2.373	4.343	6.850
	TH-TL	9.291	6.351	4.414	2.382
12	t-stat	4.172	4.605	4.692	3.113

Panel C. Commodity market

		Holding month(s)			
Ranking month(s)	Annual Returns (%)	1	3	6	12
	TH	3.689	2.851	2.638	2.18
	TL	-4.582	-3.951	-2.518	-2.53
	TH-TL	8.271	6.802	5.156	4.71
3	t-stat	2.593	3.532	3.306	4.282
	TH	2.216	2.928	3.381	1.734
	TL	-6.114	-4.333	-4.035	-3.539
	TH-TL	8.33	7.261	7.415	5.272
6	t-stat	2.413	3.444	4.733	4.657
	TH	3.771	3.28	2.011	0.031
	TL	-6.142	-5.807	-4.557	-3.19
	TH-TL	9.913	9.086	6.568	3.221
12	t-stat	3.039	4.738	4.519	2.427

Table 4.3 Panel A. reports the annualised time-series momentum returns in all assets. The ranking month are 3,6, and 12, and the holding months are 1,3,6,12. The strategy returns of the looking back and holding period of 9,24,36 months are also calculated. Due to the massive size of the table, they are not included. New (old) portfolios are formed (closed) on a monthly basis. The reported are the annualised mean equal weighted returns of the overlapping portfolios. TH denotes the long position of the standard time-series momentum strategy, TL denotes the short position of the standard time-series momentum strategy, and TH-TL is the return of the overall strategy. t-stat are the t-statistics. Panel B and C reports the annualised time-series momentum returns in equity indices and commodity indices, respectively.

Table 4. 3 Information discreteness grouped time-series momentum returns

Panel A. All Assets

	Holding month(s)	1				3				6				12			
Ranking month(s)	Annual Returns (%)	IL	IH	IL-IH	t-stat	IL	IH	IL-IH	t-stat	IL	IH	IL-IH	t-stat	IL	IH	IL-IH	t-stat
	TH	9.913	4.843	5.07	1.338	9.214	3.615	5.599	3.058	8.349	4.14	4.209	3.335	8.719	4.576	4.143	3.861
	TL	-1.365	2.827	-4.192	-1.329	0.329	3.058	-2.73	-1.767	1.44	2.578	-1.138	-0.426	1.599	3.063	-1.464	-1.611
	TH-TL	**11.279**	2.017	9.262	1.548	**8.885**	0.556	**8.329**	3.464	**6.909**	1.561	5.347	2.809	**7.12**	1.514	5.606	3.736
3	t-stat	4.596	1.15			5.162	-0.188			5.432	0.717			7.738	1.15		
	TH	9.928	3.226	6.702	2.306	9.704	5.086	4.619	2.489	8.864	6.767	2.097	1.567	8.203	5.744	2.459	2.159
	TL	-3.578	2.186	-5.764	-2.471	-0.581	1.288	-1.869	-1.544	-0.267	0.84	-1.108	-1.308	0.499	2.676	-2.177	-3.187
	TH-TL	**13.506**	1.04	**12.466**	3.236	**10.286**	3.798	6.488	2.909	**9.132**	5.927	3.205	2.089	**7.704**	3.068	4.636	3.744
6	t-stat	4.861	-0.052			5.144	1.086			6.256	3.49			7.971	2.286		
	TH	10.783	4.857	5.926	1.939	10.064	5.208	4.855	2.768	8.852	5.163	3.688	2.894	7.998	4.838	3.16	3.404
	TL	-4.813	-2.848	-1.965	-0.821	-2.775	-1.648	-1.127	-0.86	-0.397	-0.935	0.538	0.198	0.389	2.702	-2.313	-2.673
	TH-TL	**15.596**	7.705	7.891	1.572	**12.839**	6.856	5.982	2.683	**9.249**	6.099	3.15	1.96	**7.609**	2.137	5.473	3.944
12	t-stat	5.326	2.575			6.516	3.151			6.005	4.111			7.328	1.87		

Panel B. Equity indices

	Holding month(s)	1				3				6				12			
Ranking month(s)	Annual Returns (%)	IL	IH	IL-IH	t-stat	IL	IH	IL-IH	t-stat	IL	IH	IL-IH	t-stat	IL	IH	IL-IH	t-stat
3	TH	11.875	5.052	6.823	1.836	10.492	7.079	3.413	2.018	9.957	7.428	2.529	2.013	10.337	7.582	2.755	2.979

	TL	4.216	6.42	-2.204	0.097	3.766	7.782	-4.016	-1.232	5.493	7.18	-1.688	-0.095	5.789	7.415	-1.626	-1.199
	TH-TL	7.659	-1.368	9.027	1.2	6.726	-0.703	7.429	2.197	4.464	0.247	4.217	1.131	4.548	0.167	4.381	2.386
	t-stat	3.046	0.164			4.263	-0.388			4.205	1.101			5.58	0.14		
	TH	11.617	4.376	7.241	2.137	10.826	7.312	3.513	2.523	10.659	8.544	2.115	1.99	10.011	8.338	1.673	2.358
	TL	1.468	4.478	-3.01	-0.315	3.46	4.961	-1.502	-0.667	4.648	4.312	0.336	0.293	6.155	6.867	-0.711	-0.578
	TH-TL	10.149	-0.103	10.252	2.009	7.366	2.351	5.015	2.306	6.011	4.233	1.779	1.578	3.856	1.471	2.384	2.014
6	t-stat	3.589	-0.205			5.159	1.005			5.645	2.879			4.842	1.193		
	TH	10.297	7.707	2.59	0.049	10.503	8.087	2.416	1.137	10.411	7.869	2.542	2.012	10.187	8.345	1.842	2.02
	TL	-1.376	0.572	-1.947	-0.24	1.296	2.667	-1.371	-0.404	3.859	3.63	0.228	0.574	5.861	8.07	-2.209	-0.693
	TH-TL	11.673	7.136	4.537	0.342	9.207	5.42	3.787	1.063	6.552	4.239	2.313	0.986	4.326	0.275	4.051	1.168
12	t-stat	3.252	1.972			4.579	2.018			5.199	2.15			4.44	0.556		

Panel C. Commodities

	Holding month(s)	1				3				6				12			
Ranking month(s)	Annual Returns (%)	IL	IH	IL-IH	t-stat	IL	IH	IL-IH	t-stat	IL	IH	IL-IH	t-stat	IL	IH	IL-IH	t-stat
	TH	3.226	3.626	-0.4	0.01	3.737	0.572	3.165	1.432	3.297	-0.71	4.007	1.981	2.701	-1.292	3.993	2.747
	TL	-7.026	-1.293	-5.733	-1.241	-4.224	-3.147	-1.078	-0.175	-3.016	-3.366	0.351	0.098	-3.168	-2.636	-0.532	-0.669
	TH-TL	10.252	4.92	5.333	0.632	7.961	3.718	4.243	1.251	6.312	2.657	3.656	1.457	5.869	1.344	4.525	2.775
3	t-stat	2.139	0.826			2.682	0.569			2.932	0.11			3.698	0.016		
	TH	6.121	-1.255	7.377	1.528	5.011	-0.746	5.756	2.19	4.176	0.918	3.258	1.501	2.709	-1.21	3.919	2.105
	TL	-9.077	-0.405	-8.671	-1.666	-4.82	-2.293	-2.527	-1.012	-4.532	-3.251	-1.281	-1.33	-4.539	-2.754	-1.785	-2.582
	TH-TL	15.198	-0.85	16.048	1.999	9.831	1.547	8.283	2.187	8.708	4.168	4.539	1.921	7.248	1.544	5.704	3.605
6	t-stat	2.88	-0.063			3.589	-0.039			4.191	1.154			5.049	-0.083		
	TH	10.286	-3.187	13.473	2.944	6.653	-1.142	7.794	2.161	3.55	-0.463	4.013	1.519	1.701	-2.603	4.304	2.828
12	TL	-7.673	-6.801	-0.872	0.342	-5.971	-5.678	-0.293	0.421	-4.969	-5.816	0.847	0.668	-4.661	-3.368	-1.293	-0.949

TH-TL	17.959	3.615	14.345	1.562	12.624	4.537	8.087	1.243	8.519	5.353	3.167	0.412	6.362	0.765	5.597	2.766
t-stat	4.059	1.522			4.904	1.75			3.888	2.668			3.714	1.04		

Table 4.3 Panel A demonstrates the performance of the information discreteness grouped time-series momentum strategy returns across all assets. The details of ID construction is shown in Section 3.1.1. The long and short portfolio of the standard time-series momentum strategy are divided into two parts: the part with negative information discreteness (continuous information) and the part with positive information discreteness (discrete information). The ranking month are 3,6, and 12, and the holding months are 1,3,6,12. The strategy returns of the looking back and holding period of 9,24,36 months are also calculated. Due to the massive size of the table, they are not included in this report. New (old) portfolios are formed (closed) on a monthly basis. The reported are the annualised mean equal weighted returns of the overlapping portfolios. TH denotes the long position of the standard time-series momentum strategy, TL denotes the short position of the standard time-series momentum strategy, IL denotes the negative information discreteness, IH denotes the positive information discreetness, and TH-TL is the return of the overall strategy. t-stat are the t-statistics. Panel B reports the strategy performance in equity market and Panel C reports the strategy performance in commodity market. Panel B and C reports the annualised information discreteness grouped time-series momentum returns in equity indices and commodity indices, respectively.

4.6 Multivariate regression analysis after controlling for other effects

This section demonstrates the multivariate regression model and the application of the model to test the relationship between time-series momentum returns and information diffusion measures. Via this multivariate regression, the influence of information diffusion measures on time-series momentum returns can be decomposed to the impact on TS winners, and the impact on TS losers, so that the results can be compared with the previous section as a robustness test.

Bird et al. (2017) set CSM long position returns, CSM short position returns, TSM long position returns, and TSM short position returns as dummy variables in their multivariate regression model. Then they regress individual stock returns on size effect and the dummies. They demonstrate the incremental impact of the TSM strategies on stock returns and show the superiority of TSM over CSM. In this section, conditional variables are introduced, and test the effect of information diffusion (in this work, it is surrogated by ID, ID_{MAG}, ARV, and AT) on the time-series momentum effect by using their multivariate regression analysis. Since it is at the asset index level, static and dynamic Fama-French factor risk are not considered. The following multivariate regression model is run to capture the impact of information discreteness on time-series momentum returns:

$$\begin{aligned} R_{i,t}^{s} = \mathrm{b}_{0\mathrm{jt}} &+ \mathrm{b}_{1\mathrm{jt}} IL_{i,t-j}^{s} + \mathrm{b}_{2\mathrm{jt}} TH_{i,t-j}^{s} + \mathrm{b}_{3\mathrm{jt}}\left(TH_{i,t-j}^{s} * IL_{i,t-j}^{s}\right) \\ &+ \mathrm{b}_{4\mathrm{jt}} ARVL_{i,t-j}^{s} + \mathrm{b}_{5\mathrm{jt}}\left(TH_{i,t-j}^{s} * ARVL_{i,t-j}^{s}\right) \\ &+ \mathrm{b}_{6\mathrm{jt}} ATL_{i,t-j}^{s} + \mathrm{b}_{7\mathrm{jt}}\left(TH_{i,t-j}^{s} * ATL_{i,t-j}^{s}\right) + e_{i,t}^{s} \end{aligned} \qquad (15)$$

where $R_{i,t}^{s}$ is the return of asset i in asset class s at time t, TH_{t-j}^{s} equals to 1 if the previous performance (from month t-j to month t) is in the long position in Moskowitz et al.'s time-series momentum strategies, and it equals to 0 otherwise; IL_{t-j}^{s} equals to 1 if the information discreteness (from month t-j to month t) is below zero, and it equals to 0, otherwise; $ARVL_{t-j}^{s}$ equals to 1 if the previous abnormal return volatility (from month t-j to month t) is below zero, and it equals to 0 otherwise; ATL_{t-j}^{s} equals to 1 if the previous abnormal turnover (from month t-j to month t) is below zero, and it equals to 0 otherwise; j= 3,6,12 months.

After hedging out all other effects, $\mathrm{b}_{1\mathrm{jt}}$ measures information discreteness for low time-series momentum group, $\mathrm{b}_{2\mathrm{jt}}$ measures times series momentum effect, $\mathrm{b}_{3\mathrm{jt}}$ measures the information discreteness for high time-series momentum group, $\mathrm{b}_{4\mathrm{jt}}$ measures abnormal return volatility for low time-series momentum group, $\mathrm{b}_{5\mathrm{jt}}$ measures abnormal return volatility for high time-series momentum groups, $\mathrm{b}_{6\mathrm{jt}}$ measures abnormal turnover for low time-series momentum group, $\mathrm{b}_{7\mathrm{jt}}$ measures abnormal turnover for high time-series momentum groups.

$$R_{i,t}^{s} = \mathrm{b}_{0\mathrm{jt}} + \mathrm{b}_{1\mathrm{jt}} IL_{MAG}{}_{i,t-j}^{s} + \mathrm{b}_{2\mathrm{jt}} TH_{i,t-j}^{s} + \mathrm{b}_{3\mathrm{jt}} (TH_{i,t-j}^{s} * IL_{MAG}{}_{i,t-j}^{s}) \qquad (16)$$
$$+ \mathrm{b}_{4\mathrm{jt}} ARVL_{i,t-j}^{s} + \mathrm{b}_{5\mathrm{jt}} (TH_{i,t-j}^{s} * ARVL_{i,t-j}^{s})$$
$$+ \mathrm{b}_{6\mathrm{jt}} ATL_{i,t-j}^{s} + \mathrm{b}_{7\mathrm{jt}} \left(TH_{i,t-j}^{s} * ATL_{i,t-j}^{s}\right) + e_{i,t}^{s}$$

where $R_{i,t}^{s}$ is the return of asset i in asset class s at time t, TH_{t-j}^{s} equals to 1 if the previous performance (from month t-j to month t) is in the long position in Moskowitz et al.'s time-series momentum strategies, and it equals to 0 otherwise; $IL_{MAG}{}_{t-j}^{s}$ equals to 1 if the previous return magnitude adjusted information discreteness (from month t-j to month t) is below 0, and it equals to 0, otherwise; $ARVL_{t-j}^{s}$equals to 1 if the previous abnormal return volatility (from month t-j to month t) is below 0, and it equals to 0 otherwise; j = 3,6,12 months.

After hedging out all other effects, $\mathrm{b}_{1\mathrm{jt}}$ measures modified information discreteness for low time-series momentum group, $\mathrm{b}_{2\mathrm{jt}}$ measures the times series momentum effect, $\mathrm{b}_{3\mathrm{jt}}$ measures modified information discreteness for high time-series momentum groups,$\mathrm{b}_{4\mathrm{jt}}$ measures abnormal return volatility for low time-series momentum groups, $\mathrm{b}_{5\mathrm{jt}}$ measures abnormal return volatility for high time-series momentum groups, $\mathrm{b}_{6\mathrm{jt}}$ measures abnormal turnover for low time-series momentum groups, $\mathrm{b}_{7\mathrm{jt}}$ measures abnormal turnover for high time-series momentum groups.

Table 4.7 and Table 4.8 show the multivariate regression test for ID and ID_{MAG} adjusted time-series momentum performance, respectively. Due to the lack of turnover data for the commodity market, the across asset multivariate regression analysis uses a reduced version of the regression model. The full model is applied for the equity market, which is reported in panel B.

In Table 4.7, I regress time t monthly asset returns on low information discreteness dummies (IL), time-series momentum dummies (TH), the interaction between the two (TH*IL), low abnormal return volatility dummies (ARVL), and the interaction between low abnormal return volatility and high time-series momentum (TH*ARVL). The dummies are calculated monthly according to the measures from month t-j to month t and j = 3,6,12 months.

As is shown in Table 4.7 panel A, for all assets, after controlling the effect of information diffusion measures, it can be found that in all 12 strategies, the improvement of TSM returns under negative information discreteness is composed of more positive returns from the long positions (i.e., TH(IL)>TH), and more negative returns from the short positions (i.e., TL(IL)<TL). This is reflected in the significantly positive TH*IL coefficients, and significantly negative IL coefficients, respectively.

For example, for a 12-1 strategy (12-month looking back period and 1-month holding period), the average monthly unexplained return is approximately 0.1% (constant 0.001 with t-stat = 0.533), which is economically small and statistically insignificant. This indicates that information diffusion may explain time-series momentum returns for 12-1 strategy. TH*IL (coefficient 0.012 with t-stat = 6.570) and IL (coefficient -0.006 with t-stat = -4.190) are the 2 most important predictors. The former implies that low information discreteness improves the high time-series momentum group (i.e., TSM long position TH) returns, which contributes to the improvement of TSM returns under low information discreteness. This is reflected in around 2% higher returns in TH(IL) (10.783%) compared to TH (8.739%), which mainly contributes to TSM returns improvement under low information discreteness. The latter implies that the information discreteness for the low time-series momentum group (i.e., TSM short position) significantly influences TSM returns as well. Compared to TL (-3.606%), the return of TL(IL) (-4.813%) is more negative by around 1.2%, contributing to the improvement of TSM returns under low information discreteness as well. Thus, compared to annual 12.345% (t-stat = 5.536) standard TSM returns, the TSM under negative information discreteness increase to 15.596% (t-stat = 5.326), which is around a 3.2% increase. Thus, it is the increase in long position and decrease in short position returns under negative information discreteness that jointly improves the TSM returns. This is consistent with the analysis in the previous section. Similar phenomena are observed in most of the equity indices strategies and commodity indices in panels B and C. Therefore, it provides further evidence supporting Hypothesis 4.2 that the time series momentum effect is enhanced under greater information continuity (i.e., negative information discreteness).

It can also be observed that the coefficient of TH*ARVL is either negative or insignificantly positive at a 5% significance level in most cases, indicating that low abnormal return volatility fails to improve TSM long position returns. In addition, the coefficient of ARVL is either significantly positive or insignificant in most cases, implying that low abnormal return volatility fails to make TSM short portfolios returns more negative. Therefore, low abnormal return volatility either have no impact on TSM returns, or deteriorate TSM returns in most cases. It is consistent with the findings in the previous section that there is no sufficient evidence supporting the Hypothesis 4.2 that the time series momentum effect is enhanced under more abnormal return volatility.

Table 4.8 panel A shows the regressions of time t monthly asset returns on low modified information discreteness dummies (IL_{MAG}), time-series momentum dummies (TH), the interaction between the two ($TH*IL_{MAG}$), low abnormal return volatility dummies (ARVL), and the interaction between low abnormal return volatility and high time-series momentum (TH*ARVL). The dummies are calculated monthly according to the measures from month t-j to month t and j=3,6,12 months.

It can be found that $TH*IL_{MAG}$ coefficients are significantly positive in all 3-month ranking periods strategies, but are insignificant in most of the remaining strategies. IL_{MAG} coefficients are insignificant in most the strategies. Therefore, compared to the original information discreteness grouped time-series momentum strategies, the improvement on TSM returns induced by negative modified information discreteness is far less.

For example, for 12-1 strategy, the coefficient of IL_{MAG} is 0.000 (t-stat = -0.202), which is insignificant at the 5% level, and the coefficient of TH*IL_{MAG} is 0.002 (t-stat = 1.229), which is also insignificant. This indicates that the modified negative information discreteness has insignificant impact on long and short positions of TSM strategies. This is reflected by TL(IL_{MAG}) returns of -3.934% and TH(IL_{MAG}) returns of 7.756%, which are similar to TH returns of 8.739% and TL returns of -3.606%, respectively. Therefore, negative modified information discreteness fails to improve TSM returns.

The roles of TH*ARVL and ARVL on time-series momentum returns are similar to what we observe in the multivariate regression with original information discreteness. It is consistent with findings in the previous section that there is no sufficient evidence supporting the Hypothesis 4.2 that time series momentum effect is enhanced under more abnormal return volatility. Similar results can be observed in equity indices and commodity indices in panels B and C.

The relationship between abnormal turnover and time-series momentum returns are shown in panel B of Tables 4.7 and 4.8. It can be observed that in most cases, the coefficients of AT are either insignificant or significantly positive, and the coefficients of TH*AT are insignificant. Since AT is the influence of AT on TSM short position and TH*AT is the influence of AT on TSM long position, AT is either having no impact on TSM returns or deteriorating the returns. Therefore, it supports the previous finding that there is insufficient evidence to support the hypothesis that the time series momentum effect is enhanced under more abnormal turnover.

Table 4. 4 Multivariate regression: Comparison among IL, TH, ARVL strategies and their interactions

Panel A. All assets

Ranking months	Holding months	1		3		6		12	
		coefficients	t-stat	coefficients	t-stat	coefficients	t-stat	coefficients	t-stat
	constant	-0.002	-1.294	0.001	1.535	0.002	3.426	0.001	3.250
	IL	-0.004	**-3.202**	-0.003	**-3.422**	-0.002	**-3.068**	-0.001	**-2.481**
	TH	0.005	2.542	0.001	1.307	0.001	0.805	0.001	2.054
	TH*IL	0.010	**5.265**	0.008	**6.817**	0.006	**6.680**	0.004	**6.491**
	ARVL	0.003	2.140	0.000	-0.413	0.000	-0.593	0.001	1.511
3	TH*ARVL	-0.001	-0.825	0.001	1.213	0.001	1.540	0.001	1.315
	constant	-0.001	-0.612	0.000	-0.367	0.000	0.239	0.001	3.365
	IL	-0.006	**-4.557**	-0.004	**-4.237**	-0.003	**-3.921**	-0.002	**-3.977**
	TH	0.005	2.750	0.004	3.240	0.005	5.641	0.002	2.910
	TH*IL	0.012	**6.619**	0.009	**7.961**	0.006	**6.560**	0.005	**7.718**
	ARVL	0.004	**2.768**	0.003	**3.368**	0.002	**2.652**	0.001	2.911
6	TH*ARVL	-0.005	**-3.000**	-0.003	**-2.694**	-0.002	**-1.992**	0.000	-0.735
	constant	0.001	0.533	0.001	1.720	0.002	3.696	0.003	7.781
	IL	-0.006	**-4.190**	-0.004	**-4.218**	-0.003	**-4.263**	-0.003	**-5.323**
	TH	0.001	0.577	0.001	0.584	0.000	0.143	-0.002	-2.914
	TH*IL	0.012	**6.570**	0.009	**8.067**	0.007	**8.055**	0.006	**9.649**
	ARVL	-0.001	-0.422	-0.001	-1.157	0.000	-0.049	0.001	1.963
12	TH*ARVL	0.003	1.748	0.003	**2.804**	0.002	1.806	0.000	0.600

Panel B. Equity indices

Ranking months	Holding months	1		3		6		12	
		coefficients	t-stat	coefficients	t-stat	coefficients	t-stat	coefficients	t-stat
3	constant	0.001	0.282	0.002	1.469	0.003	3.139	0.003	4.112

	IL	-0.004	-2.413	-0.002	-1.716	-0.001	-1.626	-0.001	-0.887
	TH	0.003	1.130	0.002	1.116	0.002	1.556	0.002	1.953
	TH*IL	0.010	4.239	0.007	4.618	0.004	3.720	0.003	3.411
	ARVL	0.000	0.094	0.000	0.273	0.001	0.876	0.002	2.512
	AT	0.000	-0.072	0.000	0.346	0.000	0.437	0.001	0.682
	TH*AT	0.001	0.596	0.002	1.505	0.002	2.667	0.001	2.266
	TH*ARVL	0.002	1.073	0.000	0.157	-0.001	-1.199	-0.001	-0.671
	constant	0.002	0.955	0.000	0.075	0.001	0.788	0.003	4.622
	IL	-0.008	-4.138	-0.004	-3.262	-0.002	-2.909	-0.002	-2.984
	TH	0.004	1.457	0.005	3.287	0.006	5.579	0.002	2.551
	TH*IL	0.013	5.738	0.009	5.790	0.004	3.786	0.004	4.719
	ARVL	0.003	1.610	0.003	3.004	0.003	3.811	0.002	3.560
	AT	-0.006	-2.543	-0.005	-3.196	-0.004	-3.448	-0.001	-1.016
	TH*AT	0.000	0.083	0.003	2.967	0.002	2.423	0.002	2.828
6	TH*ARVL	0.001	0.586	-0.002	-1.613	-0.001	-0.988	-0.001	-1.697
	constant	0.007	3.557	0.005	4.081	0.005	5.516	0.006	9.486
	IL	-0.011	-5.721	-0.005	-4.041	-0.003	-3.300	-0.003	-3.906
	TH	-0.004	-1.526	-0.001	-0.978	-0.001	-0.925	-0.004	-4.552
	TH*IL	0.015	6.496	0.009	6.270	0.006	5.272	0.005	6.813
	ARVL	-0.003	-1.372	-0.001	-0.749	0.001	1.048	0.001	2.167
	AT	0.004	1.543	0.003	2.132	0.001	0.794	0.001	1.007
	TH*AT	-0.001	-0.347	0.000	-0.296	0.000	-0.237	0.001	1.269
12	TH*ARVL	0.003	1.491	0.001	0.801	0.001	1.159	0.000	0.496

Panel C. Commodity market

	Holding months	1		3		6		12
Ranking months		coefficients	t-stat	coefficients	t-stat	coefficients	t-stat	coefficients

	constant	-0.006	-2.544	-0.001	-0.879	-0.001	-0.891	-0.001	-1.501
	IL	-0.004	-1.649	-0.004	-2.336	-0.002	-2.218	-0.002	-2.762
	TH	0.008	2.213	0.001	0.318	-0.001	-0.343	-0.001	-0.594
	TH*IL	0.006	1.647	0.007	3.326	0.007	4.326	0.006	4.892
	ARVL	0.005	2.133	-0.002	-1.238	-0.002	-1.652	-0.001	-1.128
3	TH*ARVL	-0.004	-1.229	0.003	1.419	0.002	1.037	0.001	0.949
	constant	-0.004	-1.991	-0.004	-2.669	-0.002	-2.253	-0.002	-2.412
	IL	-0.004	-1.723	-0.003	-1.804	-0.003	-2.343	-0.002	-2.544
	TH	0.005	1.567	0.002	0.939	0.001	0.939	0.000	-0.315
	TH*IL	0.008	2.357	0.008	4.022	0.007	4.380	0.006	5.431
	ARVL	0.003	1.422	0.002	1.099	0.000	-0.276	0.000	-0.193
6	TH*ARVL	-0.004	-1.350	-0.001	-0.407	0.000	0.211	0.000	-0.045
	constant	-0.007	-3.313	-0.003	-2.506	-0.001	-1.505	-0.001	-1.880
	IL	0.001	0.503	-0.001	-0.805	-0.002	-2.231	-0.002	-2.988
	TH	0.001	0.302	-0.001	-0.494	-0.003	-1.763	-0.002	-2.352
	TH*IL	0.007	2.158	0.008	3.881	0.008	4.944	0.007	5.978
	ARVL	0.001	0.425	-0.002	-1.185	-0.001	-0.800	0.000	0.315
12	TH*ARVL	0.006	1.815	0.005	2.700	0.003	1.982	0.000	0.374

Table 4.7 Panel A shows the comparison and interaction among time-series momentum long position dummies (TH), negative information discreteness dummies (IL), and negative abnormal return volatility dummies (ARVL) across all assets. TH=1 if the asset is in the long position of the standard time-series momentum strategy, and TH=0, otherwise. IL=1 if the asset has negative information discreteness, and IL=0, otherwise. ARVL=1 if abnormal return volatility of the asset is negative, and ARVL=0, otherwise. The details of the regression model are demonstrated in Section 4.6. t-stat denotes t statistics. Panel B and C reports the results for equity indices and commodity indices, respectively.

Table 4. 5 Multivariate regression: comparison among IL_{MAG}, TH, ARVL strategies and their interactions

Panel A. All assets

Ranking months	Holding months	1		3		6		12	
		coefficients	t-stat	coefficients	t-stat	coefficients	t-stat	coefficients	
	constant	-0.002	-1.587	0.001	0.864	0.001	2.027	0.001	2.448
	IL_{MAG}	-0.004	**-3.225**	-0.002	**-2.691**	-0.001	-1.237	0.000	-0.752
	TH	0.007	3.876	0.003	3.016	0.003	3.423	0.003	4.658
	TH*IL_{MAG}	0.007	**4.074**	0.005	**4.310**	0.002	**2.949**	0.001	**2.299**
	ARVL	0.002	1.827	-0.001	-0.927	0.000	-0.638	0.001	1.339
3	TH*ARVL	-0.001	-0.666	0.003	**2.656**	0.002	**2.458**	0.001	**2.227**
	constant	-0.003	-2.714	-0.001	-1.820	-0.001	-1.560	0.000	0.724
	IL_{MAG}	-0.001	-0.557	-0.001	-1.142	0.000	-0.298	0.001	1.515
	TH	0.010	5.606	0.006	6.108	0.006	7.984	0.004	6.739
	TH*IL_{MAG}	0.003	1.398	0.003	**2.686**	0.002	1.839	0.000	0.136
	ARVL	0.002	1.828	0.002	2.127	0.001	1.648	0.001	1.999
6	TH*ARVL	-0.004	**-2.112**	-0.002	-1.380	-0.001	-0.887	0.000	0.326
	constant	-0.002	-1.382	-0.001	-0.659	0.001	1.220	0.001	3.330
	IL_{MAG}	0.000	-0.202	0.000	0.090	0.000	-0.038	0.001	2.115
	TH	0.006	3.280	0.004	4.058	0.003	3.377	0.002	2.830
	TH*IL_{MAG}	0.002	1.229	0.001	1.266	0.001	1.717	0.000	-0.720
	ARVL	-0.001	-0.694	-0.001	-0.942	0.000	0.141	0.001	2.015
12	TH*ARVL	0.003	1.509	0.003	**2.887**	0.002	1.828	0.001	0.873

Panel B. Equity market

Ranking months	Holding months	1		3		6		12	
		coefficients	t-stat	coefficients	t-stat	coefficients	t-stat	coefficients	
3	constant	0.002	1.018	0.003	2.541	0.002	2.924	0.003	4.212

	IL_{MAG}	-0.005	-2.768	-0.003	-3.109	-0.001	-1.344	-0.001	-1.206
	TH	0.003	1.228	0.002	1.149	0.002	2.193	0.002	2.900
	$TH*IL_{MAG}$	0.009	3.911	0.007	4.762	0.003	3.082	0.002	2.264
	ARVL	-0.001	-0.433	-0.001	-0.783	0.000	0.079	0.001	1.955
	AT	0.000	0.109	0.002	1.398	0.001	1.383	0.001	1.410
	TH*AT	-0.001	-0.500	0.001	1.063	0.002	2.510	0.002	2.584
	TH*ARVL	0.005	2.060	0.001	0.764	-0.001	-1.023	-0.001	-0.790
	constant	-0.002	-0.972	-0.001	-0.853	-0.001	-0.682	0.001	1.359
	IL_{MAG}	0.000	0.151	-0.002	-1.560	-0.001	-1.426	0.001	1.545
	TH	0.008	3.453	0.008	5.367	0.008	6.944	0.005	5.783
	$TH*IL_{MAG}$	0.003	1.261	0.003	2.435	0.002	2.047	0.000	-0.247
	ARVL	0.001	0.546	0.002	2.016	0.003	3.232	0.002	3.034
	AT	-0.003	-1.417	-0.003	-2.156	-0.003	-2.597	0.000	-0.229
	TH*AT	-0.001	-0.334	0.003	3.082	0.002	2.941	0.002	3.552
6	TH*ARVL	0.002	1.086	-0.002	-1.749	-0.001	-1.279	-0.002	-2.082
	constant	0.002	1.152	0.001	1.208	0.002	2.612	0.003	4.846
	IL_{MAG}	0.000	-0.202	0.001	0.788	0.001	0.855	0.002	2.996
	TH	0.002	0.863	0.003	2.011	0.002	1.818	0.001	1.197
	$TH*IL_{MAG}$	0.003	1.079	0.001	0.886	0.001	0.768	-0.002	-2.369
	ARVL	-0.004	-2.422	-0.001	-1.081	0.001	0.708	0.001	2.114
	AT	0.005	2.266	0.004	2.515	0.001	1.211	0.001	1.191
	TH*AT	-0.001	-0.532	0.000	0.087	0.000	0.122	0.001	1.684
12	TH*ARVL	0.003	1.477	0.000	0.321	0.001	0.820	0.000	0.061

Panel C. Commodity market

	Holding months	1		3		6		12	
Ranking months		coefficients	t-stat	coefficients	t-stat	coefficients	t-stat	coefficients	

	constant	-0.008	-3.395	-0.004	-2.873	-0.002	-2.402	-0.003	-3.795
	IL_{MAG}	-0.003	-1.200	-0.001	-0.475	-0.001	-0.950	0.000	0.214
	TH	0.008	2.480	0.003	1.674	0.002	1.711	0.003	2.589
	$TH*IL_{MAG}$	0.005	1.455	0.002	0.814	0.001	0.945	-0.001	-0.452
	ARVL	0.006	2.577	0.000	-0.327	-0.001	-0.675	0.000	-0.471
3	TH*ARVL	-0.004	-1.293	0.004	2.012	0.002	1.339	0.002	1.336
	constant	-0.006	-2.498	-0.005	-3.687	-0.004	-3.661	-0.003	-3.902
	IL_{MAG}	-0.001	-0.519	0.001	0.394	0.002	1.368	0.001	1.762
	TH	0.008	2.641	0.005	2.550	0.005	3.183	0.003	3.082
	$TH*IL_{MAG}$	0.000	-0.142	0.000	0.208	-0.002	-1.158	-0.002	-2.096
	ARVL	0.003	1.272	0.001	0.924	-0.001	-0.618	-0.001	-0.703
6	TH*ARVL	-0.004	-1.156	0.000	0.211	0.001	0.664	0.000	0.328
	constant	-0.007	-3.335	-0.004	-2.961	-0.003	-2.497	-0.003	-3.870
	IL_{MAG}	0.002	0.871	0.001	0.607	0.001	0.467	0.001	1.252
	TH	0.006	1.937	0.004	2.215	0.002	1.282	0.002	1.605
	$TH*IL_{MAG}$	-0.003	-0.864	-0.004	-1.703	-0.002	-1.504	-0.002	-1.565
	ARVL	0.003	1.139	-0.001	-0.518	0.000	-0.358	0.001	0.756
12	TH*ARVL	0.003	0.864	0.005	2.328	0.003	1.576	0.000	-0.017

Table 4.8 Panel A shows the comparison and interaction among time-series momentum long position dummies (TH), negative modified information discreteness dummies (IL_{MAG}), and negative abnormal return volatility dummies (ARVL) across all assets. TH=1 if the asset is in the long position of the standard time-series momentum strategy, and TH=0, otherwise. IL=1 if the asset has negative information discreteness, and IL=0, otherwise. ARVL=1 if abnormal return volatility of the asset is negative, and ARVL=0, otherwise. The details of the regression model are demonstrated in Section 4.6. t-stat denotes t statistics. Panel B and C reports the results for equity indices and commodity indices, respectively.

4.7 Conclusion

Built mainly upon the studies of information diffusion on asset returns and the time-series momentum effect, the hypothesis that time-series momentum effect is more prominent under greater information diffusion is tested, which is measured in three aspects (information continuity, information uncertainty and information dispersion). Information discreteness, abnormal return volatility and abnormal turnover are served as the surrogates for the three information diffusion dimensions, respectively.

By adding an information diffusion dimension to standard TSM strategies, and testing in global equity indices and commodity futures, this work extends the influence of information diffusion on time-series momentum effects to broader asset classes, and shows supporting evidence to the existing TSM literature by demonstrating that TSM profits are clustered in a continuous information environment, but disappear in a discrete information environment. This implies that investors tend to underreact to price information more in continuous information environment. After controlling for other effects, the findings are still significant. If we assume that a continuous information environment has a slower information diffusion, then the result is consistent with Hong and Stein’s (1999) information diffusion hypothesis.

The behavioural explanation of this finding that investors tend to underreact to price signals only in continuous information environments could be as follows: investors fail to react immediately or react fully to the price signal in a continuous information environment, as there is no major publicly available fundamental news, or just a few pieces of news that do not arouse public interest. However, in the discrete information environment, where lots of news arrives, or some pieces of unanticipated breaking news comes, they absorb information promptly, which is reflected in the insignificant improvement of time-series momentum returns.

By showing this phenomenon, the present study complements time-series momentum literature by the demonstrating what specific elements of information diffusion that significantly influence asset returns are treated differently from other information contained in asset prior price changes. By demonstrating the insignificant influence of abnormal return volatility and abnormal turnover, the current study shows that investors treat noise in the prior asset price information similarly to other information that is contained in the prior asset price changes. That is, investors tend to be less attentive to the information arrival scale than the noises contained in the prior asset price changes. For global asset fund managers, the predictability of the equity market and commodity market returns makes it unnecessary for them to diversify across these assets. They may invest on specific assets in certain periods following low ID time-series momentum portfolios to increase portfolio alphas, or they may construct ID-neutral portfolios to reduce risks that are induced by information arrival scales.

4.8 Appendices

Table 4. 6 Modified information discreteness grouped time-series momentum returns

Panel A. All assets

	Holding month(s)	1				3				6				12			
Ranking month(s)	Annual Returns (%)	IL_{MAG}	IH_{MAG}	IL_{MAG} - IH_{MAG}	t-stat	IL_{MAG}	IH_{MAG}	IL_{MAG} - IH_{MAG}	t-stat	IL_{MAG}	IH_{MAG}	IL_{MAG} - IH_{MAG}	t-stat	IL_{MAG}	IH_{MAG}	IL_{MAG} - IH_{MAG}	t-stat
	TH	7.536	5.646	1.89	0.044	6.639	4.703	1.936	0.714	5.527	5.551	-0.024	-0.159	6.397	6.097	0.3	0.128
	TL	-0.561	-1.07	0.509	0.394	1.076	0.544	0.531	0.57	2.132	1.188	0.944	1.18	1.624	1.536	0.088	0.117
	TH-TL	8.098	6.716	1.381		5.563	4.158	1.405		3.395	4.363	-0.968		4.773	4.561	0.212	
3	t-stat	2.713	2.72	-0.202		3.174	2.78	0.074		2.97	4.523	-0.731		6.213	6.58	0.098	
	TH	4.992	7.282	-2.29	-0.652	6.172	5.803	0.369	0.532	6.086	6.19	-0.104	0.776	5.639	5.894	-0.255	0.259
	TL	0.625	-1.539	2.163	1.01	1.026	1.445	-0.419	-0.252	0.529	1.022	-0.492	-0.46	1.347	1.964	-0.617	-0.516
	TH-TL	4.367	**8.821**	-4.454		5.147	4.358	0.788		5.556	5.168	0.388		4.292	3.93	0.362	
6	t-stat	1.502	3.707	-0.695		3.202	2.909	0.653		5.006	5.359	1.043		5.306	5.6	0.618	
	TH	7.756	5.693	2.063	1.459	7.106	6.015	1.091	1.757	6.451	5.734	0.717	1.878	5.852	5.661	0.19	1.254
	TL	-3.934	-2.852	-1.082	-0.297	-2.555	-0.612	-1.943	-1.337	-0.498	0.799	-1.297	-1.359	1.18	2.505	-1.325	-1.54
	TH-TL	11.69	8.545	3.145		9.661	6.627	3.034		6.949	4.935	2.014		4.671	3.156	1.515	
12	t-stat	4.801	3.995	0.858		6.696	4.793	2.078		6.908	4.856	2.178		6.463	4.085	1.855	

Panel B. Equity indices

	Holding month(s)	1	3	6	12

Ranking month(s)	Annual Returns (%)	IL_{MAG}	IH_{MAG}	IL_{MAG} - IH_{MAG}	t-stat	IL_{MAG}	IH_{MAG}	IL_{MAG} - IH_{MAG}	t-stat	IL_{MAG}	IH_{MAG}	IL_{MAG} - IH_{MAG}	t-stat	IL_{MAG}	IH_{MAG}	IL_{MAG} - IH_{MAG}	t-stat
	TH	9.145	7.984	1.161	-0.519	8.025	8.008	0.018	-0.84	7.204	8.97	-1.766	-2.296	8.233	8.614	-0.382	-0.85
	TL	2.33	4.244	-1.914	-1.013	3.464	5.55	-2.086	-1.721	5.468	5.426	0.042	-0.047	5.675	5.621	0.055	-0.01
	TH-TL	6.815	3.74	3.075	0.319	4.561	2.457	2.104	0.332	1.735	3.543	-1.808	-1.438	2.557	2.994	-0.436	-0.412
3	t-stat	2.119	1.485			1.971	2.175			1.385	3.648			2.698	3.682		
	TH	6.55	9.356	-2.806	-1.209	8.622	8.924	-0.301	-0.383	8.452	9.528	-1.076	-1.657	8.503	9.092	-0.589	-1.396
	TL	2.979	1.868	1.111	0.726	3.063	4.983	-1.92	-0.67	3.352	4.841	-1.489	-0.812	5.719	5.651	0.068	0.491
	TH-TL	3.57	7.488	-3.917	-0.766	5.559	3.941	1.618	0.461	5.1	4.687	0.413	0.026	2.784	3.441	-0.657	-0.841
6	t-stat	1.817	2.021			4.086	2.575			5.139	4.469			2.975	3.587		
	TH	8.304	7.511	0.793	0.168	8.838	8.214	0.624	0.427	8.484	8.922	-0.438	-0.731	8.96	8.608	0.352	0.614
	TL	-0.831	0.141	-0.971	0.442	1.04	3.05	-2.011	-0.353	3.106	3.73	-0.624	0.417	5.43	6.221	-0.79	0.414
	TH-TL	9.135	7.37	1.765	-0.308	7.798	5.163	2.634	0.182	5.378	5.192	0.186	-0.602	3.53	2.387	1.142	-0.136
12	t-stat	2.687	2.594			4.259	3.211			4.378	4.532			4.25	2.889		

Panel C. Commodities

	Holding month(s)	1				3				6				12			
Ranking month(s)	Annual Returns (%)	IL_{MAG}	IH_{MAG}	IL_{MAG} - IH_{MAG}	t-stat	IL_{MAG}	IH_{MAG}	IL_{MAG} - IH_{MAG}	t-stat	IL_{MAG}	IH_{MAG}	IL_{MAG} - IH_{MAG}	t-stat	IL_{MAG}	IH_{MAG}	IL_{MAG} - IH_{MAG}	t-stat
	TH	5.665	-1.163	6.828	1.475	3.18	-1.154	4.334	1.806	1.521	-1.393	2.914	1.573	1.553	0.164	1.389	1.228
	TL	-3.329	-7.01	3.681	0.428	-1.487	-6.065	4.578	1.977	-1.577	-4.23	2.653	1.946	-3.076	-4.092	1.017	1.043
	TH-TL	8.993	5.847	3.146	0.603	4.667	4.911	-0.244	0.209	3.097	2.837	0.26	0.613	4.629	4.256	0.373	0.674
3	t-stat	1.43	1.443			1.581	2.341			1.665	1.956			3.666	3.861		

	TH	-1.139	0.934	-2.073	-0.959	-0.377	-0.415	0.038	-0.29	0.861	0.755	0.106	-0.002	-0.261	-0.445	0.183	0.127
	TL	-0.278	-5.934	5.656	0.832	-0.873	-3.863	2.989	1.587	-0.936	-3.845	2.909	1.724	-2.609	-2.95	0.342	0.958
	TH-TL	-0.861	6.868	-7.729	-0.994	0.496	3.448	-2.952	-0.471	1.797	4.6	-2.803	-0.643	2.347	2.506	-0.158	-0.313
6	t-stat	-0.089	1.62			0.469	1.77			1.033	3.241			2.167	2.469		
	TH	2.135	0.465	1.67	0.293	-0.053	2.541	-2.594	-1.068	-1.775	-0.178	-1.598	0.241	-3.137	-1.944	-1.193	0.282
	TL	-4.98	-6.647	1.667	0.48	-6.233	-4.174	-2.058	-0.655	-5.255	-2.386	-2.869	-0.968	-4.384	-2.476	-1.908	-0.031
	TH-TL	7.115	7.112	0.003	-0.254	6.179	6.715	-0.536	-0.527	3.48	2.208	1.272	0.41	1.247	0.532	0.716	0.114
12	t-stat	1.458	1.974			2.147	2.942			2.184	0.769			1.821	0.182		

Table 4.4 demonstrates the performance of the modified information discreteness grouped time-series momentum strategy returns. Modified information discreteness measure is the information discreteness measure with daily return magnitude modification. The details are shown in Section 3.1.2. The long and short portfolio of the standard time-series momentum strategy are divided into two parts: the part with negative modified information discreteness (continuous information) and the part with positive modified information discreteness (discrete information). The ranking month are 3,6, and 12, and the holding months are 1,3,6,12. The strategy returns of the looking back and holding period of 9,24,36 months are also calculated. Due to the massive size of the table, they are not included in this report. New (old) portfolios are formed (closed) on a monthly basis. The reported are the annualised mean equal weighted returns of the overlapping portfolios. TH denotes the long position of the standard time-series momentum strategy, TL denotes the short position of the standard time-series momentum strategy, IL_{MAG} denotes the negative modified information discreteness, IH_{MAG} denotes the positive modified information discreetness, and TH-TL is the return of the overall strategy. t-stat are the t-statistics. Panel A reports the strategy performance cross all assets. Panel B reports the strategy performance in equity market and Panel C reports the strategy performance in commodity market.

Table 4. 7 Abnormal return volatility grouped time-series momentum returns

Panel A. All assets

	Holding month(s)	1				3				6				12			
Ranking month(s)	Annual Returns (%)	AL	AH	AL-AH	t-stat	AL	AH	AL-AH	t-stat	AL	AH	AL-AH	t-stat	AL	AH	AL-AH	t-stat
	TH	9.657	9.274	0.383	-0.265	8.454	7.939	0.515	0.232	7.445	7.313	0.131	0.096	7.552	7.545	0.006	0.000
	TL	0.383	-1.246	1.628	0.809	0.384	2.154	-1.769	-0.965	1.668	2.434	-0.766	-0.687	2.214	1.437	0.777	0.668
	TH-TL	9.275	**10.52**	-1.245		**8.07**	5.785	2.284		**5.777**	4.879	0.897		5.338	**6.108**	-0.77	
3	t-stat	3.755	3.468	-0.824		4.015	2.664	0.767		4.045	3.208	0.374		6.388	5.947	-1.231	
	TH	7.249	8.284	-1.035	-0.531	8.356	7.991	0.365	0.298	7.910	8.466	-0.555	-0.593	7.016	7.862	-0.847	-1.479
6	TL	-0.429	-1.757	1.328	0.463	1.414	-1.635	3.049	2.226	0.971	-1.401	2.372	2.366	1.923	-0.108	2.031	2.429

	TH-TL	7.678	**10.041**	-2.363		6.942	**9.627**	-2.685		6.940	**9.867**	-2.927		5.093	**7.971**	-2.878	
	t-stat	2.704	3.202	-0.664		3.314	5.511	-0.946		5.089	8.014	-1.76		5.656	8.932	-2.543	
	TH	10.381	7.330	3.050	1.086	8.493	7.56	0.934	0.706	7.900	6.739	1.161	1.186	6.812	6.715	0.096	-0.027
	TL	-4.182	-2.48	-1.701	-0.922	-1.56	-2.503	0.943	0.505	-0.178	-0.732	0.555	0.272	1.841	0.903	0.938	0.333
	TH-TL	**14.563**	9.811	4.752		10.054	10.063	-0.009		8.078	7.471	0.606		4.971	**5.813**	-0.842	
12	t-stat	5.019	3.554	1.161		5.019	5.723	-0.148		5.400	6.159	0.128		5.025	6.252	-1.144	

Panel B. Equity indices

	Holding month(s)	1				3				6				12			
Ranking month(s)	Annual Returns (%)	AL	AH	AL-AH	t-stat	AL	AH	AL-AH	t-stat	AL	AH	AL-AH	t-stat	AL	AH	AL-AH	t-stat
	TH	11.320	8.307	3.013	0.825	10.047	9.646	0.402	-0.302	10.002	9.212	0.790	-0.006	10.288	9.788	0.500	-0.376
	TL	2.902	4.791	-1.889	-0.349	4.871	6.138	-1.266	-0.685	5.952	6.945	-0.993	-0.254	6.679	6.791	-0.112	0.255
	TH-TL	8.418	3.516	4.902	0.732	5.176	3.508	1.668	0.195	4.050	2.267	1.783	0.226	3.609	2.997	0.612	-0.323
3	t-stat	3.554	1.498			3.142	1.834			3.698	2.253			4.326	3.168		
	TH	9.339	9.129	0.210	-0.624	9.636	10.335	-0.699	-0.888	9.588	10.622	-1.034	-1.415	9.326	10.241	-0.915	-1.514
	TL	2.427	1.448	0.979	0.263	5.172	0.770	4.402	2.757	6.187	1.847	4.341	3.187	7.826	4.587	3.239	2.699
	TH-TL	6.912	7.681	-0.769	-0.078	4.464	9.566	-5.101	-2.136	3.401	8.776	-5.375	-2.785	1.500	5.654	-4.154	-2.479
6	t-stat	2.176	2.006			2.789	4.921			3.276	6.723			2.072	5.487		
	TH	10.115	9.199	0.916	-0.202	9.482	9.658	-0.176	-0.447	9.307	9.770	-0.463	-0.694	9.391	9.943	-0.553	-0.693
	TL	-1.133	2.739	-3.872	-0.648	3.805	3.717	0.089	0.595	5.473	4.769	0.705	0.408	7.236	6.316	0.920	0.457
	TH-TL	11.248	6.460	4.787	0.710	5.677	5.941	-0.265	-0.578	3.834	5.001	-1.167	-0.549	2.155	3.628	-1.473	-0.603
12	t-stat	4.778	1.537			4.236	2.818			4.393	3.538			3.567	3.040		

Panel C. Commodities

	Holding month(s)	1				3				6				12			
Ranking month(s)	Annual Returns (%)	AL	AH	AL-AH	t-stat	AL	AH	AL-AH	t-stat	AL	AH	AL-AH	t-stat	AL	AH	AL-AH	t-stat

	TH	5.630	4.045	1.585	0.321	4.109	2.124	1.984	1.144	2.454	2.169	0.286	0.298	1.781	1.716	0.065	0.474
	TL	-1.806	-7.772	5.966	1.825	-4.447	-2.663	-1.784	-0.964	-3.588	-1.794	-1.793	-1.045	-3.161	-3.443	0.282	0.377
	TH-TL	7.435	11.817	-4.381	-0.830	8.555	4.787	3.768	1.456	6.042	3.963	2.079	0.686	4.942	5.159	-0.217	0.562
3	t-stat	1.344	2.424			2.368	1.037			2.431	1.207			3.510	2.551		
	TH	1.888	1.897	-0.009	0.088	4.395	0.564	3.832	1.391	4.198	1.986	2.212	1.091	1.586	0.942	0.643	-0.332
	TL	-5.352	-6.944	1.592	0.603	-3.259	-5.080	1.821	0.599	-4.157	-4.117	-0.040	-0.333	-3.688	-4.160	0.472	-0.089
	TH-TL	7.240	8.840	-1.600	-0.006	7.654	5.644	2.011	1.354	8.355	6.103	2.252	1.776	5.274	5.102	0.172	0.250
6	t-stat	0.737	1.450			2.269	1.135			4.104	1.997			3.170	2.491		
	TH	6.807	-1.451	8.258	2.362	3.898	-0.458	4.355	2.156	2.767	-0.841	3.608	2.548	0.060	-1.901	1.961	1.963
	TL	-6.483	-4.299	-2.184	-0.646	-5.761	-4.694	-1.067	-0.708	-4.936	-3.812	-1.124	-0.953	-3.325	-3.668	0.343	-1.053
	TH-TL	13.291	2.849	10.442	2.212	9.658	4.236	5.422	2.478	7.703	2.972	4.731	2.969	3.385	1.767	1.617	2.278
12	t-stat	2.922	1.031			3.859	1.415			3.987	0.632			2.686	0.022		

Table 4.5 Panel A presents the performance of the abnormal return volatility grouped time-series momentum strategy returns across all assets. ARV is the residual from the Connolly and Stivers (2003) regression. The details are shown in Section 3.1.3. The long and short portfolio of the standard time-series momentum strategy are divided into two parts: the part with negative abnormal return volatility and the part with positive abnormal return volatility. The ranking month are 3,6, and 12, and the holding months are 1,3,6,12. The strategy returns of the looking back and holding period of 9,24,36 months are also calculated. Due to the massive size of the table, they are not included in this report. New (old) portfolios are formed (closed) on a monthly basis. The reported are the annualised mean equal weighted returns of the overlapping portfolios. TH denotes the long position of the standard time-series momentum strategy, TL denotes the short position of the standard time-series momentum strategy, AL denotes the negative abnormal return volatility, AH denotes the positive abnormal return volatility, and TH-TL is the return of the overall strategy. t-stat are the t-statistics. Panel B reports the strategy performance in equity market and Panel C reports the strategy performance in commodity market.

Table 4. 8 Abnormal turnover grouped time-series momentum returns (Equity market)

	Holding month(s)	1				3				6				12			
Ranking month(s)	Annual Returns (%)	AL	AH	AL-AH	t-stat	AL	AH	AL-AH	t-stat	AL	AH	AL-AH	t-stat	AL	AH	AL-AH	t-stat
	TH	11.327	8.103	3.225	0.780	10.311	8.580	1.732	0.699	10.377	8.192	2.185	1.503	9.166	8.178	0.988	0.939
	TL	2.744	0.931	1.813	1.146	4.191	4.704	-0.513	0.598	6.655	5.082	1.573	1.126	7.182	5.732	1.450	0.848
	TH-TL	8.583	7.171	1.411	-0.633	6.120	3.875	2.245	0.272	3.722	3.110	0.612	-0.115	1.984	2.446	-0.462	-0.136
3	t-stat	2.270	3.032			2.630	2.181			2.339	2.903			2.166	3.196		
	TH	9.638	6.405	3.233	1.317	9.661	8.563	1.099	1.237	9.416	8.775	0.641	1.321	8.359	8.837	-0.478	0.250
	TL	2.085	-1.701	3.786	0.268	4.812	0.600	4.212	1.807	5.310	3.176	2.134	1.260	6.091	5.606	0.485	-0.263
6	TH-TL	7.553	8.106	-0.553	0.118	4.850	7.963	-3.113	-1.131	4.106	5.599	-1.493	-0.509	2.268	3.231	-0.963	0.375

	t-stat	1.772	2.344			2.339	4.125			2.875	4.369			2.692	3.584		
	TH	8.812	7.060	1.752	0.915	7.776	8.911	-1.135	-0.534	7.479	8.553	-1.074	-0.754	8.135	8.145	-0.009	0.303
	TL	0.998	-2.093	3.092	1.128	2.681	3.185	-0.504	1.041	4.639	3.994	0.644	1.761	6.373	6.360	0.012	0.784
	TH-TL	7.813	9.153	-1.340	-1.188	5.095	5.726	-0.631	-1.305	2.840	4.558	-1.718	-1.868	1.763	1.785	-0.022	0.240
12	t-stat	2.160	3.812			2.459	2.764			2.373	3.697			3.793	2.964		

Table 4.6 demonstrates the performance of the abnormal turnover grouped time-series momentum strategy returns in equity market. The details of AT construction are shown in Section 3.1.4. The long and short portfolio of the standard time-series momentum strategy are divided into two parts: the part with negative abnormal turnover and the part with positive abnormal turnover. The ranking month are 3,6, and 12, and the holding months are 1,3,6,12. The strategy returns of the looking back and holding period of 9,24,36 months are also calculated. Due to the massive size of the table, they are not included in this report. New (old) portfolios are formed (closed) on a monthly basis. The reported are the annualised mean equal weighted returns of the overlapping portfolios. TH denotes the long position of the standard time-series momentum strategy, TL denotes the short position of the standard time-series momentum strategy, AL denotes the negative abnormal turnover, AH denotes the positive abnormal turnover, and TH-TL is the return of the overall strategy. t-stat are the t-statistics.

Chapter 5 Time-series industry momentum and information diffusion

5.1 Abstract

This chapter, to the best of the authors knowledge, is the first to examine the existence of the time-series momentum effect within US industries. The impact of information diffusion on the time-series industry momentum effect is analysed via the two elements of information diffusion: information discreteness (proxied by Da et al.'s (2014) information discreteness), and information uncertainty (proxied by Connolly and Stivers' (2003) abnormal return volatility). Information discreteness measures the scale of information arrival, and abnormal return volatility measures the level of noise contained in the information. Findings show that investors tend to underreact to absolute continuous industry price information. Portfolios of absolute continuous information time-series industry momentum strategies generate significant annual returns of 12.402% (with t-stat = 3.575) for 12-month lookback period and 1-month holding period (compare with time-series individual stock momentum returns as is shown in Lim et al. (2018), and time-series momentum returns at asset level 12.345% (with t-stat = 5.536), as is shown in the previous chapter). Time-series industry momentum performance pattern shows no consistent improvement under different abnormal return volatility, and disappears under low and high abnormal return volatility. The performance of time-series industry momentum strategies is enhanced in expansions but deteriorates in recessions.

5.2 Introduction

Chapter 4 demonstrates the influence of information diffusion on TSM at global asset classes. Here, investors tend to underreact to broad asset price information that arrives consistently in small pieces. This chapter focuses on the time-series momentum effect in US industries, and the existence of time-series industry momentum is explored for the first time. To the best of the authors knowledge, this chapter is the first to examine significant time-series industry momentum returns. Industry momentum is studied only in the cross-sectional context in prior literature. By demonstrating the time-series industry momentum effect, it is shown that the time-series momentum effect is not only confined to across asset, and individual stock, levels. This study also complements time-series momentum literature and cross-sectional industry momentum literature by demonstrating the linkage between the time-series industry momentum effect and information diffusion. For the investment community, the findings in this study provide sector fund managers and individual investors information diffusion signals to eliminate strategy risks and increase strategy returns.

The reasons TSM is analysed at the industry level are as follows: first, as is argued by Moskowitz and Grinblatt (1999), industry performance plays an important role in corporate finance literature on Initial Public Offerings (IPOs), Mergers and Acquisitions (M&As), Seasoned Equity Offerings (SEOs) as well as in financial and investment policy making. Thus, studies on stock performance around IPOs, M&As, and SEOs are based on industry-adjusted stock returns and studies on firm financial and investment policies takes into account industry specific influences. The study of the existence of the time-series industry momentum effect may provide evidence for these studies on whether to filter out the influence of the time-series industry momentum effect in future research.

Second, when the time-series momentum effect is first found by Moskowitz et al. (2012), they examined it at a broad asset class level. Subsequent time-series momentum studies also mostly focused on the broad asset class level. However, time-series momentum effects were found at the individual stock level (Goyal and Jegadeesh, 2018; Lim et al., 2018). Though no consensus has been achieved on whether the cross-sectional industry momentum effect can explain individual stock momentum effect, cross-sectional individual stock momentum, is at least to some extent be influenced by cross-sectional industry momentum. In addition, in strategic management frameworks, managers are required to take into account the influence of industries when conducting firm performance forecasts and decision making. Since individual firms within industries are influenced by the industry performance, the study on the existence of the time-series industry momentum effect may provide hints for time-series individual stock momentum researchers on whether they should include the industry components in future studies, to understand whether it is the industries, the individual firms, or the mutual influence of the two, that leads to time series momentum effect at individual stock level.

Third, when Moskowitz et al. (2012) first examined the time-series momentum effect by extending Jegadeesh and Titman (1993) traditional momentum effect to a time-series context, they argued that time-series momentum effect is a more direct application of underreaction theories (i.e., Daniel et al., 1998, Barberis et al., 1998, and Hong and Stein, 1999), because the theories focus on investor reaction to prior absolute price changes of assets, rather than the relative price changes. Cross-sectional industry momentum strategies generate statistically significant monthly returns and are found to drive a significant portion of individual stock momentum returns (Moskowitz and Grinblatt, 1999; Scowcroft and Sefton, 2005). If underreaction theories hold at the industry level as well, applying the same logic as in Moskowitz et al. (2012) on time-series momentum at the broad asset class level, this work argues that time-series industry momentum is a more direct application of the underreaction theories compared to cross-sectional industry momentum. This is because these theories focus on investor reaction to prior absolute price changes of industries rather than prior relative industry price changes. Supporting evidence is required that investors tend to underreact to prior absolute industry performance changes, and that industries with positive (negative) returns in the past tend to generate positive (negative) returns in the following periods. The study of the time-series industry momentum effect may complement cross-sectional momentum studies by extending the industry momentum effect to the time-series context.

Fourth, industry as a unit of analysis provides a potential tactical asset allocation method for sector rotation strategies in terms of risk control and return generation. Moskowitz and Grinblatt (1999) argue that the tendency of a high correlation of individual firms in industries makes industries the unit of analysis, because the firms in the same industries are exposed to the same regulatory environment, similar corporate finance behaviour, similar sensitivity to macroeconomic news, and similar supply and demand changes. If the time-series momentum occurs at industry level, practitioners may invest on or construct industry-neutral funds to eliminate the extra momentum risk induced by industry risk, and capture the industry level alpha when designing sector rotation strategies to generate better alpha (Scowcroft and Sefton, 2005). O'Neal (2000) suggests investment on actively trading industry-sector mutual funds in real world implementation because of the quantifiable transaction costs (i.e., commission fees and market impact costs) and the manageable size of industry-sector mutual funds. In addition, compared to individual stock momentum, industry momentum is of more manageable size for practitioners. Individual stock momentum strategies usually choose the top and bottom 10% to 30% stocks to form portfolios, which may contain hundreds of stocks. However, there are only 49 industries in the time-series industry momentum strategies.

Finally, by nature, cross-sectional industry momentum is the continuity of the relative industry performance, which is composed of relative return scale continuation and return sign continuation. However, time-series industry momentum is the continuity of the absolute industry performance (i.e., the continuity of the industry return signs). Thus, the source of significant cross-sectional industry momentum returns may be the relative industry return scale continuation, the industry return sign continuation, or the joint impact of both. In this sense, the study of time-series industry momentum existence may provide evidence to future cross-sectional industry momentum studies on whether it is meaningful to further explore the extent to which significant cross-sectional industry momentum returns are induced by the time-series components.

Motivated by the above reasons, I focus on the examination of the time-series momentum effect in industries in this chapter. Since the US market is found in prior literature to lead global markets, the US industry is a good starting point to study whether TSM exists at the industry level. If the time-series momentum effect does occur at industry level, then fund managers can construct industry-neutral trading strategies to manage industry-specific risk. For those investors who utilise sector rotation strategies, they can improve their strategy returns by adding a second time-series industry momentum dimension. In addition, firm financial and investment policy makers may better predict and intervene firm performance based on prior industry performance.

This chapter also examines whether the time-series industry momentum effect is enhanced under greater information diffusion, and is measured from two dimensions: information discreteness and information uncertainty. Since cross-sectional industry momentum returns were documented, there has been no consensus on its profit channel in the extant literature (Grundy and Martin, 2001; Chordia and Shivakumar, 2002). Slow information diffusion, induced by investor underreaction to information contained in prior industry returns, are studied as a potential explanation of the effect (Hou, 2007). Information diffusion literature shows that investors tend to underreact to price changes in uncertain information environments (Zhang, 2006; Da et al., 2014). Thus, to study the time-series industry momentum performance in different information environment, the two measures of information diffusion from the prior literature are used: information discreteness from Da et al. (2014), as a proxy for information discreteness; and abnormal return volatility from Connolly and Stivers (2003), as a proxy for information uncertainty. These information environment proxies (or information diffusion proxies) capture differing elements. Information discreteness captures whether the information generally arrives in big chunks or small pieces, whereas abnormal return volatility captures whether information is noisy and therefore gets obscured.

The profitability of industry momentum in the cross-sectional context can be explained by underreaction theories (i.e., Moskowitz and Grinblatt, 1999; Scowcroft and Sefton, 2005). This chapter studies the relationship between information diffusion and time-series industry momentum from two aspects of information diffusion: information discreteness; and information uncertainty. It demonstrates that investors react differently to absolute industry price changes of the same direction when the absolute magnitude and consistency of these price changes differs. They react too much to sudden large scale (negative) absolute price changes, whereas they fail to pay enough attention to continuous small scale positive (negative) absolute price changes. This is reflected in the improved return continuity in the industries with absolute information continuity (i.e., negative information discreteness) across almost all lookback and holding horizon combinations. The relationship between the time-series industry momentum effect and information discreteness is consistent with the information diffusion hypothesis that asset returns are enhanced under greater information diffusion. The predictability of time-series industry momentum returns makes it sub-optimal for investors to engage in industry diversification. However, abnormal return volatility makes time-series industry momentum returns disappear, and therefore questions the robustness of the time-series industry momentum effect.

This chapter is also related to the literature on limited investor attention that documents investors' relative inattention to relative asset price changes (Zhang, 2006; Hershleifer, et al., 2009; Da et al., 2014). This literature focuses on the cross-sectional comparison among asset performance and investor attention on individual stocks. This chapter complements them in a time-series context by demonstrating that industry investors underreact to absolute price signals, if the signals arrive in small pieces persistently. Information discreteness matters not just in relative individual stock performance as is shown in Da et al. (2014), but also for absolute industry performance in the current study.

Lim et al. (2018) has a similar section analysing the relationship between individual stock momentum and information discreteness. They find consistent return behaviour, as is shown in Da et al. (2014), on cross sectional individual stock momentum. Here, momentum returns are enhanced under information continuity (i.e., negative information discreteness). However, though information discreteness from Da et al. (2014) is utilised in the present study, its application in my time-series industry momentum strategies is different from Lim et al. (2018) and Da et al. (2014) in their time-series individual stock momentum and cross-sectional individual stock momentum strategies, respectively. Instead of using information discreteness quintiles (as is in the aforementioned studies), only the sign of information discreteness is taken into consideration when adding a second dimension to my time-series industry momentum strategies. This is because what differentiates time-series momentum and cross-sectional momentum, is that the former uses absolute asset performance as investment criterion, whereas the latter uses relative performance. Therefore, it is natural to introduce absolute information diffusion measures when doing the double sort in this time-series momentum study rather than introducing relative information diffusion measures.

Since negative information discreteness and positive information discreteness have valid meanings, information discreteness is suitable to be introduced as an absolute information diffusion measure to time-series industry momentum strategies. Negative information discreteness is equivalent to information continuity, and it is used interchangeably with low information discreteness, because the information discreteness is only divided into two groups (positive and negative) in this chapter. If the signs of the ranking months' industry returns are determined by the persistent and small-scale industry daily returns, the ranking period information discreteness of the industry will be negative. If the signs of the ranking months' industry returns are determined by the infrequent but large-scale industry daily returns, the ranking period information discreteness of the industry will be positive. In brief, information discreteness is capturing whether the information generally arrives in big chunks or small pieces. Information discreteness means big chunks of information, whereas information continuity means small pieces of information.

Connolly and Stivers (2003) abnormal return volatility, a proxy for information uncertainty, is another measure that is suitable to be utilised as an absolute information diffusion measure for time-series industry momentum strategies. Here, positive (negative) abnormal return volatility means the remaining part of the industry return volatility that is not explained by the autoregressive behaviour of return volatility, and the changes induced by the sign and absolute scale of previous period returns are abnormally high (low). In brief, abnormal volatility captures whether information is noisy and therefore gets obscured. Low abnormal return volatility means a low level of noise in information whereas high abnormal return volatility means a high level of noise in information. This measure satisfies the selection criteria that both positive abnormal return volatility and negative abnormal return volatility also have valid meanings so that abnormal return volatility does not involve cross-industry comparison when it comes to form time-series industry momentum portfolios under different information diffusion environments. Due to data unavailability of French 49 industry turnover, Connolly and Stivers' (2003) abnormal turnover is not utilised as another proxy of information diffusion.

The structure of this chapter is as follows. Section 5.3 demonstrates the development of the hypotheses. Section 5.4 details the data and summary statistics, and then section 5.5 shows the US industry time-series momentum performance. Section 5.6 then demonstrates time-series industry momentum performance conditioning on absolute information discreteness and abnormal return volatility, with section 5.7 concluding the chapter.

5.3 Hypothesis Development

This chapter first examines the existence of time-series industry momentum and then analyses the impact of information diffusion on the time-series industry momentum effect. Two aspects of information diffusion are studied in this relationship: information discreteness and information uncertainty. The development of the hypotheses are shown in the following subsections.

5.3.1 The importance of industry performance analysis in time-series momentum studies

Starting from Moskowitz et al. (2012), the studies on the time-series momentum effect are focused on broad asset class level, and only recently studies extend this to the individual stock level (e.g., Goyal and Jegadeesh, 2018; Lim et al., 2018). The importance of industry performance analysis in corporate finance literature aroused the interest in examining cross-sectional industry momentum (e.g., Moskowitz and Grinblatt, 1999). Though there is no consensus as to whether cross-sectional individual stock momentum can be fully explained by cross-sectional industry momentum in the prior literature, the potential link between cross-sectional individual stock momentum and cross-sectional industry momentum effect has been well established. In addition, strategic management frameworks introduce the influence of industries on individual firms that belong to these industries. Therefore, managers take into consideration industry factors when making financial and investment decisions for individual firms. These indicate the relationship between individual firms and the corresponding industries that the firms belong to. Therefore, it is natural to study the industry components of time-series individual stock momentum for future research. The examination of the existence of time-series industry momentum in this chapter is a good starting point for further research into the relationship between time-series individual stock momentum and industry momentum.

The study of time-series industry momentum is not only important for future time-series individual stock momentum studies, but also important for further cross-sectional industry momentum studies. By nature, cross-sectional industry momentum is the relative industry return continuation. Therefore, the profits of the strategies are determined by industry relative return scale continuation and return sign continuation. More details of this argument will be shown in the tables and the relevant explanations in Section 6.3.1 of chapter 6. Since time-series industry momentum is the industry absolute return sign continuation, it is natural to study the relationship between time-series industry momentum and cross-sectional industry momentum to see the extent to which the cross-sectional industry momentum returns can be explained by time-series industry momentum. Thus, the examination of the existence of time-series industry momentum is an important first step for this future research. If there is no time-series industry momentum effect, the study of this relationship is no longer necessary.

5.3.2 Time-series industry momentum is the direct application of behavioural theories (Hypothesis 5.1)

Cross-sectional industry momentum strategies are found to generate significant returns by Moskowitz and Grinblatt (1999), with returns are still significant after adjusting for Fama French factors, individual stock momentum effect, cross-sectional variation in unconditional mean returns and microstructure. This indicates that the cross-sectional momentum effect also occurs at the industry level. When Moskowitz et al. (2012) first extended the cross-sectional momentum effect to the time-series context and thus document time-series momentum effect, they argued that the difference between cross-sectional momentum and time-series momentum is that the former is relative asset return continuation whereas the latter is the absolute asset return continuation. Therefore, the time-series momentum effect is a more direct application of behavioural theories, because these theories only focus on investor reaction to prior absolute price changes rather than relative price changes.

Following Moskowitz et al.’s (2012) logic and argument, it is argued that time-series industry momentum is a more direct application of behavioural theories compared to the cross-sectional industry momentum effect, because these theories only focus on investor reaction to prior absolute industry performance changes rather than relative industry performance changes. Therefore, if behavioural theories hold at the industry level, supporting evidence then should be shown that prior positive (negative) return industries should generate positive (negative) returns, indicating that investors tend to underreact to prior absolute industry performance changes. Thus, the following hypotheses are presented:

H5.1 Investors tend to underreact to absolute industry return information.

5.3.3 Time-series industry momentum and market state (Hypothesis 5.1a)

Cooper et al. (2004) extends both Daniel et al.'s (1998) theory and Hong and Stein's (1999) theory to predict cross-sectional individual stock momentum performance in different market states. They predict that under DHS, the greater investor confidence following good market states (i.e., up markets) leads to greater overreaction, which induces greater momentum returns. Under HS, they argue that, since there is a negative relationship between investor risk aversion and investor wealth, and HS demonstrates a negative relationship between investor risk aversion and momentum returns, momentum returns should be positively related to investor wealth. Therefore, they predict that momentum returns are stronger following good market states. Supporting evidence is shown by Cooper et al. (2004) that lagged market returns can explain the momentum effect, and that the relationship between lagged market returns and momentum is non-linear. Here, momentum profits summit around the median level of market returns, starting to dissipate after the median. Following Cooper et al.'s (2004) extension of the two behavioural theories, it is argued that if DHS and HS also hold for industry level investors, time-series industry momentum returns should be stronger following up markets, and weaker following down markets. Therefore, the following hypothesis is constructed:

H5.1a Time-series industry momentum returns are stronger in expansions and weaker in recessions.

5.3.4 Cross-sectional momentum and information diffusion

The three mainstream behavioural theories (i.e., DHS, BSV, and HS) that are designed to explain the momentum effect, though based on different investor cognitive biases and type of investors, all assume that information travels slowly, and all establish links between information diffusion and asset return continuation. To test these behavioural theories, empirical studies on the cross-sectional momentum effect develop information diffusion measures such as earnings surprises (Chan, Jegadeesh, and Lakonishok, 1996), abnormal turnover (Connolly and Stivers, 2003), abnormal return dispersion (Connolly and Stivers, 2003), order imbalance (Chordia, Roll, and Subrahmanyam, 2002; Andrade, Chang, and Seasholes, 2008; Lou, 2012), consumption growth shocks (Li and Zhang, 2016), and price jumps (Jiang and Zhu, 2017).

5.3.5 Time-series industry momentum and information diffusion (Hypothesis 5.2 and 5.3)

The influence of information diffusion should also occur at industry level if investors are by nature constrained by limited attention and limited ability to deal with information properly and promptly. Therefore, a link between time-series industry momentum and information diffusion can be established. However, instead of directly borrowing information diffusion measures from cross-sectional momentum literature, a selection criteria needs to be established to fit the purpose of the time-series industry momentum study. That is, the information diffusion measure should have valid meanings when the value of the measure is negative and positive, respectively. This is because the major difference between time-series industry momentum and cross-sectional industry momentum is that the former is the absolute industry performance continuation, and the latter is the relative industry performance continuation. Therefore, when studying the influence of information diffusion on time-series industry momentum, it is natural to choose the measures that do not require cross-industry comparison. In this sense, Da et al.'s (2014) information discreteness, and Connolly and Stivers' (2003) abnormal return volatility and abnormal turnover are chosen. Due to industry level data availability, the measures are narrowed down to information discreteness and abnormal return volatility.

Information discreteness captures whether the information generally arrives in big chunks or small pieces, whereas abnormal return volatility captures whether information is noisy and therefore gets obscured. Da et al. (2014) find that cross-sectional individual stock momentum effects are enhanced following information that arrives in small pieces. Connolly and Stivers (2003) find that abnormal return volatility is positively related to momentum in weekly equity indices. Therefore, the following hypotheses are established:

H5.2 The time-series industry momentum effect is enhanced under greater information continuity (negative information discreteness).

H5.3 The time-series industry momentum effect is enhanced under greater abnormal return volatility.

Combinations of H5.1a Time-series industry momentum returns are stronger in expansions and weaker in recessions and H5.2 and H5.3, respectively. Therefore, the following two hypotheses are presented.

H5.2a The time-series industry momentum effect under greater information continuity is enhanced more in expansions than recessions

H5.3b The time-series industry momentum effect under greater abnormal return volatility is enhanced more in expansions than recessions

5.4 Data and summary statistics

5.4.1 Sample Data Description

Monthly and daily industry returns are collected from Kenneth R. French Data Library 49 industry portfolios from 1st January 1959 to 1st March 2019. NYSE, AMEX, and NASDAQ firms are allocated to industry portfolios according to four-digit Compustat SIC codes in June of fiscal year t-1. If the code is not available, they use CRSP four-digit SIC code of fiscal year t instead. Then the returns are calculated from July in year t to June in year t+1.

The peak months and trough months are collected from NBER US Business Cycle Dates. Recessions (expansions) are defined as periods starting with peak (trough) months and ending with the next trough (peak) months. To exclude the impact of the month with the turning point on the recession/ expansion period returns for the strategies, the start of each recession/ expansion period in this chapter is one month after the NBER turning point and the end of the periods are one month before the NBER turning point. The format of the dates is yyyymm. For example, the start month of the recession period 196005-196101 (i.e., May 1960 to January 1961) is one month after the peak month 196004 (i.e., April 1960) and one month before the next trough month 196101 (i.e., January 1961).

Information discreteness is constructed according to Da et al. (2014) as the ranking period cumulative return sign multiplied by the difference between ranking period percentage of negative return days and the corresponding percentage of positive return days. The details are shown in section 3.1.1 of Chapter 3. The difference is that absolute information discreteness is added as a second dimension in the present time-series industry momentum strategies, whereas Da et al. (2014) only use relative information discreteness as a second dimension in their cross-sectional individual stock momentum strategies.

The abnormal return volatility is the volatility residuals gained from the time-series regression model on autoregressive return volatilities and movements with the market in terms of portfolio return sign and magnitude in Connolly and Stivers (2003). The details of abnormal return volatility construction are shown in section 3.1.3 of chapter 3. The positive abnormal return volatility is classified as high abnormal return volatility and negative abnormal return volatility is classified as low abnormal return volatility. Abnormal return volatility is regarded as the second aspect of information diffusion in this chapter to be adopted as a second dimension in time-series industry momentum strategies. This is to examine the relationship between information diffusion and time-series industry momentum.

Abnormal turnover, the turnover residuals gained from the time-series regression model on autoregressive turnover components and movements with the market in terms of signs and magnitude of portfolio returns in Connolly and Stivers (2003), is supposed to be the third aspect of information diffusion to be adopted as a second dimension in time-series industry momentum strategies. This is to study the impact of information diffusion on time-series industry momentum performance. However, due to industry level turnover data availability, this aspect of information diffusion has not been added in this chapter.

5.4.2 Summary Statistics

This section summarises industry returns, the industry returns in recession and expansion periods, and information diffusion measures.

Table 5.1 panel A demonstrates the mean returns by industries. It can be observed that the entertainment industry generates the highest annualised mean returns of 16.279%, with standard deviation 26.243%, whereas the steel works etc industry generates the lowest annualised mean returns of 7.943%, with standard deviation 25.001%. The skewness ranges from -0.455 (restaurants, hotels, motels industry) to 0.822 (real estate industry) and the excess kurtosis ranges from 0.878 (construction industry) to 11.349 (real estate industry).

From Table 5.1 panel B, we can observe that the annualised mean returns for US industries are 11.9%, with standard deviation 22.3%. The annualised mean returns for US industries are much higher than average global equity index returns (6.49%) and the average commodity market returns (-2.091%) in chapter 4. The annualised standard deviation is of similar scale to international equity index returns (23.427%) and lower than that of the commodity market (28.443%). The skewness is slightly negative, and the excess kurtosis is 2.534.

Table 5. 1 Summary statistics

Panel A. Mean returns by industries

	Annualized mean return (%)	Standard deviation (%)	Skewness	Excess Kurtosis
Agriculture	10.841	22.836	0.035	1.273
Food Products	12.644	15.184	0.112	1.993
Candy and Soda	13.772	21.650	0.129	4.345
Beer and Liquor	12.968	17.416	-0.010	2.479
Tobacco Products	16.044	20.966	-0.113	2.393
Recreation	10.306	25.600	-0.078	1.166
Entertainment	16.279	26.243	-0.200	2.806
Printing and Publishing	11.027	20.420	-0.014	1.870

Consumer Goods	11.472	16.232	-0.305	1.697
Apparel	13.055	21.806	-0.072	2.643
Healthcare	12.198	28.078	-0.048	2.677
Medical Equipment	14.018	18.676	-0.177	1.387
Pharmaceutical Products	12.909	17.390	0.128	2.453
Chemicals	10.937	18.845	-0.129	2.279
Rubber and Plastic Products	12.551	20.606	-0.205	2.584
Textiles	12.028	24.277	0.382	9.330
Construction Materials	11.475	20.786	-0.051	4.031
Construction	11.145	24.632	-0.068	0.878
Steel Works Etc	7.943	25.001	-0.156	2.266
Fabricated Products	9.221	24.987	-0.096	1.208
Machinery	11.513	20.990	-0.375	2.468
Electrical Equipment	13.084	21.325	-0.190	1.582
Automobiles and Trucks	9.899	22.762	0.224	6.094
Aircraft	14.054	22.921	-0.267	1.590
Shipbuilding, Railroad Equipment	11.783	24.297	-0.001	1.744
Defence	14.227	22.661	-0.152	1.987
Precious Metals	11.439	36.113	0.748	4.909
Non-Metallic and Industrial Metal Mining	12.333	25.156	-0.272	1.925
Coal	13.112	34.748	0.173	2.236
Petroleum and Natural Gas	11.548	18.547	0.035	1.249
Utilities	10.268	13.617	-0.124	1.142
Communication	10.609	15.839	-0.190	1.198
Personal Services	8.876	23.477	-0.149	1.443
Business Services	11.891	19.232	-0.369	2.392
Computers	12.320	24.067	-0.192	1.702
Computer Software	11.890	39.040	0.819	5.098
Electronic Equipment	11.947	25.137	-0.361	1.647
Measuring and Control Equipment	13.490	23.900	-0.192	1.174
Business Supplies	11.497	19.003	0.106	2.085
Shipping Containers	11.422	19.137	-0.366	1.996
Transportation	11.412	19.681	-0.228	1.260
Wholesale	11.891	19.143	-0.325	2.215
Retail	12.881	18.331	-0.193	2.194
Restaurants, Hotels, Motels	13.404	20.710	-0.455	2.557
Banking	11.432	20.325	-0.262	2.003
Insurance	11.971	19.577	-0.012	2.074
Real Estate	8.213	26.732	0.822	11.349
Trading	12.763	20.759	-0.386	1.390

Other	7.971	23.562	-0.434	1.695

Panel B. Return Distribution

Annualized Mean Return	Standard Deviation	Skewness	Excess Kurtosis
0.119	0.223	-0.072	2.534

Table 5.1. Panel A reports annualised mean return, annualised standard deviation, skewness, and excess kurtosis for 49 US industries and Panel B reports annualised mean return, annualised standard deviation, skewness, and excess kurtosis of the US industries. The industry data range from 02 January 1959 to 01 March 2019 and are from French Data Library.

Table 5.2 demonstrates the business cycles, and the corresponding industry returns are demonstrated in table 5.3. We may observe that most industry returns are positive and highly significant in expansions, whereas insignificant and mostly negative in recessions. The electrical equipment industry performs best in expansions with average monthly returns 1.338% and t-statistic 5.432. The tobacco products industry is the best performer in recessions, with average monthly returns 1.484% (t-statistic = 1.647).

Table 5. 2 Business cycles

Panel A. NBER turning points

Peak month	Trough month
195708	195804
196004	196102
196912	197011
197311	197503
198001	198007
198107	198211
199007	199103
200103	200111
200712	200906
202002	

Panel B. Recession and expansion periods

Recession periods	Expansion periods
196005-196101	196103-196911
197001-197010	197012-197310
197312-197502	197504-197912
198002-198006	198008-198106
198108-198210	198212-199006

199008-199102	199104-200102
200104-200110	200112-200711
200801-200905	200907-201903

Table 5.2 Panel A shows the NBER recession and expansion dates. Panel B shows the recession and expansion periods that are utilised in this chapter. The start of each period is one year after the turning point and the end of the periods is one year before the turning points. The purpose is to exclude the year with the turning points for recessions and expansions.

Table 5. 3 Annual performance of 49 industries in recessions and expansions

	Recession (%)	t-stat	Expansion (%)	t-stat
Agriculture	-6.929	-0.639	12.716	4.306
Food Products	13.118	1.055	12.626	6.035
Candy and Soda	0.061	0.005	15.568	4.918
Beer and Liquor	4.856	0.380	14.333	5.832
Tobacco Products	17.813	1.647	15.671	5.263
Recreation	2.713	-0.196	9.055	3.110
Entertainment	0.971	-0.230	19.051	5.547
Printing and Publishing	-3.834	-0.981	12.955	4.898
Consumer Goods	1.891	-0.332	12.548	5.479
Apparel	3.114	0.164	14.334	4.558
Healthcare	-4.919	-0.298	14.093	3.619
Medical Equipment	6.166	-0.001	14.562	5.496
Pharmaceutical Products	4.434	0.286	14.039	5.869
Chemicals	-2.015	-0.283	13.063	5.304
Rubber and Plastic Products	-9.736	-0.919	15.599	5.353
Textiles	0.815	-0.032	13.954	4.123
Construction Materials	-4.010	-0.479	13.584	4.966
Construction	-12.755	-1.165	14.100	3.892
Steel Works Etc	-15.961	-1.344	10.768	3.170
Fabricated Products	-19.814	-1.394	11.987	3.487
Machinery	-12.310	-1.242	14.978	5.198
Electrical Equipment	-9.791	-0.787	16.054	5.432
Automobiles and Trucks	-10.264	-0.822	12.425	3.873
Aircraft	-9.959	-1.294	17.722	6.045
Shipbuilding, Railroad Equipment	-3.683	-0.451	14.582	4.328
Defence	7.456	0.597	15.325	5.259
Precious Metals	16.146	0.865	10.673	1.668
Non-Metallic and Industrial Metal Mining	-12.594	-1.327	15.974	4.230
Coal	5.279	0.136	13.817	2.479
Petroleum and Natural Gas	-2.962	-0.692	14.214	5.164
Utilities	2.659	-0.037	11.467	6.390
Communication	1.392	-0.374	11.900	5.564
Personal Services	-4.362	-0.688	10.135	3.019

Business Services	-4.734	-0.649	14.191	5.212
Computers	-3.712	-0.725	14.137	3.913
Computer Software	-11.140	-0.486	14.544	3.149
Electronic Equipment	-9.646	-0.862	14.321	4.237
Measuring and Control Equipment	-7.373	-0.700	15.340	4.503
Business Supplies	-5.248	-0.619	14.070	5.325
Shipping Containers	3.210	0.168	12.604	4.648
Transportation	-4.056	-0.558	13.816	5.007
Wholesale	-2.418	-0.454	14.156	5.321
Retail	5.600	0.434	13.519	5.118
Restaurants, Hotels, Motels	0.390	-0.071	15.544	5.583
Banking	-0.577	-0.382	13.874	5.348
Insurance	-5.472	-0.828	14.856	6.273
Real Estate	-15.343	-0.968	10.931	2.875
Trading	-7.218	-0.854	16.015	5.496
Other	-17.990	-1.795	12.066	3.269

Table 5.3 reports average annual returns of 49 US industries in recessions and expansions. The industry data range from 02 January 1959 to 01 March 2019 and are from French Data Library.

From Table 5.4, we may observe that the 25th, 50th, 75th and the mean of information discreteness are all negative, indicating that the information continuity (i.e., negative information discreteness) dominates the data. In chapter 4, for equity indices and commodity markets, the mean ID is -0.158 and -0.124, respectively. These are more negative than the US industry ID (ranging from -0.068 to -0.106). The 25th, 50th, 75th are all negative for equity indices and commodity indices. In addition, the number of negative ID assets in equity portfolios (ranging from 6 to 15) and commodity portfolios (ranging from 5 to 7) are much higher than positive ID assets in the two markets (ranging from 3 to 7 for equity indices, and ranging from 2 to 3 for commodity market). This implies that negative ID assets also dominate the data at global asset classes in the previous chapter; this is consistent with the value of ID in Da et al. (2014) as well. In Da et al. (2014), they divide ID into five quintiles and calculate the average ID in each quintile. Only the top quintile has positive ID values (defined as discrete in Da et al. 2014) and the remaining quintiles are all negative. These indicate that in each asset classes, the information predominantly arrives in small pieces and the size of information arrival scales in US industries is larger than those in equity indices and commodity indices.

The standard deviation of abnormal return volatility is slightly higher than that of information discreteness in the 3- and 6-month formation periods, and the difference is much larger in the 12-month formation period. It can also be observed that the longer the formation period, the lower the average standard deviation of information discreteness and abnormal return volatility. The mean ARD is 0.844 in US industries, which is much higher than mean ARD in equity indices (0.000) and commodity indices (0.000). The 25th, 50th, and 75th ARD are all positive in US industries, whereas 25th and 50th ARD in equity indices are -0.010 and -0.002, respectively and the 25th and 50th ARD in commodity indices are -0.014 and -0.002, respectively. Compared to the standard deviation of ARD in equity indices (0.019) and commodity indices (0.024), the standard deviation of the abnormal return volatility of US industries is of a much larger scale (ranging from 0.622 to 1.125). These indicate that US industry returns contain much more noise, and the noise levels are more spread out than global equity indices and commodity indices.

Table 5. 4 Information diffusion measures

Panel A. Measure Distribution

ID

	25th	50th	75th	Mean	Standard Deviation
3	-0.178	-0.106	-0.035	-0.106	0.117
6	-0.138	-0.084	-0.028	-0.083	0.091
12	-0.112	-0.068	-0.025	-0.068	0.072

ARD

	25th	50th	75th	Mean	Standard Deviation
3	-0.531	-0.205	0.109	-0.221	1.125
6	-0.317	-0.097	0.123	-0.100	0.729
12	0.545	0.760	1.055	0.844	0.622

Panel B. Pearson Correlation

		ID	ARD
	ID	1.000	-0.004
3	ARD	-0.004	1.000
	ID	1.000	0.082
6	ARD	0.082	1.000
	ID	1.000	0.279
12	ARD	0.279	1.000

Panel C. Number of industries in each portfolio

Formation month(s)		IND	ID		ARV	
			IL	IH	AL	AH
3	TH	30	25	4	20	8
	TL	18	13	4	12	8
6	TH	32	27	4	18	9
	TL	16	12	4	11	9
12	TH	34	29	4	1	26
	TL	14	10	4	1	19

Table 5.4 Panel A reports the distribution pattern of ID and ARD for 3,6, and 12-month formation periods, respectively. Panel B reports the correlation between ID and ARD for 3,6, and 12-month formation period, respectively. Panel C reports average number of industries in each portfolio and the numbers are rounding to integers. The data range from 02 January 1959 to 01 March 2019.

From Table 5.4 panel B, it can be seen that information discreteness and abnormal return volatility are slightly correlated in the 3- and 6- month formation periods (-0.004 and 0.082 respectively). For the 12-month formation period, though the correlation rises to 0.279, the correlation is not high, indicating that the two variables measure two different dimensions of information diffusion. This is consistent with the purpose to measure two different elements of information diffusion. That is, information discreteness is used to measure the size of information arrival and abnormal return volatility is used to measure the noise in the information.

Table 5.4 panel C demonstrates that in all formation periods, positive return industries outnumber negative return industries. This is consistent with the upward trend of the US equity market from 1959 to 2019. In addition, industries with continuous information outnumber industries with discrete information. In the 3- and 6-month formation periods, the number of low abnormal return volatility industries are more than its high counterparts. In the 12-month formation period, the opposite occurs. The sum of the average number of industries in each formation period groups is around 48, for the 3^{rd}, 20^{th}, 26^{th}, 27^{th} and 36^{th} industry, it is from the 55^{th} month and 11^{th} industry data is from 127^{th} month, due to data availability in DataStream.

5.5 Empirical results

The details on the information diffusion proxies and portfolio construction are shown in section 3.1 and section 3.2 of chapter 3 methods. This section is on the relevant findings and analysis. All the findings are based on 3, 6-, and 12-month ranking periods. The reason that one-month ranking period strategies are excluded is because one month ranking period strategies are short term reversal strategies, which are not within the scope of momentum studies.

Table 5. 5 Time-series industry momentum returns

Panel A. Overall time-series industry momentum returns (%)

Formation month(s)	Holding month(s)	1	t-stat	3	t-stat	6	t-stat	12	t-stat
	TH	14.476	5.244	14.799	5.568	14.763	5.625	15.255	5.805
	TL	9.823	3.607	9.705	3.944	10.005	4.388	9.295	4.427
3	TH-TL	4.653	1.580	5.094	1.923	4.758	2.188	5.960	3.442
	TH	16.118	5.647	15.329	5.447	15.826	5.652	16.015	5.772
	TL	8.186	3.018	8.713	3.526	8.404	3.573	8.396	3.892
6	TH-TL	7.932	2.582	6.615	2.251	7.422	2.756	7.619	3.432
	TH	17.689	5.754	16.936	5.516	16.639	5.432	15.981	5.208
	TL	6.744	2.664	7.240	3.052	7.456	3.335	8.141	4.065
12	TH-TL	10.945	3.335	9.697	2.951	9.184	2.927	7.840	2.831

Panel B. Time-series industry momentum returns (%) in recessions and expansions

Ranking month(s)	Holding month(s)	1	3	6	12
	Recessions	-7.485	-8.346	-9.534	-4.947
	t-stat	-0.557	-0.703	-0.976	-0.668
	Expansions	7.236	7.332	6.678	7.506
3	t-stat	2.372	2.833	3.104	4.317
	Recessions	-10.142	-9.057	-2.449	-3.937
	t-stat	-0.741	-0.718	-0.213	-0.407
	Expansions	10.187	8.431	8.523	9.351
6	t-stat	3.259	2.906	3.206	4.314
	Recessions	-4.124	-6.958	-7.225	-7.623
	t-stat	-0.296	-0.506	-0.572	-0.732
	Expansions	12.752	11.623	11.147	9.935
12	t-stat	3.847	3.580	3.583	3.502

Table 5.5 Panel A reports time-series industry momentum annual returns and the corresponding t-statistics for 3,6,12 and 1,3,6,12 formation and holding month combinations from 02 January 1959 to 01 March 2019. TH is high time-series industry momentum (long portfolio), and TL is low time-series industry momentum (short portfolio). Panel B reports the performance in NBER recessions and expansions. The recession and expansion periods are demonstrated in Table 5.2.

5.5.1 Does time-series industry momentum effect exist?

Table 5.5 panel A demonstrates the evidence of the time-series industry momentum effect. It can be observed that time-series industry momentum strategies generate annual returns of 10.945% (t-statistic = 3.335), for the 12-1 strategy and 9.184% for 12-6 strategy (t-statistic = 2.927). Except the 3-1 and 3-3 strategies, the annual returns of the remaining strategies are all significant at 5% level (t-statistic =1.96). Except 3-1, 3-3, 3-6 and 6-3, the remaining strategies are all significant at 1% level (t-statistic = 2.58). Thus, it provides supporting evidence for H5.1 that investors tend to underreact to absolute industry return information.

Though overall, the time-series industry momentum returns are statistically significant, unlike cross-sectional individual stock momentum returns that are mainly from the short positions, the significant time-series industry momentum returns are mainly from the long leg of the portfolios. This is consistent with what Moskowitz and Grinblatt's (1999) findings on cross-sectional industry momentum, that the long positions of cross-sectional industry momentum drive the cross-sectional industry momentum returns.

Due to concerns such as quantifiable transaction costs (i.e., commission fees and market impact costs) and the manageable size of industry-sector mutual funds, practitioners may choose actively trading industry-sector mutual funds instead of constructing industry portfolios via individual stocks in real world investment, as is suggested in O'Neal (2000). Therefore, it is very important that the main source of profit for industry level strategies are from the long side rather than the short side, because the industry-sector mutual funds cannot be short sold. Therefore, the long positions as drivers of time-series industry momentum returns may make the practitioners feel interested in time-series industry momentum strategies.

Table 5.5 panel B further analyses the time-series industry momentum effect in recessions and expansions. It may be found that for all ranking period and holding period combinations, time-series industry momentum returns are significantly positive in expansions. In recessions, all ranking period and holding period combinations generate negative returns, though statistically insignificant. Therefore, these finding support H5.1a that time-series industry momentum returns are stronger in expansions and weaker in recessions.

For the 12-1 strategy (i.e., 12-month lookback period and 1-month holding period), the annual returns are 12.752% (t-statistic = 3.847) in expansions and -4.124% (t-statistic = -0.296) in recessions. Hutchinson and O'Brien (2020) study the relationship between futures market time-series momentum returns and market states from 1950 to 2014. In their 12-1 time-series momentum strategies in the futures market, they find that time-series momentum returns in all future markets are positive in expansions. In recessions, only time-series momentum returns in the foreign exchange market are negative. The returns are of larger scale in expansions in equity indices, bond markets, and the foreign exchange market than in recessions, whereas in the commodity market, recession period time-series momentum returns are higher than expansion periods. The statistically significant expansion period time-series industry momentum returns, and negative but statistically insignificant recession period returns complement Hutchinson and O'Brien (2020). The return signs in time-series momentum return in equity indices, commodity indices and bond markets in Hutchinson and O'Brien (2020) are positive, whereas the return signs of the present study's time-series industry momentum in recessions are negative. This may indicate that the influence of market states on time-series industry momentum returns is stronger than that on equity indices, commodity indices and bond market time-series momentum returns. The reasons behind this phenomenon need further research in the future.

For the 6-6 strategy (i.e., 6-month lookback period and 6-month holding period), the time-series industry momentum returns in expansions are 8.523% (t-statistic = 3.206) and in recessions are -2.449% (t-statistic = -0.213). Cooper et al. (2004) extend both Daniel et al.'s (1998) theory and Hong and Stein's (1999) theory, and examine the relationship between cross-sectional individual stock momentum and market states. In their 6-6 strategies, they find positive average monthly returns (0.93%, with t-statistic = 8.41) in recessions, which is equivalent to annual 11.16% and negative average monthly returns (-0.37%, with t-statistic = -0.65) in recessions, which is equivalent to annual -4.44%. The statistically significant expansion period time-series industry momentum returns, and negative but statistically insignificant recession period returns complement the Cooper et al.'s (2004) findings on cross-sectional individual stock momentum and market states to time-series industry momentum.

Following Cooper et al.'s (2004) extension of DHS, the greater expansion periods time-series industry momentum returns can be explained by the greater industry investor confidence following good market states (i.e., up markets). Investor confidence level increases lead to greater overreaction to prior industry information, and therefore induces more time-series industry momentum returns. Following Cooper et al.'s (2004) extension of HS, the better time-series industry momentum performance in expansions can be explained by the positive relationship between time-series industry momentum returns and industry investor wealth. Cooper et al. (2004) argue that prior literature demonstrates a negative relationship between industry investor risk aversion and industry investor wealth, and HS demonstrates a negative relationship between industry investor risk aversion and momentum returns. Therefore, the relationship between momentum returns and investor wealth should be positive. Following this logic, it is argued in the hypothesis development section that if this applies to time-series industry momentum, time-series industry momentum returns should be positively related to industry investor wealth. Therefore, the finding that time-series industry momentum returns are stronger in expansions and weaker in recessions supports the prediction that time-series industry momentum returns are stronger following good market states, but weaker following bad market states.

For practitioners, they may invest on or construct industry-neutral funds to eliminate the extra momentum risk induced by industries, and capturing industry level alpha when designing sector rotation strategies to generate better alpha. As is emphasized in O'Neal (2000), practitioners prefer strategies with return persistency and consistency. The advantage of the time-series industry momentum strategy is that the long portfolio returns are the main return driver, facilitating their investment on actively trading industry-sector funds. The positive strategy returns are statistically significant in expansions and insignificantly negative in recessions, indicating that practitioners will be better off if only utilising this strategy in up markets.

5.5.2 Is Time-series industry momentum effect enhanced under greater information continuity (i.e., negative information discreteness)?

Table 5.6 demonstrates the performance of information discreteness grouped time-series industry momentum strategies. It demonstrates that time-series industry momentum returns are improved under continuous information and are deteriorated under discrete information. For example, for the 12-1 strategy (i.e., 12-month ranking period and 1 month holding period), under continuous information environment, time-series industry momentum annual returns are 12.402% (t-statistic = 3.575), whereas without information discreteness dimension, it is annual 10.945% (t-statistic = 3.335) in the original time-series industry momentum annual returns demonstrated in Table 5.5 panel A. 3-1 (i.e., 3-month ranking period and 1 month holding period) and 6-3 strategies are among the strategies adding greater returns under continuous information, with annual return increase of 2.134% and 1.751%, respectively. 3-12 and 6-12 are among the strategies of the least addition in returns under continuous information, with annual return increases of 0.713% and 0.721%, respectively.

Under discrete information environment, the 12-1 time-series industry momentum strategy performance deteriorates from 10.945% (t-statistic = 3.335) to 6.839% (t-statistic = 1.985) annually compared to standard time-series industry momentum counterparts. The greatly reduced return magnitude after taking into account discrete information environments indicate that once the industry price information comes in a large scale in an abrupt manner, investors quickly react to the price information. Therefore, the returns for time-series industry momentum strategies with positive information discreteness are much lower than the standard time-series industry momentum strategies. 3-1 and 3-3 are among the strategies with the most return decrease, with the annual return decreases of 9.561% and 8.071%, respectively, whereas 12-1 and 12-6 are among the strategies with the least return decreases under the discrete information environment, with the annual return decrease of 4.106% and 4.186%, respectively.

Hong and Stein (1999) hypothesise that asset returns are better under greater information diffusion. Empirical studies, such as Da et al. (2014) in cross-sectional individual stock momentum, and Lim et al. (2018) in time-series individual stock momentum, show that investors tend to underreact to prior stock price information more under the information environment. By demonstrating that investors tend to underreact to prior industry price information more under continuous information, this finding support hypothesis 5.2 that the time-series industry momentum effect is enhanced under greater information continuity (negative information discreteness). This finding complements Da et al. (2014) by extending this to the time-series industry momentum context and therefore lends further support to Hong and Stein's (1999) information diffusion hypothesis.

If we take a further look at the return components, we may find that it is investors enhanced underreaction to TS winners with continuous information, and overreaction to TS losers with discrete information, that enhances negative information discreteness time-series industry momentum returns, and deteriorate positive information discreteness time-series industry momentum returns, respectively. It can be observed that in TS winner industry portfolios (TH), the ones with continuous information (IL) significantly outperform the ones with discrete information (IH) across all formation and holding months combinations at a 5% significance level. However, in prior TS loser industry portfolios (TL), the ones with continuous information significantly underperform the ones with discrete information in 3-month ranking period strategies at 5% significance level. In most other ranking period strategies, the underperformance is statistically insignificant. This indicates that investors tend to underreact more to prior industry price information under negative discrete information environment is not always the case. When it comes to time-series industry losers, the industries with more discrete information generate much higher returns compared to the industry losers with continuous information. This phenomenon observed in the time-series loser industries is also observed in Da et al.'s (2014) cross-sectional individual stock losers. In their sequential double sorts involving previous cumulative returns and information discreteness, they show that the cross-sectional losers with discrete information tend to outperform the counterparts with continuous information. However, their cross-sectional individual stock winners do not show a similar pattern as the present study's time-series industry winners. It is shown that the middle quintile information discreteness individual cross-sectional stock winner groups outperform the other quintile groups and the two most extreme groups (i.e., top quintile discrete information and top quintile continuous information groups) generate similar returns.

Table 5.6 panel B demonstrates the negative information discreteness time-series industry momentum returns in recessions and expansions. It can be observed that negative ID time-series industry momentum returns are enhanced in expansions and weakened in recessions. For example, the 12-1 strategy negative ID time-series industry momentum returns are annual 12.402%, whereas the annual returns are 14.853% and -6.086% in expansions and recessions, respectively. We may also observe that the negative information discreteness time-series industry momentum returns are more significant in expansions for all ranking month and holding month combinations. For example, for the 12-1 strategy, the t-statistic is 4.172 in expansions, however, the t-statistic is 3.575 in panel A without business cycle classification. In addition, the returns are negative and statistically insignificant in recessions.

Table 5.6 panel C demonstrates the positive information discreteness time-series industry momentum returns in recessions and expansions. It can be observed that positive ID time-series industry momentum returns are enhanced in expansions and weakened in recessions for all portfolios as well. For example, the 12-1 strategy positive ID time-series industry momentum returns are annual 6.839%, whereas the annual returns are 7.068% and 2.298% in expansions and recessions, respectively. We may also observe that the positive information discreteness time-series industry momentum returns are insignificant in expansions and recessions for most ranking month and holding month combinations. For example, for the 12-1 strategy, the t-statistic is 1.833 in expansions and 0.166 in recessions. In addition, the return signs are mixed in recessions and expansions.

Therefore, the above evidence supports the hypothesis 5.2a that the time-series industry momentum effect under greater information continuity is enhanced, and more so in expansions than recessions. The indications are that investors underreact to prior industry price information, and they underreact more when the information arrives in small pieces. For practitioners, to eliminate risk, they need to invest in or construct industry- and ID-neutral funds to eliminate extra momentum risk induced by industries and information arrival size. To capture industry level alpha when designing sector rotation strategies, they may introduce a second dimension of low ID to generate a better alpha. Investors will be better off if adopting the low ID time-series industry momentum strategies in expansions periods.

Table 5. 6 Absolute information discreteness grouped time-series industry momentum performance

Panel A. Overall absolute information discreteness grouped time-series industry momentum returns

Return (%)	Holding month(s)	1				3				6				12			
Formation month(s)		IL	IH	IL-IH	t-stat	IL	IH	IL-IH	t-stat	IL	IH	IL-IH	t-stat	IL	IH	IL-IH	t-stat
	TH	15.728	10.747	4.981	2.211	15.655	11.319	4.336	2.109	15.641	10.546	5.095	3.157	15.968	12.277	3.691	2.848
	TL	8.941	15.655	-6.714	-1.998	9.211	14.296	-5.084	-2.521	9.794	13.835	-4.041	-2.416	9.295	12.050	-2.755	-2.143
	TH-TL	6.787	-4.908	11.694		6.444	-2.977	9.420		5.847	-3.289	9.136		6.673	0.228	6.445	
3	t-stat	2.106	-0.810	2.467		2.210	-0.941	2.689		2.399	-1.691	3.196		3.375	0.164	2.779	
	TH	17.447	12.962	4.485	2.071	16.500	9.708	6.792	3.148	17.067	11.685	5.382	2.890	16.942	13.117	3.825	2.493
	TL	8.017	9.775	-1.758	-0.204	8.135	10.923	-2.789	-1.035	8.092	10.145	-2.054	-0.977	8.603	10.811	-2.208	-1.425
	TH-TL	9.430	3.186	6.244		8.366	-1.216	9.581		8.975	1.539	7.435		8.340	2.307	6.033	
6	t-stat	2.877	1.059	1.311		2.652	-0.217	2.319		3.061	0.729	2.133		3.386	1.327	2.143	
	TH	19.058	13.761	5.297	2.484	18.261	12.125	6.136	2.565	17.564	13.008	4.556	2.130	17.042	11.310	5.732	3.046
	TL	6.657	6.922	-0.265	0.390	7.039	6.697	0.342	0.430	7.390	8.009	-0.620	-0.116	7.688	9.838	-2.150	-1.210
	TH-TL	12.402	6.839	5.562		11.221	5.428	5.793		10.174	4.998	5.176		9.354	1.472	7.882	
12	t-stat	3.575	1.985	1.249		3.218	1.851	1.281		3.021	1.919	1.317		3.147	0.642	2.484	

Panel B. Low ID TS industry momentum performance in recessions and expansions

Ranking month(s)	Holding month(s)	1	3	6	12
	Recession (%)	-5.983	-9.057	-8.095	-5.902
	t-stat	-0.408	-0.676	-0.748	-0.702
	Expansion (%)	9.125	8.711	7.500	8.242
3	t-stat	2.781	3.091	3.097	4.156
6	Recession (%)	-6.918	-7.572	-2.168	-5.952

	t-stat	-0.473	-0.545	-0.173	-0.567
	Expansion (%)	11.581	10.279	10.245	10.348
	t-stat	3.447	3.284	3.525	4.283
	Recession (%)	-6.086	-8.672	-10.036	-8.816
	t-stat	-0.416	-0.600	-0.755	-0.794
	Expansion (%)	14.853	13.669	12.658	11.793
12	t-stat	4.172	3.913	3.768	3.875

Panel C. High ID TS industry momentum performance in recessions and expansions

Ranking month(s)	Holding month(s)	1	3	6	12
	Recession (%)	-9.654	-5.785	-9.486	3.087
	t-stat	-0.628	-0.557	-1.369	0.847
	Expansion (%)	-0.463	-1.342	-2.012	0.386
3	t-stat	-0.129	-0.509	-0.990	0.254
	Recession (%)	-14.870	-4.666	3.055	9.952
	t-stat	-1.072	-0.472	0.412	1.455
	Expansion (%)	6.681	-0.570	1.106	1.424
6	t-stat	1.706	-0.182	0.433	0.811
	Recession (%)	2.298	5.317	8.348	3.309
	t-stat	0.166	0.427	0.737	0.340
	Expansion (%)	7.068	5.749	4.522	1.131
12	t-stat	1.833	1.714	1.617	0.476

Table 5.6 Panel A reports information discreteness grouped time-series industry momentum annual returns and the corresponding t-statistics for 3,6,12 and 1,3,6,12 formation and holding month combinations from 02 January 1959 to 01 March 2019. TH is high time-series industry momentum (long portfolio), TL is low time-series industry momentum (short portfolio), IL is low information discreteness, and IH is high information discreteness. Panel B reports the annual performance of negative information discreteness industries in recessions and expansions. Panel C reports the average yearly performance of positive information discreteness industries in recessions and expansions.

Table 5. 7 Abnormal return volatility grouped time-series industry momentum performance

Panel A. Overall abnormal return volatility grouped time-series industry momentum returns

	Holding month(s)	1				3				6				12			
Ranking month(s)		ARL	ARH	ARL-ARH	t-stat	ARL	ARH	ARL-ARH	t-stat	ARL	ARH	ARL-ARH	t-stat	ARL	ARH	ARL-ARH	t-stat
	TH	15.048	11.530	3.518	-0.180	14.505	14.224	0.281	-0.867	14.927	14.118	0.808	-2.125	14.476	15.055	-0.580	-1.459
	TL	10.765	13.923	-3.158	-0.196	11.850	13.817	-1.966	0.275	10.753	13.423	-2.670	0.381	11.181	12.656	-1.476	1.838
	TH-TL	4.282	-2.393	6.675		2.655	0.407	2.247		4.174	0.696	3.478		3.295	2.399	0.896	
3	t-stat	1.463	1.270	2.005		0.833	1.283	0.234		2.221	2.679	0.689		0.731	2.502	-0.636	
	TH	15.096	13.545	1.551	-1.336	15.615	13.250	2.366	-1.486	14.981	14.823	0.158	-1.622	14.966	15.039	-0.073	-1.779
	TL	9.247	14.357	-5.110	0.086	10.183	12.700	-2.517	0.274	10.861	13.095	-2.234	1.029	10.429	12.517	-2.088	2.078
	TH-TL	5.849	-0.812	6.661		5.433	0.550	4.883		4.120	1.728	2.392		4.537	2.522	2.014	
6	t-stat	1.803	1.871	1.259		2.386	2.742	1.591		1.737	2.703	0.133		1.908	3.625	-0.115	
	TH	10.605	13.607	-3.002	-2.297	14.044	13.981	0.063	-0.221	14.392	14.149	0.243	2.000	16.433	14.288	2.145	2.934
	TL	17.165	11.054	6.111	0.822	17.112	11.198	5.913	1.413	18.798	11.053	7.745	1.979	17.966	10.527	7.438	3.195
	TH-TL	-6.560	2.553	-9.113		-3.067	2.783	-5.850		-4.406	3.096	-7.501		-1.533	3.761	-5.294	
12	t-stat	-0.905	-0.208	-3.538		-0.797	0.076	-1.264		-1.963	-0.793	-0.320		-2.208	-0.536	0.974	

Panel B. Low ARD TS industry momentum performance in recessions and expansions

Ranking month(s)	Holding month(s)	1	3	6	12
	Recession	-1.856	-14.445	0.634	-0.555
	t-stat	-0.147	-1.647	0.118	-0.137
	Expansion	6.104	3.562	3.936	1.135
3	t-stat	1.786	1.515	2.383	0.852

	Recession	5.255	6.358	2.307	-1.131
	t-stat	0.502	0.914	0.459	-0.307
	Expansion	4.725	4.440	2.611	2.383
6	t-stat	1.548	2.173	1.811	2.146
	Recession	13.474	-3.374	0.392	-6.159
	t-stat	0.903	-0.280	0.037	-0.643
	Expansion	-4.847	-2.840	-5.713	-4.136
12	t-stat	-1.433	-0.874	-2.038	-1.905

Panel C. High ARD TS industry momentum performance in recessions and expansions

Ranking month(s)	Holding month(s)	1	3	6	12
	Recession	-14.230	-14.529	-6.832	-4.491
	t-stat	-0.938	-1.483	-0.975	-1.023
	Expansion	6.106	4.974	5.715	4.423
3	t-stat	1.910	2.517	3.751	3.136
	Recession	-9.307	-3.420	-7.681	-3.461
	t-stat	-0.693	-0.438	-1.285	-1.020
	Expansion	7.167	6.609	5.720	5.666
6	t-stat	2.433	3.298	3.738	4.172
	Recession	1.783	-13.052	-8.134	-9.366
	t-stat	0.070	-0.764	-0.648	-1.051
	Expansion	-1.265	1.134	-1.575	0.340
12	t-stat	-0.254	0.318	-0.536	0.163

Table 5.7 Panel A reports annual abnormal return volatility grouped time-series industry momentum returns and the corresponding t-statistics for 3,6,12 and 1,3,6,12 formation and holding month combinations from 02 January 1959 to 01 March 2019. TH is high time-series industry momentum (long portfolio), TL is low time-series industry momentum (short portfolio), ARL is low abnormal return volatility and ARH is high abnormal return volatility. Panel B reports the annual returns of negative abnormal return volatility industries in recessions and expansions. Panel C reports the annual returns of positive abnormal return volatility industries in recessions and expansions.

5.5.3 Is Time-series industry momentum effect enhanced under greater abnormal return volatility?

Table 5.7 panel A shows the performance of abnormal return volatility grouped time-series industry momentum strategies. No improvements of strategy returns are found compared to original time-series industry momentum returns. In most cases except for the 12-month formation period industries with low abnormal return volatility (ARL), TS winners outperform TS losers. In prior TS winner industries (TH), the ones with low abnormal return volatility significantly underperform the ones with high abnormal return volatility in three strategies (3-6, 6-12, and12-1), and insignificantly underperform the ones with high abnormal return volatility in seven strategies. They significantly outperform the ones with high abnormal return volatility in two strategies (12-6 and 12-12). In prior TS loser industries (TL), the ones with low abnormal return volatility significantly outperform in four strategies (3-12, 6-12, 12-6, and 12-12), and insignificantly outperform in seven strategies. They insignificantly underperform their high abnormal return volatility counterparts in only one strategy (3-1). In addition, the abnormal return volatility grouped time-series industry returns are statistically insignificant, indicating that TSM profits disappear after taking into account abnormal return volatility. This challenges the robustness of TSM at industry level and may indicate that the noisy information is processed similarly to other information contained in prior industry price information. Therefore, the evidence does not support hypothesis 5.3b that the time-series industry momentum effect under greater abnormal return volatility is enhanced more in expansions than recessions.

Zhang (2006) demonstrates that the positive returns accompanied by the positive news are more positive whereas the negative returns accompanied by the negative news are more negative under greater information uncertainty. He defines the source of information uncertainty to be firm fundamental volatility and poor information, and therefore proxy information uncertainty by firm size, firm age, analyst coverage, dispersion in analyst forecasts, return volatility and cash flow volatility. Connolly and Stivers (2003) show that abnormal return volatility is positively related to momentum in weekly equity indices. The insignificant influence of abnormal return volatility on time-series industry momentum is not consistent with these findings. The different time horizons adopted in this chapter compared to the time horizon in Connolly and Stivers

(2003) may make a difference. In their study, weekly horizons are adopted whereas in this chapter, monthly horizon are adopted. Another potential reason could be that investors pay enough attention to industry return volatilities, and when the volatilities are out of normal ranges (i.e., abnormally high or abnormally low), investors' attentions are immediately attracted, and they start to react properly to prior industry price information. That is, noisy information is processed similarly to other information contained in prior industry price information. Further research is needed to explore further reasons behind it.

5.5.4 Which part of information diffusion is important?

Hong and Stein's (1999) information diffusion hypothesis suggests that more lucrative profits should be generated among larger information diffusion assets. Two different elements of information diffusion are introduced in this study to examine the relationship between time-series industry momentum and information diffusion. The above findings suggests that industry investors are less attentive to industry information that arrives in small pieces persistently. However, noisy information (proxied by abnormal return volatility) is processed similarly to other industry information. Therefore, in the two elements of information diffusion that are analysed in this chapter, information discreteness is more important element. Therefore, more focus can be put on the influence of information discreteness in future time-series industry momentum studies.

5.6 Conclusion

To conclude, this chapter focuses on US industry TSM performance by testing whether TSM exists in US industries and whether the performance is enhanced under greater information diffusion. This is motivated by time-series momentum, cross-sectional industry momentum, and information diffusion literature. To the best of the authors knowledge, this work is the first to examine the existence of time-series industry momentum effect, and it contributes to the industry momentum literature and time-series momentum literature by demonstrating that: 1) time-series momentum is not confined to across asset level and individual stock level, and industry momentum is not confined to the cross-sectional context; 2) time-series industry momentum investors tend to underreact to absolute information continuity, which is reflected by the better time-series industry momentum performance under low information discreteness; and 3) abnormal return volatility does not have a significant influence on time-series industry momentum returns, since noisy information is processed similarly to other information by industry level investors.

Via the demonstration of the connection between time-series industry momentum and information diffusion, the results show that the time-series industry momentum effect is stronger when information arrival is continuous (i.e., persistently arrives in small pieces). This finding extends Da et al.'s (2014) findings on cross-sectional momentum to the time-series context. I also show that information uncertainty proxied by abnormal return volatility, has an insignificant impact on the time-series industry effect. No consistent improvements of time-series industry momentum performance have been observed under different abnormal return volatility, and time-series industry momentum returns disappear under both high and low abnormal return volatility. These challenge the robustness of time-series industry momentum returns. The potential reason could be that abnormally low or high return volatility attract more investor attention so that they react promptly to prior industry return information. Accordingly, the noisy information is processed similarly to other information by industry investors.

The implications of the findings within this chapter for researchers, are that future research can focus on the relationship between cross-sectional industry momentum and time-series industry momentum, or the relationship between time-series individual stock momentum and time-series industry momentum, to further analyse the existence of the time-series industry momentum effect.

The implications of the findings within this chapter for fund managers are that it is unnecessary for them to allocate capital to all industries to diversify industry-specific risk. Instead, they can adopt negative information discreteness time-series industry momentum strategies to predict industry returns. Since the main driver of the strategy returns are the long positions, the managers are advised to construct the long portfolios by using the strategies, and construct short portfolios by using cross-sectional momentum strategies. This is because the main profit driver of cross-sectional momentum strategies are the short positions.

5.7 Appendices

For brevity, I take the portfolio of 3-month ranking, 3-month holding, and 1 month skipping period (j=3, k=3) in a 3 industries scenario as an example. $r_{3,1}$ is the cumulative return for month 3 industry 1. NaNs in the tables below means not satisfying the selection criteria in the table. For example, in the positive cumulative returns table, the month 3 industry 1 value is NaN, indicating that $r_{3,1}$ is non-positive. In the negative cumulative returns table, the corresponding value is 1, indicating that $r_{3,1}$ is negative. The ranking return sign ('1' or 'NaN') multiplied by ID sign ('1' or 'NaN') generates tables that include 2 selection criteria. For example, in the positive ranking return and positive ID table, month 1 industry 1 satisfied the criteria of positive ranking return and positive ID. Thus, a value of '1' is allocated. The portfolio return tables are generated by multiplying ranking period sign by holding period return. For example, in the positive ranking return and positive ID portfolio return table, month 5 industry 1 return is 1* $r_{5,1}$.

Cumulative industry returns

	Industry				Industry		
Month	1	2	3	Month	1	2	3
1	$r_{1,1}$	$r_{1,2}$	$r_{1,3}$	5	$r_{5,1}$	$r_{5,2}$	$r_{5,3}$
2	$r_{2,1}$	$r_{2,2}$	$r_{2,3}$	6	$r_{6,1}$	$r_{6,2}$	$r_{6,3}$
3	$r_{3,1}$	$r_{3,2}$	$r_{3,3}$	7	$r_{7,1}$	$r_{7,2}$	$r_{7,3}$

Month 4 is the gap month between portfolio ranking and holding period

Positive cumulative ranking period returns				Negative cumulative ranking period returns			
	Industry				Industry		
Month	1	2	3	Month	1	2	3
1	1	NaN	NaN	1	NaN	1	1
2	1	1	1	2	NaN	NaN	NaN
3	NaN	1	1	3	1	NaN	NaN
Positive ranking period ID				**Negative ranking period ID**			
	Industry				Industry		
Month	1	2	3	Month	1	2	3
1	1	NaN	NaN	1	NaN	1	NaN
2	1	NaN	1	2	NaN	1	NaN
3	NaN	NaN	1	3	1	1	NaN

Positive ranking return and positive ID				Positive ranking return and negative ID			
	Industry				Industry		
Month	1	2	3	Month	1	2	3
1	1	NaN	NaN	1	NaN	NaN	NaN
2	1	NaN	1	2	NaN	1	NaN
3	NaN	NaN	1	3	NaN	1	NaN
Negative ranking return and positive ID				**Negative ranking return and negative ID**			
	Industry				Industry		
Month	1	2	3	Month	1	2	3
1	NaN	NaN	NaN	1	NaN	1	NaN
2	NaN	NaN	NaN	2	NaN	NaN	NaN
3	NaN	NaN	NaN	3	1	NaN	NaN

Positive ranking return and positive ID portfolio return				Positive ranking return and negative ID portfolio return			
	Industry				Industry		
Month	1	2	3	Month	1	2	3
5	$r_{5,1}$	NaN	NaN	5	NaN	NaN	NaN
6	$r_{6,1}$	NaN	$r_{6,3}$	6	NaN	$r_{6,2}$	NaN
7	NaN	NaN	$r_{7,3}$	7	NaN	$r_{7,2}$	NaN
Negative ranking return and positive ID portfolio return				**Negative ranking return and negative ID portfolio return**			
	Industry				Industry		
Month	1	2	3	Month	1	2	3
5	NaN	NaN	NaN	5	NaN	$r_{5,2}$	NaN
6	NaN	NaN	NaN	6	NaN	NaN	NaN
7	NaN	NaN	NaN	7	$r_{7,1}$	NaN	NaN

Chapter 6 Time-series industry momentum and time-varying risk

6.1 Abstract

This chapter analyses the impact of time-varying risk on the performance of time-series industry momentum. It is found that time-series industry momentum is related to the joint impact of standard macroeconomic factors and the interaction among the macroeconomic factors and market liquidity risk. Time-series momentum investors' underreaction to absolute information continuity (negative information discreteness) is also related to these factors, though to a lesser extent. Broader macroeconomic factors are not as good as standard macroeconomic factors in explaining the returns, though the introduction of market liquidity and market volatility may still improve the explanatory power of the factor analysis models without conditional time-varying risk factors. Value premium, as a conditional time-varying risk factor, weakly increases the performance of standard macroeconomic models, and plays an unimportant role in increasing the explanatory power of factor analysis models.

6.2 Introduction

This chapter examines the relationship between time-series industry momentum and time-varying risk by adopting conditional models. The previous chapter demonstrates the impact of information diffusion on the time-series industry momentum effect. Here, investors tended to underreact to prior industry price information that arrives continuously in small pieces, whereas their reaction to prior industry price information that are accompanied by abnormal return volatility did not demonstrate any patterns. In this chapter, alongside macroeconomic risk factors, three other time-varying risk factors (value premium, market liquidity, and market volatility) are introduced to understand the phenomenon. By examining whether time-varying risk can explain time-series industry momentum, it can provide further understanding whether it is the investor behaviour (i.e., investor underreaction to prior industry price information) or priced risk that leads to the time-series industry momentum effect. This chapter complements the prior time series momentum literature by adopting a broader set of time-varying risks, and extends the study to time-series industry momentum. This contributes to the literature by demonstrating a clearer relationship between time-series industry momentum and time-varying risk. In addition, this study provides practitioners (fund managers and individual investors) with advice that information diffusion signals should be applied in up market to increase strategy returns, and that narrowly scoped macroeconomic factors and market liquidity can be considered to manage strategy risk.

CAPM model alone cannot explain asset price anomalies (e.g., size, value and momentum) due to the existence of risk other than market risk and its static nature according to asset price anomalies literature (Ferson et al., 1987; Hansen and Richard, 1987; Harvey, 1989). Conditional models allow the variation in factor loadings when condition variables are added, which improves the explanatory power of these models compared to static beta models (Avramove and Chordia, 2006; Ho and Hung, 2009; Jordan, 2012; Cooper and Maio, 2019). For example, Jordan (2012) demonstrates that the models conditioning on market factors increase the explanatory ratio of standard macroeconomic models in terms of explaining cross-sectional reversal.

Value premium (HML), the hypothesised risk factor in Fama and French (1992, 1993) is demonstrated to predict future market returns and economic growth in empirical studies (e.g., Kothari and Shanken, 1997; Liew and Vassalou, 2000) and theoretical papers (e.g., Vassalou, 2003). Market liquidity (LIQ), proposed by Amihud (2002) as a systematic risk factor, is shown to be strongly linked to business cycle (Naes et al., 2011; Bernile et al., 2015). Market volatility (VOL), modelled as an asset pricing factor in Ang et al. (2006) and Adrian and Rosenberg (2008), is found to be positively related to market risk premium (Kim et al., 2004) and is related to economic activities and business cycle (Schwert, 1989; Adrian and Rosenberg, 2008; Choudhry et al., 2016). These variables are linked to the market equity premium and the market equity premium depends on them. Thus, it is novel to introduce value premium, market volatility, and market liquidity in a conditional CAPM style macroeconomic model. As is demonstrated in chapter 5, time-series industry momentum returns are related to business cycle (i.e., time-series industry momentum returns are enhanced in expansions and weakened in recessions). Therefore, HML, VOL, and LIQ as time-varying conditional risk factors help to understand which element of the business cycle influences time-series industry momentum performance most, showing clearer the relationship between the time-series industry momentum effect and macroeconomic risk.

Findings show that, although the relationship between time-series industry momentum and standard macroeconomic factors is weak, after introducing value premium (HML), market volatilities (VOL), and market liquidity (LIQ) as conditional time-varying risk factors (following the approach of Jordan's (2012) models), the models demonstrate that time-series industry momentum returns with 12-month lookback period and 1-month holding period returns are related to the joint impact of standard macroeconomic factors, and the interaction among these factors and liquidity factor. For the same investment and holding horizon, time-series momentum investors' underreaction to absolute information continuity are also related to these factors. In Jordan's (2012) conditional models on LIQ, which outperform the other two conditional models (i.e., the models conditioning on HML and VOL) in terms of explaining strategy returns, the t-statistic for the unexplained time-series industry momentum returns is 1.516, whereas for the unexplained time-series momentum (conditioning on absolute information continuity), it is 1.708. This indicates that time-series industry momentum could be compensating for market liquidity risk rather than an anomaly.

The differences between this work and Jordan (2012) and Maio and Phillips (2018) are that this work: 1) introduces new conditional variables (i.e., value premium, market volatility, and market liquidity); and 2) applies them to time-series industry momentum. Except for market risk, which is adopted in Jordan (2012), in the standard macroeconomic model, value premium, market liquidity, and market volatility are used as conditional factors, because they are risk factors that are related to economic activities.

As a robustness test, to minimise the chances of missing relevant macroeconomic variables and correlations among independent variables, factor analysis is used. Results identify seven common processes from 128 macroeconomic variables (from Research Division of Federal Reserve Bank of St. Louis by Michael W. McCracken. This is an approach to select common factors from a wide range of possible indicators, based on information criteria. It is found that the explanatory power of common processes on time-series industry momentum returns, as well as negative information discreteness time-series industry momentum returns, are weaker than that of standard macroeconomic variables. This may be because the macroeconomic common processes measure different aspects of macroeconomic risk from what is measured by standard macroeconomic factors. However, though the introduction of the time-varying risk factors as conditional variables fails to help the model fully explain time-series industry momentum returns, or negative information discreteness grouped time-series industry momentum returns, the explanatory power of the factor analysis models is improved. The most improvement is found when market liquidity is introduced as a conditional time-varying risk factor, and the least improvement occurs when value premium is introduced.

This chapter is related to time-series momentum (e.g., Moskowitz et al., 2012; Goyal and Jegadeesh, 2018; Lim et al., 2018) and industry momentum effect literature (e.g., Moskowitz and Grinblatt, 1999; Scowcroft and Sefton, 2005). Time-series momentum literature does not examined time-varying risk as an explanation of time-series momentum returns. Therefore, this chapter fills this gap by establishing a link between time-varying risk and time-series industry momentum. By showing which time-varying risk plays the most role in understanding time-series industry momentum returns. This chapter provides potential sources of the common risk conjectured in Moskowitz et al. (2012) on time-series momentum, which may cause higher correlations amongst different asset classes compared to the correlation of the asset themselves for future studies. The relationship between time-varying risk and time-series industry momentum returns under different information diffusion elements (i.e., absolute information continuity and abnormal return volatility) is also examined.

This chapter is also related to the literature on limited investor attention that documents investors' relative inattention to relative asset price changes (Zhang, 2006; Hershleifer, et al., 2009; Da et al., 2014). The literature focuses on cross-sectional comparisons among asset performance and investor attention in individual stocks. However, this work complements them by demonstrating that industry investors underreact towards absolute information continuity, and that this can be partially explained by the joint impact of macroeconomic activities and market liquidity.

The structure is as follows: Section 6.3 shows the hypothesis development; section 6.4 then discusses the data; section 6.5 first shows the relationship among the strategy performance and macroeconomic risk factors by applying macroeconomic conditional models. This is then followed by factor analysis and the conditional models, with section 6.6 concluding the chapter.

6.3 Hypothesis development

This chapter examines the relationship between time-series industry momentum and time-varying risk. By examining this relationship, a more in depth understanding of the time series industry momentum effect, in terms of whether it is simply the compensation for time-varying risk, can be developed. The time-varying risks that are included in this chapter are macroeconomic risk, value premium, market liquidity, and market volatility. The hypotheses are developed in this section.

6.3.1 Cross-sectional industry momentum and macroeconomic risk

As is reviewed in section 2.1.2 of chapter 2, prior studies on the role of macroeconomic risk in the cross-sectional industry momentum effect do not achieve consensus on which macroeconomic model to use. Thus, the role remains controversial. Chordia and Shivakumar (2002) and Maio and Philip (2018) are among those who demonstrate that cross- sectional industry momentum is related to macroeconomic risk. The former uses standard macroeconomic risk factors (i.e., dividend yield, term spread, default spread, and 3-month T-bill yield), demonstrating that industry momentum disappears after controlling for macroeconomic variables. The latter adopts variables that are purely and directly linked to economic activities and are not contingent on asset prices (i.e., growth rate of industrial production index, capacity utilization rate changes, retail sales growth, and the growth in Conference Board Coincident Economic Index). They show that past cross-sectional industry winners tend to outperform past cross-sectional industry losers, because the winners bear higher macroeconomic risk.

If such a relationship between cross-sectional industry momentum and macroeconomic risk exists, by applying momentum behavioural theories, it implies that investors should underreact to the macroeconomic information that is contained in prior industry price changes. However, Moskowitz et al. (2012) argue that time-series momentum is a more direct application of these behavioural theories. Since the theories are focused on investor reaction to prior absolution price changes rather than prior relative price changes, it is more reasonable to study the relationship between time-series industry momentum and macroeconomic risk.

The cross-sectional industry momentum effect is, by nature, relative industry performance continuation. This continuation is composed of two parts; the continuation of industry return signs, and the continuation of return scale difference. From the table below, we can see that in normal times, cross-sectional industry momentum returns are only related to the sign continuation, whereas in expansions and recessions, the strategy returns are determined mutually by sign and scale continuation. For example, in normal times, if cross-sectional industry momentum winners with positive return signs continue to have positive return signs in the portfolio holding period, and losers with negative return signs continue to have negative signs in the portfolio holding period, then the strategy generates positive returns no matter whether the scale differences of the returns continue. Alternatively, if cross-sectional industry momentum winners with positive return signs discontinue to have positive return signs (i.e., winners have negative return signs) in the portfolio holding period, and losers with negative return signs also discontinue to have negative signs (i.e., losers have positive return signs) in the portfolio holding period, then the strategy generates negative returns no matter whether the scale difference of the returns continue.

By definition and construction, time-series industry momentum is directly linked to the continuation of industry return signs. Thus, studying the relationship between time-series industry momentum and macroeconomic risk may help understand which part of the two components of cross-sectional industry momentum is more related to macroeconomic risk. For future cross-sectional industry momentum studies, it is important to have a more in-depth understanding of the roles of macroeconomic risk in cross-sectional industry momentum effect.

Normal

		Sign	
		Continue	Discontinue
	Continue	P	N
Scale	Discontinue	P	N

Expansion

		Sign	
		Continue	Discontinue
	Continue	P	N
Scale	Discontinue	N	P

Recession

		Sign	
		Continue	Discontinue
	Continue	P	N
Scale	Discontinue	N	P

Normal times are when past cross-sectional industry momentum winners have positive return sign and losers have negative return sign. Expansions are when both past cross-sectional industry momentum winners and losers have positive return sign. Recessions are when both past cross-sectional industry momentum winners and losers have negative return sign. I define the times when both past cross-sectional industry momentum winners and losers have positive return sign as expansions because this is more likely to happen in expansions. Similarly, I define the times when both past cross-sectional industry momentum winners and losers have negative return sign as recessions because this is more likely to happen in recessions. The remaining one scenario when past cross-sectional industry momentum winners have positive return sign and losers have negative return sign are normal times. Thus, the definition of the normal times, expansions and recessions are just for brevity of three scenarios, they are not directly corresponding to NBER expansion and recession definition. P denotes positive holding period cross-sectional industry momentum returns and N denotes negative holding period cross-sectional industry momentum returns.

6.3.2 Time-series industry momentum and macroeconomic risk (Hypothesis 6.1)

Industry returns are highly correlated (Figure 6.1), and time-series industry returns are also correlated, though to a lesser extent (Figure 6.2). Thus, it is natural to ask whether there are any common processes that drive the industry level co-movements. The relationship between macroeconomic risk and time-series momentum is established by Hutchinson and O’Brien (2020), with time-series momentum returns better in expansion periods and when macroeconomic uncertainty is low. However, studies at the industry level are yet be conducted. It is important to understand the relationship between the time-series industry momentum effect and macroeconomic risk because: 1) it may help understand which component of cross-sectional industry momentum (i.e., industry return sign continuation or industry return scale continuation) is more related to macroeconomic risk in the future cross-sectional industry momentum studies, generating a more in-depth understanding of the roles of macroeconomic risk in cross-sectional industry momentum effect; 2) it may extend the influence of macroeconomic risk on the time-series momentum effect to industry level; and 3) the study of the relationship can provide industry trend chasers and sector rotation strategy users the guidance whether, and to what degree, macroeconomic risk should be taken into account when constructing their investment portfolios.

Table 5.1 from section 5.4 in chapter 5 demonstrates that time-series industry momentum returns are significantly positive at the 5% level in expansions, but insignificant negative in all portfolios formation and holding period combinations. This indicates the potential impact of business cycle on time-series industry momentum returns. Thus, the following hypotheses are presented.

H6.1 The time-series industry momentum effect is impacted by macroeconomic risk.

Figure 6.1 Monthly Industry Return Pearson Correlation Distribution

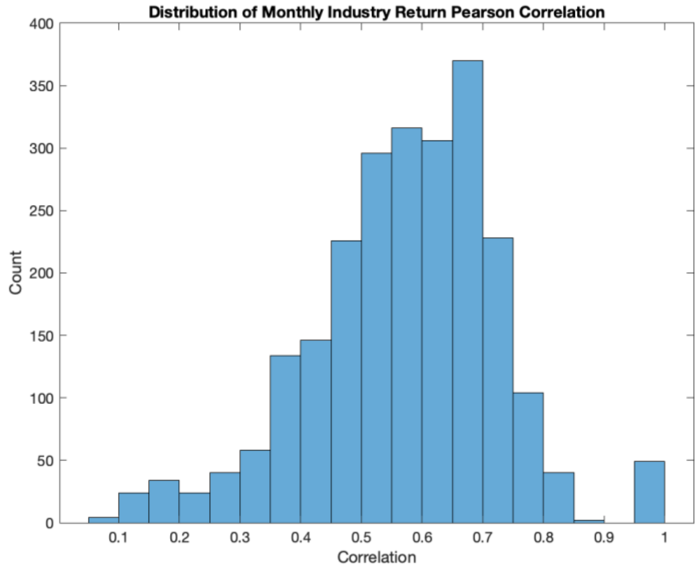
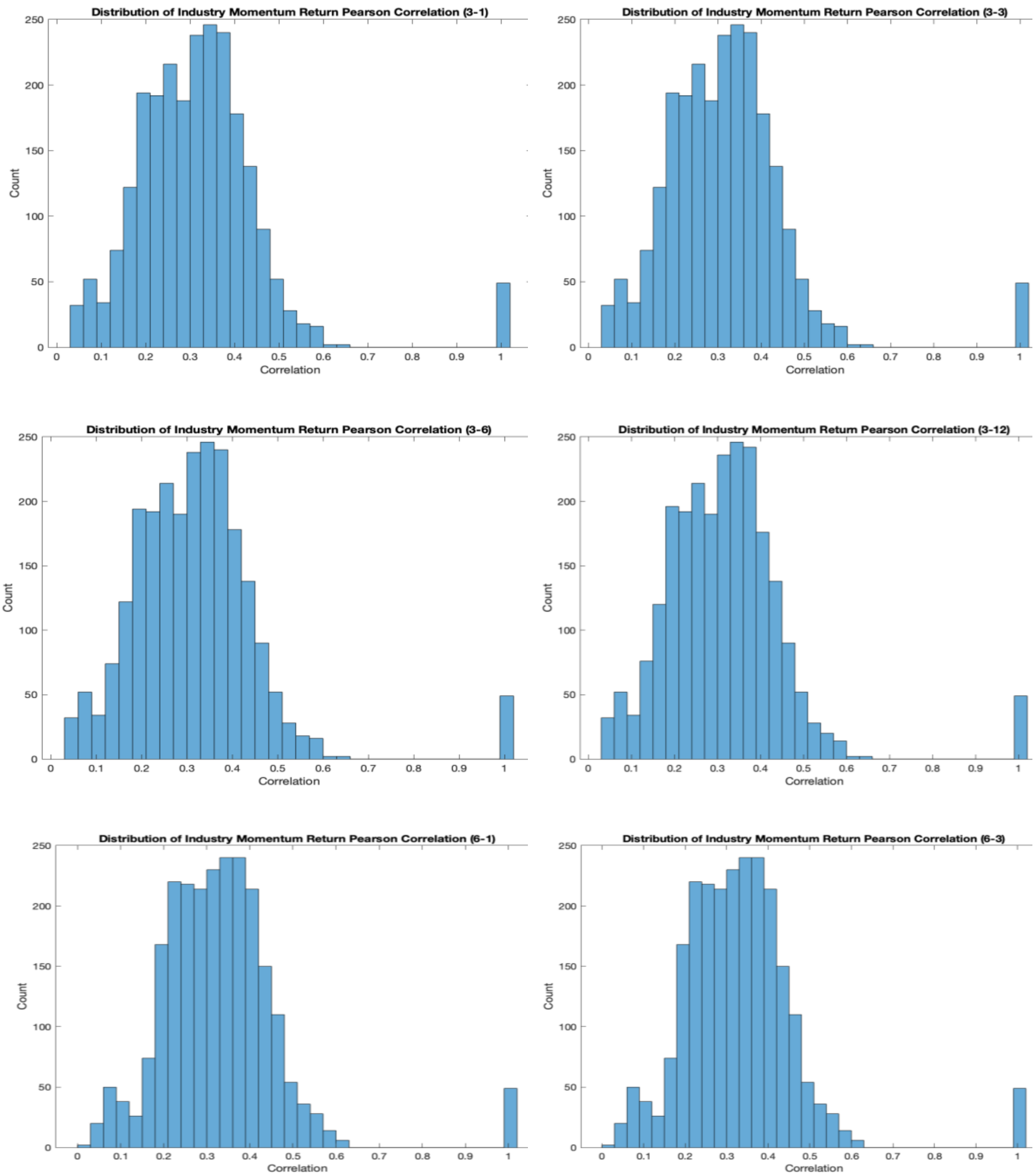
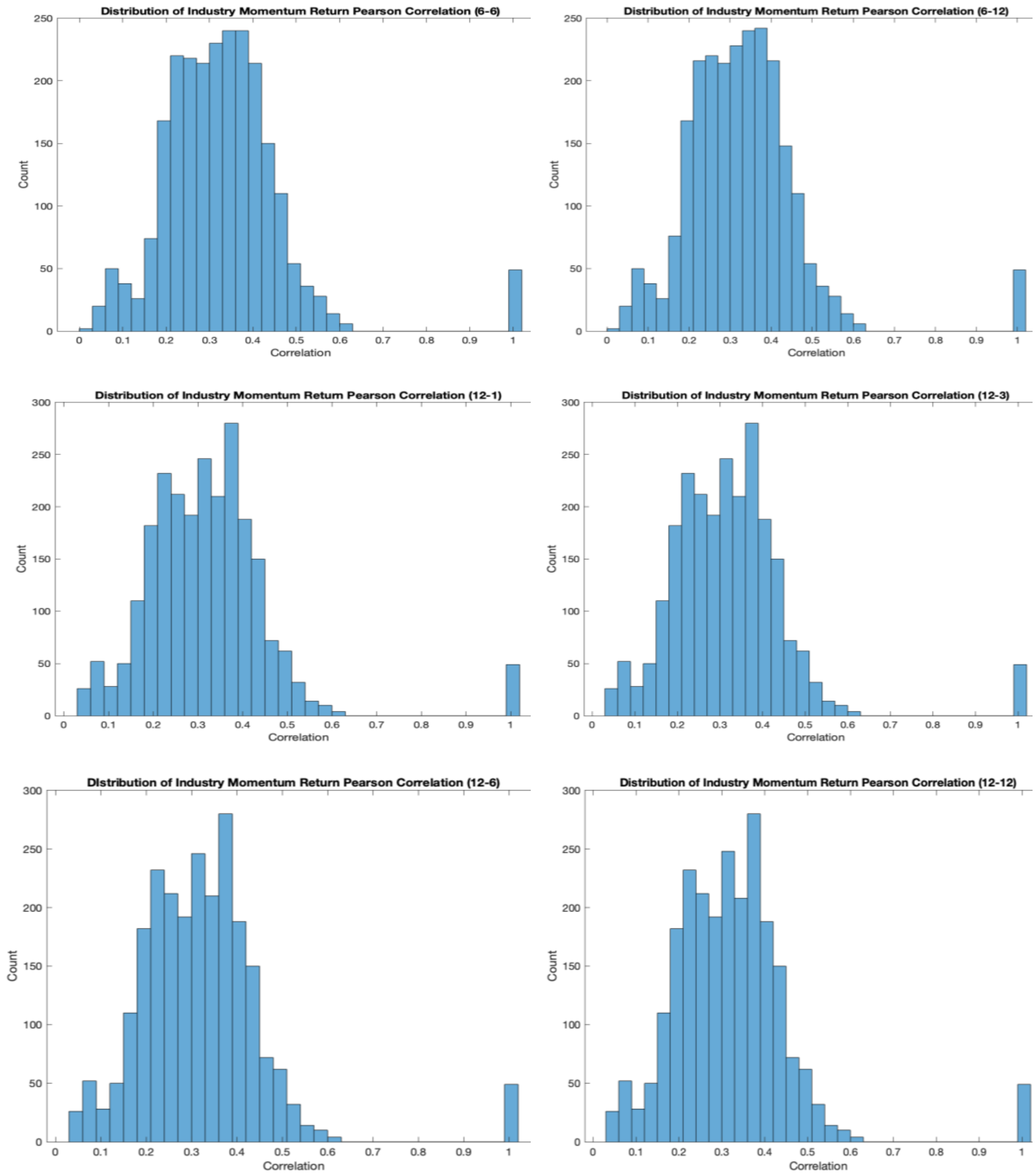


Figure 6.2 Industry Momentum Return Pearson Correlation Distribution





6.3.3 Time-series industry momentum, Economic activities, and Time-varying risk (Hypotheses 6.2-6.4)

Prior literatures demonstrates that value premium, market liquidity, and market volatility are risk factors, and introduce them to asset pricing models. They are related to market returns as well as economic growth. Fama and French (1992, 1993) hypothesise value premium (HML), as a risk factor, and empirical studies (e.g., Kothari and Shanken, 1997; Liew and Vassalou, 2000) and theoretical works (e.g., Vassalou, 2003) discuss that HML can predict future market returns and economic growth. Amihud (2002) proposes market liquidity (LIQ) as a systematic risk factor and supporting evidence (e.g., Naes et al., 2011; Bernile et al., 2015) shows that LIQ is strongly linked to business cycle. Ang et al. (2006) and Adrian and Rosenberg (2008) model market volatility (VOL) as an asset pricing factor. The positive relationship between VOL and market risk premium is found in Kim et al. (2004) and researchers (e.g., Schwert, 1989; Adrian and Rosenberg, 2008; Choudhry et al., 2016) demonstrate its relationship with economic activities and business cycle.

There is no consensus on the impact of macroeconomic environment on the time-series momentum effect and no study on the relationship between time-varying risk and time-series industry momentum. It is demonstrated in chapter 5 that the time-series industry momentum effect is enhanced in expansions and weakened in recessions, and it is discussed in section 6.3.2 that the correlation between time-series momentum returns across industries may indicate the common process that drive the correlated TSM performance across industries. Since the three risk factors are related to market equity premium and market equity premium depends on the three factors, the introduction of the three risk factors as conditional time-varying risk factors to the CAPM style macroeconomic model may help to: 1) disentangle the relationship between macroeconomic risk and time-series industry momentum; and 2) explore the relationship between the time-series industry momentum effect and time-varying risk from three different dimensions that reflect business cycle. Thus, the importance of each of the time-varying risk factor, in terms of understanding the time-series industry momentum effect, can be demonstrated. The test of this relationship may provide new angles for momentum strategy improvements, help policy makers to construct more effective policies to influence industry performance, and help practitioners to design more lucrative investment strategies at industry level. Therefore, the hypotheses are constructed below. Therefore, by further developing Hypothesis 6.1 (i.e., the time-series industry momentum effect is impacted by macroeconomic risk) via introducing the three risk factors as conditional time-varying risk factors to the model, hypotheses are developed below.

H6.2 The time-series industry momentum is influenced by the joint impact of value premium and macroeconomic risk.

H6.3 The time-series industry momentum is influenced by the joint impact of macroeconomic risk and market volatility.

H6.4 The time-series industry momentum is influenced by the joint impact of macroeconomic risk and market liquidity.

6.4 Data

This section describes the relevant data and methods. The construction details of time series industry momentum strategies, information discreteness grouped time series industry momentum strategies, and abnormal return volatility grouped time series industry momentum strategies are described in section 3.2.2 of chapter 3.

Monthly and daily returns from 49 industries, and market returns in excess of risk-free rate, are collected from Kenneth R. French data library. The risk-free rate in French Data Library is one-month t bill returns are from Ibbotson and Associates. Seven common processes are estimated by using 128 macroeconomic variables that are collected from research division of Federal Reserve Bank of St. Louis by Michael W. McCracken from 1st January 1959 to 1st March 2019. The underlying meaning of the 7 common processes are shown in Table 6b.16 of section 6.6 (appendices). According to French data library, their industry returns are calculated from July of year t to June of year t+1 of all NYSE, AMEX, and NASDAQ stocks that are allocated to 49 industries according to 4-digit SIC code at June end of year t, and calculate the return for the fiscal year ending in calendar year t-1. If the Compustat SIC codes are missing, the CRSP SIC code is used instead. Market returns (MKT), volatility (VOL), liquidity (LIQ), and high-minus-low (HML) are four market condition proxies.

6.5 Empirical results

In this section, Jordan's (2012) conditional model and factor analysis are conducted to analyse the relationship between time-series industry momentum and time-varying risk. 12-month lookback period and 1-month holding period returns are reported for all the strategies, for this is the most studied momentum strategy in prior literature. I also report 6-month lookback period and 1-month holding period returns are also reported in section 6.6 (appendices) for robustness purposes.

6.5.1 Is time-series industry momentum effect influenced by macroeconomic risk?

Standard time-series industry momentum

Table 6a.1 panel A demonstrates that the strategy returns are around 0.9% monthly (constant 0.009 with t-statistic = 3.335) and are statistically significant (model 1). January effect has no significant influence on the returns (model 3). Concurrent market effect can only partially explain time-series industry momentum returns (model 2). After controlling for month t-1 standard macroeconomic factors (TS, DS, TB, and DY) in model 6, the time-series industry momentum returns are less significant, though still significant at 5% level (t-statistic = 2.235). This indicates a weak relationship between TS industry momentum returns and business cycle. As is shown in model 5, time-series industry momentum returns are significant at 1% level (t-statistic = 2.953) after controlling for the joint impact of market and macroeconomic risk. Compared to the t-statistic of the constant (2.439) of model 4, where macroeconomic factors are not included, and the t-statistic of the constant (2.235) of model 6 where the joint impact of market and macroeconomic risk are not included, the t-statistic of the constant (2.953) of model 5 is higher. Therefore, the interactive factors among market and standard macroeconomic factors fail to increase the explanatory power. The full model (model 7) demonstrates that the returns of time-series industry momentum are significantly positive after controlling for all factors, implying that standard macroeconomic variables and the interactive factors among them and market factor do not help to explain time-series industry momentum returns.

If a 1% significant level (t-statistic = 2.5758) is utilised, the standard macroeconomic factors (model 6) help explain time-series industry momentum returns, although the extent of explanatory power is similar to the impact of market return on time-series industry momentum returns (model 2). If the significance level is relaxed to the 5% level (t-statistic = 1.96), neither standard macroeconomic variables, nor market factor, can fully explain the time-series industry momentum returns. Therefore, the weak relationship between time-series industry momentum and standard macroeconomic risk factors fails to support Hypothesis 6.1 that the time-series industry momentum effect is impacted by macroeconomic risk at the 5% significance level. If a 1% significance level is chosen, it can be concluded that the time-series industry momentum effect is influenced by macroeconomic risk (proxied by the standard macroeconomic factors. This finding complements Hutchinson and O'Brien (2020) on the relationship between time-series momentum and macroeconomic environment. Hutchinson and O'Brien (2020) observe that the influence of macroeconomic factors on time-series momentum is weak in their linear model at the 5% level of significance.

The implication of this finding is that macroeconomic information that is contained in prior industry price changes is at most partially processed by industry investors promptly. For fund managers who construct sector rotation strategies, or investors who invest in actively trading industry-sector funds, the impact of macroeconomic risk on their portfolio returns could be ignorable.

Hutchinson and O'Brien (2020) also find that market factor is among the most significant independent variable in their model. In model 2, the coefficient of MKT is 0.005 (t-statistic = 2.068). In the full model (model 7), most of the factors that proxy for the interplay of macroeconomic factors and market returns are among the most significant. The t-statistics of TS*MKT, DS*MKT, and TB*MKT are 2.828, -3.258, and 2.500, respectively. This implies that although the macroeconomic risk factors individually play insignificant roles in influencing time-series industry momentum returns (in model 6 where the joint impacts are not included, the t-statistics of TS, DS, and TB are -0.106, -0.761, and 0.486, respectively), the interplay of these factors and market returns may have a more significant influence on the returns.

Table 6a. 1 Jordan macroeconomic models for time-series industry momentum

Panel A. 12-1 strategy							
	M1	M2	M3	M4	M5	M6	M7
constant	0.009	0.007	0.009	0.007	0.008	0.008	0.011
t-stat	3.335	2.225	3.260	2.439	2.953	2.235	3.024
MKT		0.005		0.005	0.005	0.005	0.005
t-stat		2.068		2.076	1.807	2.110	1.824
JAN			-0.002	-0.006			-0.005
t-stat			-0.240	-0.494			-0.517
TS*MKT					0.004		0.004
t-stat					2.771		2.828
DS*MKT					-0.010		-0.010
t-stat					-3.200		-3.258
TB*MKT					0.002		0.002
t-stat					2.473		2.500
DY*MKT					-0.004		-0.004
t-stat					-1.578		-1.589
TS						0.000	-0.002
t-stat						-0.106	-0.977
DS						-0.010	-0.004
t-stat						-0.761	-0.438
TB						0.001	0.000
t-stat						0.486	-0.090
DY						0.000	0.003
t-stat						-0.083	0.815

Table 6a.1 Panel A. reports 7 Jordan macroeconomic models. Time-series industry momentum monthly returns for 12-month formation period and 1-month holding period are the dependent variable, and all the variables in the first column are the independent variables. The results are adjusted for heteroskedasticity and autocorrelation. M1-M7 are the abbreviations for Model 1- Model 7.

Information discreteness grouped time-series industry momentum

Table 6a.2 panel A demonstrates the results regressing negative information discreteness grouped time-series industry momentum returns on macroeconomic risk factors. Model 1 shows that the strategy returns are significant and are around 1.1% per month (constant 0.11, with t statistic = 3.575). Concurrent market factor can only partially explain the returns (model 2), whereas January effect has no influence (model 3). After controlling for standard macroeconomic factors (TS, DS, TB, and DY) in model 6, the unexplained negative information discreteness grouped time-series industry momentum returns are around 1% monthly (constant 0.010, with t-statistic = 2.556), which are insignificant at the 1% level, though still significant at the 5% level. This indicates that information continuity related TS industry momentum returns may be explained by macroeconomic risk to some extent. After controlling for interactive factors among market and standard macroeconomic factors (model 5), the unexplained returns (constant 0.009, with t-statistic = 3.133) become more significant. The full model (model 7) demonstrates that standard macroeconomic variables and the interactive factors among them and market factor, cannot explain time-series industry momentum returns. However, in model 5 and model 7 the interactive term between market factor and term spread (TS*MKT with t-statistic = 2.124 in M5, and t-statistic = 2.184 in M7), and the interactive term between market factor and default spread (DS*MKT with t-statistic = -3.208 in M5, and t-statistic = -3.260 in M7) may play a role.

If 1% significant level is utilized, the market factor can to some extent explain negative information discreteness grouped time-series industry momentum returns. If the significant level is relaxed to 5% level, neither standard macroeconomic variables nor market factor can fully explain the time-series industry momentum returns. Compared to the model with standard time-series industry momentum as dependent variable (Table 6a.1 Panel A), the unexplained part of return is higher and more significant in the model with negative ID time-series industry momentum as dependent variable. For example, the constant of the full model (M7) for negative ID time-series industry momentum is 0.012 (t-stat 3.257) whereas the constant of the full model (M7) for standard time-series industry momentum is 0.011 (t-stat 3.024). This indicates that macroeconomic environment as well as the joint impact of macroeconomic risk and market returns do not help to explain the time-series industry momentum returns that are induced by industry information that arrive in small pieces.

Table 6a.2 panel B (see section 6.6 appendices) demonstrates the results that regress positive information discreteness grouped time-series industry momentum returns on macroeconomic risk factors. Model 1 shows that the positive ID time-series industry momentum returns are around 0.6% per month (constant 0.006, with t-statistic = 1.985) and is statistically significant at the 5% level. This is much lower compared to its negative information discreteness counterparts, as well as standard time-series industry momentum returns, both economically and statistically. Concurrent market factor and January effect has no influence on the strategy returns (models 2 and 3). Standard macroeconomic factors and concurrent market returns jointly explain the returns, making the unexplained returns insignificant (constant 0.004, with t-statistic = 0.882) (model 6). The full model with market conditional factors (model 7) fails to outperform the standard macroeconomic factor model (model 6) in terms of explaining the positive ID time-series industry momentum returns. Because the unexplained returns (constant 0.005, with t-statistic = 1.211) is higher than in model 6. The model 7 unexplained return is equivalent to annual 6% (t-statistic = 1.211). Compared to 12-1 positive information discreteness time-series industry momentum returns (annual 6.839%, with t-statistic = 1.985) in Table 5.6, the returns are of similar scale economically and statistically, indicating that macroeconomic risk together with market factor has little impact on positive information discreteness time-series industry momentum returns.

The implication of this finding is that macroeconomic information that is contained in prior industry price changes that arrives in small pieces is at most partially processed by industry investors promptly. For fund managers who construct sector rotation strategies or investors who invest on actively trading industry-sector funds, if they want to increase strategy alpha by introducing negative ID dimension to their strategies, they do not need to take into account standard macroeconomic factors.

Similar to the findings on standard time-series industry momentum, in Table 6a.2, most of the factors that proxy for the interplay of macroeconomic factors and market returns are among the most significant in the full models (model 7) as well. For negative ID time series industry momentum (panel A), the t-statistics of TS*MKT, DS*MKT, and TB*MKT are 2.184, -3.260, and 1.939, respectively. For positive ID time-series industry momentum (panel B), the t-statistics of TS*MKT, DS*MKT, and TB*MKT are 3.100, -1.731, and 3.103, respectively. This implies that although the macroeconomic risk factors individually play insignificant roles in influencing time-series industry momentum returns (in model 6 where the joint impacts are not included, the t-statistics of TS, DS, and TB are -0.361, -1.020, and 0.483, respectively, for negative ID time-series industry momentum and the t-statistics of TS, DS, and TB are 1.193, 0.620, and 0.375, respectively, for positive time-series industry momentum), the interplay of these factors and market returns may have a more significant influence on the returns.

Abnormal return volatility grouped time-series industry momentum

Table 6a.3 panels A and Panel B (see section 6.6 appendices) demonstrate that the constants of all models are statistically insignificant, indicating the potential relationship between macroeconomic variables and abnormal return volatility grouped time-series industry momentum returns. However, as is shown in chapter 5, the introduction of abnormal return volatility to time-series industry momentum strategies reduces the time-series industry momentum returns. The potential reason for this could be that when the volatilities are out of normal ranges (i.e., abnormally high or abnormally low), investors' attentions are immediately attracted, making them react promptly to prior industry price information. That is, noisy information is processed similarly to other information contained in prior industry price. Therefore, the insignificant unexplained returns do not indicate the impact of macroeconomic risk on abnormal return volatility grouped time-series industry momentum returns.

Table 6a. 2 Jordan model for information discreteness grouped time-series industry momentum

Panel A. Negative ID time-series industry momentum (12-1 strategy)							
	M1	M2	M3	M4	M5	M6	M7
constant	0.011	0.008	0.011	0.008	0.009	0.010	0.012
t-stat	3.575	2.521	3.487	2.736	3.133	2.556	3.257
MKT		0.005		0.005	0.006	0.005	0.006
t-stat		2.203		2.211	1.999	2.272	2.024
JAN			-0.002	-0.006			-0.006
t-stat			-0.231	-0.500			-0.499
TS*MKT					0.004		0.004
t-stat					2.124		2.184
DS*MKT					-0.011		-0.011
t-stat					-3.208		-3.260
TB*MKT					0.002		0.002
t-stat					1.905		1.939
DY*MKT					-0.004		-0.004
t-stat					-1.469		-1.474
TS						-0.001	-0.003
t-stat						-0.361	-1.080
DS						-0.014	-0.006
t-stat						-1.020	-0.728
TB						0.001	0.000
t-stat						0.483	-0.002
DY						-0.001	0.003
t-stat						-0.124	0.761

Table 6a.2 Panel A. reports 7 Jordan macroeconomic models. Negative information discreteness time-series industry momentum monthly returns for 12-month formation period and 1-month holding period are the dependent variable, and all the variables in the first column are the independent variables. The results are adjusted for heteroskedasticity and autocorrelation. MKT and JAN are at month t, TS, DS, TB, and DY are at month t-1. M1-M7 are the abbreviations for Model 1- Model 7.

6.5.2 Is time-series industry momentum influenced by the joint impact of value premium and macroeconomic risk?

Table 6a.4 panel A reports Jordan's full model conditioning on HML for 12-month lookback and 1-month holding period time-series industry momentum monthly returns. The unexplained returns are about 0.7% monthly (constant 0.007, with t-statistic = 2.173) and statistically significant at the 5% level, but insignificant at 1% level. This is equivalent to annual 8.4% returns, which is less than 10.945% (t-statistic = 3.335) annual returns of the 12-1 time-series industry momentum strategy in chapter 5. Therefore, there is insufficient evidence supporting hypothesis 6.2 that time-series industry momentum is influenced by the joint impact of value premium and macroeconomic risk.

Table 6a.5 panel A reports Jordan's full model conditioning on HML for 12-month lookback and 1-month holding period negative information discreteness time-series industry momentum monthly returns. The unexplained returns are around 0.9% monthly (constant 0.009 with t-stat 2.506). Though market returns (coefficient 0.006 with t-stat 3.657), default spread (coefficient -0.025, with t-statistic = -2.280), and the interaction term of default spread and value premium (coefficient -0.015, with t-statistic = -4.587) significantly influence the strategy returns, the overall model cannot explain negative information discreteness time-series industry momentum returns at the 5% level.

As is discussed above, the introduction of value premium as a conditional factor to the standard macroeconomic model cannot fully explain time-series industry momentum returns or negative ID time-series industry momentum returns. However, it can be observed that the explanatory power of the models with value premium as conditional factors are improved, compared to the models without value premium as conditional factors. The unexplained time-series industry momentum returns in the Model 6 without value premium as conditional factor is around 0.8% monthly (constant 0.008, with t-statistic = 2.235), as is shown in Table 6a.1 panel A. The unexplained returns in the model with value premium as conditional factor is around 0.7% monthly (constant 0.007, with t-statistic = 2.173), as is shown in Table 6a.4 panel A. The unexplained negative ID time-series industry momentum returns in the model in model 6 without value premium as conditional factor is around 1% monthly (constant 0.010, with t-statistic = 2.556) as is shown in Table 6a.2 panel A, whereas the unexplained returns in the model with value premium as a conditional factor is around 0.9% monthly (constant 0.009, with t-statistic = 2.506) as is shown in Table 6a.5 panel A.

Table 6a.6 panel A (see section 6.6 appendices) reports Jordan's full model conditioning on HML for 12-month lookback and 1-month holding period positive information discreteness time-series industry momentum monthly returns. The unexplained returns are around 0.3% monthly (constant 0.003, with t-statistic = 0.629) and statistically insignificant. This is equivalent to annual 3.6%. Value premium (coefficient 0.003, with t-statistic = 2.136) and the interaction term between default spread and value premium (coefficient -0.008, with t-statistic = -3.363) significantly influence the strategy returns. Compared to the strategy annual returns (6.839%, with t-statistic = 1.985) reported in chapter 5, the t- statistic of the unexplained return in this model is no longer significant (t-statistic = 0.629) and the return scale is economically smaller. This indicates that macroeconomic risk may influence positive information discreteness time-series industry momentum returns.

Table 6a.7 panel A (see section 6.6 appendices) reports Jordan's full model conditioning on HML for 12-month lookback and 1-month holding period negative abnormal return volatility time-series industry momentum monthly returns. The unexplained returns are around monthly 0.3% (constant 0.003, with t-statistic = 0.678). This is equivalent to unexplained annual return of 3.6%. Value premium (coefficient -0.004, with t-statistic = -2.332), and the interaction term between default spread and value premium (coefficient 0.006 with t-statistic = 2.273), significantly influence the strategy returns. Compared to the strategy annual return (-6.560%, with t-statistic = -0.905) reported in Table 5.7 of chapter 5, the t statistic of the constant in the model turns positive, although it is still insignificant (t-statistic = 0.678).

Table 6a.8 panel A (see section 6.6 appendices) reports Jordan's full model conditioning on HML for 12-month lookback and 1-month holding period positive abnormal return volatility time-series industry momentum monthly returns. The unexplained returns are around 0.1% monthly (constant 0.001, with t-stat= 0.164). All independent variables are statistically insignificant. Compared to the strategy annual return (2.553%, with t-statistic = -0.208) reported in Table 5.7 of Chapter 5, the t-statistic of the constant of the model turns positive, although it is still insignificant (t-statistic = 0.164).

Table 6a. 3. Jordan conditional model for time-series industry momentum returns

Panel A. Full model conditioning on HML (Strategy 12-1)

	Estimate	SE	t-stat
constant	0.007	0.003	2.173
MKT	0.006	0.002	3.513
HML	0.003	0.002	1.269
TS	0.001	0.003	0.457
DS	-0.020	0.011	-1.888
TB	0.002	0.002	1.449
DY	-0.002	0.004	-0.349
TS*HML	0.000	0.002	-0.105
DS*HML	-0.014	0.003	-4.700
TB*HML	0.000	0.001	0.287
DY*HML	0.003	0.003	1.123

Panel B. Full model conditioning on VOL (Strategy 12-1)

	Estimate	SE	t-stat
constant	0.020	0.009	2.356
MKT	0.005	0.002	2.527
VOL	-0.001	0.001	-1.305
TS	-0.001	0.005	-0.224
DS	-0.039	0.015	-2.566
TB	-0.004	0.004	-1.044
DY	0.013	0.011	1.191
TS*VOL	0.000	0.000	0.195
DS*VOL	0.002	0.001	2.455
TB*VOL	0.000	0.000	1.420
DY*VOL	-0.001	0.001	-1.307

Panel C. Full model conditioning on LIQ (Strategy 12-1)

	Estimate	SE	t-stat
constant	0.007	0.005	1.516
MKT	0.005	0.002	2.217

LIQ	0.002	0.017	0.127
TS	0.000	0.003	-0.055
DS	-0.003	0.016	-0.183
TB	0.000	0.002	0.166
DY	0.000	0.005	0.037
TS*LIQ	0.070	0.057	1.235
DS*LIQ	-0.352	0.187	-1.880
TB*LIQ	0.064	0.031	2.049
DY*LIQ	-0.061	0.057	-1.064

Table 6a.4 Panel A reports full Jordan model conditioning on HML. Panel B reports full Jordan model conditioning on VOL. Panel C. reports full Jordan model conditioning on LIQ. Time-series industry momentum monthly returns for 12-month formation period and 1-month holding period are the dependent variable, and all the variables in the first column are the independent variables. MKT, HML, VOL, and LIQ are at month t, TS, DS, TB, and DY are at month t-1. The results are adjusted for heteroskedasticity and autocorrelation.

6.5.3 Is time-series industry momentum influenced by the joint impact of macroeconomic risk and market volatility?

Table 6a.4 panel B reports Jordan's full model conditioning on VOL for 12-month lookback and 1-month holding period time-series industry momentum monthly returns. Chapter 5 shows that the 12-1 strategy time-series industry momentum annual return is 10.945%, with t statistic 3.335. The unexplained strategy returns are around 2% monthly (constant 0.020, with t-statistic = 2.356) and statistically significant at the 5% level. Though market return (coefficient 0.005, with t-statistic = 2.527), default spread (coefficient -0.039, with t-statistic = -2.566), and interactive term between default spread and market volatility (coefficient 0.002, with t-statistic = 2.455) significantly influence strategy returns, the overall model cannot explain time-series industry momentum returns at the 5% level. Therefore, there is insufficient evidence supporting hypothesis 6.3 that time-series industry momentum is influenced by the joint impact of macroeconomic risk and market volatility.

Table 6a.5 panel B reports Jordan's full model conditioning on VOL for 12-month lookback and 1-month holding period negative information discreteness time-series industry momentum monthly returns. The unexplained returns are around 1.8% monthly (constant 0.018, with t-statistic = 2.010). Though market returns (coefficient 0.005, with t-statistic = 2.774), default spread (coefficient -0.043, with t-statistic = -2.539), and the interaction term of default spread and market volatility (coefficient 0.001, with t-statistic =1.963) significantly influence the strategy returns, the overall model cannot explain negative information discreteness time-series industry momentum returns at the 5% level.

Table 6a.6 panel B (see section 6.6 appendices) reports Jordan's full model conditioning on VOL for 12-month lookback and 1-month holding period positive information discreteness time-series industry momentum monthly returns. The unexplained returns are around 2.5% monthly (constant 0.025, with t-statistic = 3.010). Though market volatility (coefficient -0.001, with t-statistic = -2.517) and the interaction term of default spread and market volatility (coefficient 0.002, with t-statistic = 2.987) significantly influence the strategy returns, the overall model cannot explain negative information discreteness time-series industry momentum returns at the 5% level.

As is discussed above, the introduction of market volatility as a conditional factor to standard macroeconomic model cannot fully explain time-series industry momentum returns or negative ID time-series industry momentum returns. In addition, it is also found that the explanatory power of the models with market volatility as conditional factors are not improved compared to the models without market volatility as conditional factors. The unexplained time-series industry momentum returns in model 6 without market volatility as a conditional factor is around 0.8% monthly (constant 0.008, with t-statistic = 2.235), as is shown in Table 6a.1 panel A, whereas the unexplained returns in the model with market volatility as a conditional factor is around 2% monthly (constant 0.020, with t-statistic = 2.356), as is shown in Table 6a.4 panel B. The unexplained negative ID time-series industry momentum returns in the model in model 6, without market volatility as a conditional factor, is around 1% monthly (constant 0.010, with t-statistic = 2.556) as is shown in Table 6a.2 Panel A, whereas the unexplained returns in the model with market volatility as a conditional factor is around 1.8% monthly (constant 0.018, with t-statistic = 2.010) as is shown in Table 6a.5 panel B.

Table 6a.7 panel B (see section 6.6 appendices) reports Jordan's full model conditioning on VOL for 12-month lookback and 1-month holding period negative abnormal return volatility time-series industry momentum monthly returns. The unexplained returns are around -1.7% monthly (constant -0.017, with t-statistic = -2.117). Therefore, the overall model cannot explain negative information discreteness time-series industry momentum returns at the 5% level. The only independent variable that significantly influences the strategy return is market volatility (coefficient 0.001, with t-statistic = 2.135).

Table 6a.8 panel B (see section 6.6 appendices) reports Jordan full model conditioning on VOL for 12-month lookback and 1-month holding period positive abnormal return volatility time-series industry momentum monthly returns. The unexplained returns are around 0.3% monthly (constant 0.003, with t-statistic = 0.227), indicating a potential relationship between macroeconomic risk and the strategy returns. Compared to the annual return (2.553%, with t-statistic = -0.208) reported in Table 5.7 of chapter 5, the t statistics of the constant in the model turns positive, although it is still insignificant (t-statistic = 0.227). However, since the strategy returns are statistically insignificant, such a relationship is not meaningful in helping to understand the relationship between time-series industry momentum returns and market volatility.

6.5.4 Is time-series industry momentum influenced by the joint impact of macroeconomic risk and market liquidity?

Table 6a.4 panel C reports Jordan's full model conditioning on LIQ for 12-month lookback and 1-month holding period time-series industry momentum monthly returns. Chapter 5 shows that the 12-1 strategy time-series industry momentum annual return is 10.945% (t-statistic = 3.335). After controlling for interactive factors among LIQ and standard macroeconomic factors, the unexplained strategy returns are around 0.7% monthly (constant 0.007, with t-statistic = 1.516) and is statistically insignificant at the 5% level. This is equivalent to an unexplained annual return of 8.4%. Compared to the time-series industry momentum returns reported in chapter 5 Table 5.5, which is annual 10.945% (t-statistic = 3.335), the unexplained annual return is economically smaller. This finding demonstrates that introducing market liquidity as conditional time-varying risk factor helps understand the relationship between time-series industry momentum and macroeconomic risk. Therefore, it supports hypothesis 6.4 that time-series industry momentum is influenced by the joint impact of macroeconomic risk and market liquidity. This indicates that time-series industry momentum effect is not an anomaly, instead, it compensates for market liquidity risk.

Table 6a.5 panel C reports Jordan's full model conditioning on LIQ for 12-month lookback and 1-month holding period negative information discreteness time-series industry momentum monthly returns. The unexplained strategy returns are around 0.8% monthly (constant 0.008, with t-statistic = 1.708). This is equivalent to an annual unexplained return of 9.6%. Compared to the annual returns (12.402%, with t-statistic = 3.575) reported in chapter 5, the t statistic of the unexplained returns in the model is much less significant (t-statistic = 1.708), and of small economic scale. This indicates that standard macroeconomic factors, together with interactive factors among LIQ and macroeconomic factors as a whole, can explain continuous information time-series industry momentum returns at the 5% level. The implication is that introducing market liquidity as a conditional time-varying risk factor helps to understand the relationship between negative information discreteness grouped time-series industry momentum and macroeconomic risk. That is, the return from negative information discreteness time-series industry momentum is compensation for market liquidity risk.

Table 6a.6 panel C shows Jordan's full model conditioning on LIQ for 12-month lookback and 1-month holding period positive information discreteness time-series industry momentum returns. The unexplained returns are around 0.4% monthly (constant 0.004, with t-statistic = 0.888) and are statistically insignificant. This is equivalent to an annual unexplained return of 4.8%. Compared to the annual returns (6.839%, with t-statistic =1.985) reported in Table 5.6 of chapter 5, the unexplained returns are economically smaller and statistically insignificant. Therefore, the macroeconomic risk factors together with market liquidity help explain positive information discreteness time-series industry momentum returns.

Table 6a.7 panel C demonstrates Jordan's full model conditioning on LIQ for 12-month lookback and 1-month holding period for negative abnormal return volatility grouped time-series industry momentum. The unexplained returns are around 0.2% monthly (constant 0.002, with t-statistic = 0.312). This is equivalent to annual 2.4% unexplained returns. Compared to the annual return (-6.56%, with t-statistic = -0.905) reported in Table 5.6 of chapter 5, the t-statistic of the constant in the model turns positive, although it is still insignificant. None of the independent variables are statistically significant at the 5% level.

Table 6a. 4. Negative information discreteness time-series industry momentum returns

Panel A. Full model conditioning on HML (Strategy 12-1)

	Estimate	SE	t-stat
constant	0.009	0.004	2.506
MKT	0.006	0.002	3.657
HML	0.003	0.003	1.127
TS	0.001	0.003	0.197
DS	-0.025	0.011	-2.280
TB	0.002	0.002	1.400
DY	-0.002	0.005	-0.361
TS*HML	0.000	0.002	-0.064
DS*HML	-0.015	0.003	-4.587
TB*HML	0.000	0.001	0.503
DY*HML	0.003	0.003	1.005

Panel B. Full model conditioning on VOL (Strategy 12-1)

	Estimate	SE	t-stat
constant	0.018	0.009	2.010
MKT	0.005	0.002	2.774
VOL	-0.001	0.001	-0.878
TS	-0.001	0.005	-0.283
DS	-0.043	0.017	-2.539
TB	-0.004	0.004	-0.910
DY	0.012	0.012	1.027
TS*VOL	0.000	0.000	0.137
DS*VOL	0.001	0.001	1.963
TB*VOL	0.000	0.000	1.327
DY*VOL	-0.001	0.001	-1.119

Panel C. Full model conditioning on LIQ (Strategy 12-1)

	Estimate	SE	t-stat
constant	0.008	0.005	1.708
MKT	0.005	0.002	2.382
LIQ	0.004	0.018	0.247
TS	-0.001	0.003	-0.228
DS	-0.007	0.016	-0.408
TB	0.000	0.002	0.158
DY	0.000	0.005	-0.037
TS*LIQ	0.065	0.062	1.045
DS*LIQ	-0.350	0.205	-1.713
TB*LIQ	0.065	0.033	1.994
DY*LIQ	-0.064	0.063	-1.018

Table 6a.5 Panel A reports full Jordan model conditioning on HML. Panel B reports full Jordan model conditioning on VOL. Panel C. reports full Jordan model conditioning on LIQ. Negative information discreteness time-series industry momentum monthly returns for 12-month formation period and 1-month holding period are the dependent

variable, and all the variables in the first column are the independent variables. MKT, HML, VOL, and LIQ are at month t, TS, DS, TB, and DY are at month t-1. The results are adjusted for heteroskedasticity and autocorrelation.

6.5.5 Factor analysis

In the previous section, the conditional CAPM style macroeconomic models follow Jordan's (2012) model, which incorporates the standard macroeconomic variables (TS, DS, DB, and DY). However, there are hundreds of other macroeconomic variables that may play a role in understanding time-series industry momentum returns. Missing relevant independent variables may lead to biased coefficients and invalid t-statistics. Factor analysis is an approach to select common factors from a wide range of possible indicators based on information criteria, which is suitable to minimise the chances of missing relevant macroeconomic variables and correlations among independent variables. For example, to mitigate the "missing predictor" problem, Maio and Philip (2015) derive six common processes via factor analysis from 124 macroeconomic variables to study the relationship between macroeconomic environment and stock returns. In my factor analysis, seven common processes are derived from 128 macroeconomic variables via the MATLAB factor analysis package created by Michael W. McCracken.

Table 6a.9 demonstrates that macroeconomic risk does not have significant influence on time-series industry momentum returns. The unexplained return is around 0.9% monthly and statistically significant (constant 0.009, with t-statistic = 3.215). It is equivalent to 10.8% yearly, which is of little difference compared to the corresponding time-series industry momentum returns (10.945% yearly, with t-statistic = 3.335). Only one out of seven common macroeconomic processes have a significant influence on the returns (i.e., C7 with coefficient -0.059, and t-statistic = -1.968). This indicates that although the seventh common process which is related to stock market performance and industry production negatively influence time-series industry momentum returns at the 5% level, the broad macroeconomic model does not have significant explanatory power. This is consistent with the results from conditional standard macroeconomic models in Table 6a.1.

Table 6a. 5. Factor analysis: time-series industry momentum (12-1 strategy)

	Estimate	SE	t-stat
constant	0.009	0.003	3.215
C1	-0.007	0.012	-0.570
C2	-0.012	0.015	-0.778
C3	-0.005	0.014	-0.392
C4	0.006	0.020	0.305
C5	0.002	0.015	0.134
C6	-0.010	0.024	-0.401
C7	-0.059	0.030	-1.968

Table 6a.9 reports factor analysis on time-series industry momentum with 12-month lookback period and 1-month holding period. The time-series industry momentum return is dependent variable and the 7 common processes from the macroeconomic variables are independent variables. CN denotes the N^{th} common process. N is from 1 to 7.

Table 6a. 6. Factor analysis (12-1 strategy)

Panel A. Negative ID

	Estimate	SE	t-stat
constant	0.011	0.003	3.569
C1	-0.009	0.012	-0.721
C2	-0.016	0.015	-1.051
C3	-0.006	0.015	-0.380
C4	0.007	0.021	0.325
C5	-0.001	0.016	-0.086
C6	-0.017	0.025	-0.695
C7	-0.073	0.030	-2.458

Table 6a.10 Panel A reports factor analysis on negative ID time-series industry momentum with 12-month lookback period and 1-month holding period. The returns are dependent variables and the 7 common processes from the macroeconomic variables are independent variables.

Table 6a.10 panel A shows that negative information discreteness time-series industry momentum returns cannot be explained by common macroeconomic processes (constant 0.011, with t-statistic = 3.569). However, the seventh common process which is related to stock market performance and industry production may have some negative impact (t-statistic = -2.458). This is consistent with the result from conditional models in Table 6a.2 panel A.

Table 6a.11 and Table 6a.12 are both factor analyses with conditional factors. From the two tables, we can observe that though the macroeconomic variables can still not explain time-series industry momentum returns as well as negative information discreteness time-series industry momentum returns. When market volatility and market liquidity are introduced as conditional variables (panel C and panel D), the constants are less significant in comparison with Table 6a.9 and Table 6a.10, respectively.

The model with market volatility as a conditional factor has less significant unexplained time-series industry momentum returns (constant 0.009. with t-statistic = 3.182) compared to the factor analysis without market volatility factor (constant 0.009, with t-statistic = 3.215), indicating that macroeconomic factors together with the interaction with volatility may to some extent help explain time-series industry momentum returns. Here, the constant of the model is still significant at both the 1% and 5% levels. All factor analysis models for negative information discreteness time-series industry momentum returns have significant unexplained returns. The one with volatility as conditional variables has significant monthly unexplained returns of around 1.1% (constant 0.011, with t-statistic = 3.544). This model performs better than the one without conditional time-varying factors which has significant monthly unexplained returns of around 1.1% (constant 0.011, with t-statistic = 3.569) in terms of explaining negative ID time-series industry momentum returns, for the t-stat of the unexplained returns is smaller, although the economic scale does not change.

The model with liquidity has significantly less unexplained time-series industry momentum returns (constant 0.009, with t-statistic = 2.792) compared to the factor analysis without the liquidity factor (constant 0.009, with t-statistic = 3.215), indicating that macroeconomic factors, together with the interaction with liquidity, may to some extent help explain time-series industry momentum returns. The constant of the model is still significant at both the 1% and 5% levels. All factor analysis models for negative information discreteness time-series industry momentum returns have significant unexplained returns. The one with liquidity as a conditional variables has significant monthly unexplained returns of around 1% (constant 0.010, with t-statistic = 3.054). This model performs better than the one without conditional time-varying factors, which has significant monthly unexplained returns of around 1.1% (constant 0.011, with t-statistic = 3.569) in terms of explaining negative ID time-series industry momentum returns. The scale of the unexplained returns is smaller, as is the t-statistic.

At the 1% and 5% significance levels, there are no factor analysis models or factor analysis conditional models that can fully explain time-series industry momentum returns or negative information discreteness grouped time-series industry momentum returns. However, the introduction of market volatility and market liquidity as conditional time-varying risk factors, respectively, improves the performance of the factor analysis models in terms of explaining the strategy returns.

However, in a Jordan (2012) style model (as is shown in previous section), the introduction of market liquidity as a conditional factor helps to explain time-series industry momentum returns, as well as negative ID time-series industry momentum returns. In addition, previous findings show that the introduction of value premium and market liquidity, as conditional time-varying factors to standard macroeconomic models, helps to improve the explanatory power of the Jordan (2012) models. However, they explain neither time-series industry momentum returns nor negative ID time-series industry momentum returns. The potential reasons for the different conclusions from the two methods will be discussed in the section below.

6.5.6 Macroeconomic Risk Factors versus Financial Risk Factors

In the prior time-series momentum literature, the impact of macroeconomic risk on time-series momentum returns differs when the macroeconomic risk proxies are differing. For example, Lim et al. (2018) use standard macroeconomic factors (i.e., TS, DS, TB, and DY) and GDP growth to study the impact of macroeconomic environment on time-series momentum returns, finding a weak relationship between them. Hutchinson and O'Brien (2020) argue that default spread, dividend yield, monthly GDP change, monthly inflation, market returns, short term interest rate, term spread, and unemployment rate are the most important macroeconomic factors for hedge fund managers and traditional portfolio managers. Their study shows that time-series momentum returns are related to macroeconomic risk, and that the return is better in expansion periods.

In this chapter, it is shown that the Jordan (2012) style models, conditioned on market liquidity, help to explain time-series industry momentum returns as well as negative ID time-series industry momentum returns. This indicates that macroeconomic risk, together with market liquidity, may help explain time-series industry momentum returns and the returns under negative information discreteness. However, the factor analysis, based on seven common processes derived from 128 macroeconomic variables, demonstrates that macro factors don't help much in explaining time-series industry momentum returns. Additionally, the introduction of market liquidity as a conditional factor improves model explanatory power, but still cannot make the model fully explain the returns. The potential reason of the difference could be the measuring scope of the predictors. That is, standard macroeconomic risk factors (i.e., TS, DS, TB, and DY) are more related to financial risk factors, which are too narrow. However, the seven common processes derived from 128 macroeconomic risk factors are macro factors which measure macroeconomic environment in a broader manner.

Since no prior literature on the relationship between the time-series industry momentum effect and macroeconomic risks exists, the present study's results are compared against literature on the relationship between time-series momentum and macroeconomic risk. Moskowitz et al. (2012) demonstrate the relationship between time-series momentum and aggregate macroeconomic risk managed fund (Dow Jones Credit Suisse Global Macro) performance. They regress DJCS Global Macro returns on time-series momentum returns, finding that time-series momentum returns (coefficient 0.32, with t-statistic = 5.64) significantly influence DJCS Global Macro returns. This is supporting evidence that time-series momentum is a potential asset pricing factor. The finding that narrowly scoped financial-risk related macroeconomic risks, together with market liquidity risk, can explain time-series industry momentum returns, challenges Moskowitz et al.'s (2012) argument. However, the broadly scoped macroeconomic risk models do not. Therefore, future research must be conducted to further explore the relationship between macroeconomic risks and the time-series momentum effect.

Hutchinson and O'Brien (2020) show that time-series momentum returns are related to macroeconomic risk. They use default spread, dividend yield, monthly GDP change, monthly inflation, market returns, short term interest rate, term spread, and unemployment rate, to proxy for macroeconomic risk. This is because these are the most important macroeconomic factors for hedge fund managers and traditional portfolio managers. Their macroeconomic factors are closer to the narrowly scoped macroeconomic factors in this study when compared with broadly scoped macroeconomic factors. The finding that the narrowly scoped macroeconomic factors, together with market liquidity, help to explain time-series industry momentum returns at the 5% level complements Hutchinson and O'Brien's (2020) findings on the relationship between time-series momentum returns and macroeconomic risk, extending its scope to the industry level.

Table 6a. 7. Factor analysis with interactive factors (12-1 strategy): TS industry returns

Panel A. MKT

	Estimate	SE	t-stat
constant	0.013	0.003	5.144
C1	0.006	0.008	0.790
C2	-0.008	0.010	-0.736
C3	-0.008	0.011	-0.701
C4	0.038	0.015	2.598
C5	-0.007	0.015	-0.459
C6	0.035	0.017	2.045
C7	-0.073	0.017	-4.238
C1MKT	-0.015	0.002	-7.537
C2MKT	-0.002	0.003	-0.698
C3MKT	0.003	0.004	0.758
C4MKT	-0.005	0.004	-1.145
C5MKT	-0.006	0.006	-1.055
C6MKT	-0.024	0.005	-4.597
C7MKT	-0.005	0.004	-1.129

Panel B. HML

	Estimate	SE	t-stat
constant	0.009	0.003	3.247
C1	-0.010	0.009	-1.083
C2	-0.010	0.011	-0.868
C3	0.004	0.011	0.363
C4	0.010	0.018	0.561
C5	0.004	0.014	0.254
C6	0.002	0.021	0.105
C7	-0.071	0.025	-2.838
C1HML	-0.006	0.002	-2.769
C2HML	-0.007	0.004	-1.643

C3HML	-0.006	0.005	-1.217
C4HML	-0.001	0.005	-0.097
C5HML	-0.011	0.008	-1.316
C6HML	-0.019	0.006	-3.182
C7HML	-0.011	0.008	-1.257

Panel C. VOL

	Estimate	SE	t-stat
constant	0.009	0.003	3.182
C1	-0.004	0.013	-0.272
C2	0.003	0.016	0.165
C3	0.086	0.027	3.207
C4	0.125	0.035	3.602
C5	-0.040	0.035	-1.155
C6	0.092	0.033	2.821
C7	-0.156	0.033	-4.732
C1VOL	0.000	0.001	-0.211
C2VOL	-0.002	0.001	-2.764
C3VOL	-0.004	0.001	-3.350
C4VOL	-0.006	0.002	-3.841
C5VOL	0.002	0.002	1.268
C6VOL	-0.004	0.002	-2.650
C7VOL	0.003	0.002	1.709

Panel D. LIQ

	Estimate	SE	t-stat
constant	0.009	0.003	2.792
C1	-0.004	0.015	-0.254
C2	-0.004	0.018	-0.225
C3	0.008	0.016	0.513
C4	0.031	0.022	1.449
C5	0.002	0.017	0.134
C6	0.000	0.026	0.012
C7	-0.064	0.035	-1.821
C1LIQ	-0.097	0.092	-1.053
C2LIQ	-0.122	0.115	-1.061
C3LIQ	-0.226	0.145	-1.554
C4LIQ	-0.496	0.213	-2.329
C5LIQ	0.129	0.185	0.701
C6LIQ	-0.028	0.086	-0.321
C7LIQ	-0.036	0.138	-0.262

Table 6a. 8. Factor analysis with interactive factors: Negative ID (12-1 strategy)

Panel A. MKT

	Estimate	SE	t-stat
constant	0.015	0.003	5.706
C1	0.006	0.008	0.756
C2	-0.010	0.011	-0.921
C3	-0.010	0.011	-0.891
C4	0.042	0.015	2.771
C5	-0.009	0.016	-0.589
C6	0.033	0.018	1.805
C7	-0.082	0.018	-4.583
C1MKT	-0.015	0.002	-7.325
C2MKT	-0.001	0.003	-0.422
C3MKT	0.005	0.004	1.069
C4MKT	-0.007	0.004	-1.788
C5MKT	-0.007	0.006	-1.206
C6MKT	-0.028	0.005	-5.429
C7MKT	-0.006	0.004	-1.294

Panel B. HML

	Estimate	SE	t-stat
constant	0.010	0.003	3.576
C1	-0.012	0.009	-1.259
C2	-0.012	0.012	-1.033
C3	0.005	0.012	0.421
C4	0.010	0.019	0.544
C5	0.001	0.015	0.086
C6	-0.005	0.023	-0.226
C7	-0.085	0.027	-3.144
C1HML	-0.006	0.003	-2.582
C2HML	-0.007	0.004	-1.552
C3HML	-0.008	0.005	-1.482
C4HML	-0.001	0.005	-0.171
C5HML	-0.011	0.009	-1.243
C6HML	-0.018	0.006	-2.857
C7HML	-0.008	0.009	-0.932

Panel C. VOL

	Estimate	SE	t-stat
constant	0.011	0.003	3.544
C1	-0.003	0.015	-0.230
C2	0.001	0.018	0.038
C3	0.086	0.028	3.034

C4	0.118	0.038	3.134
C5	-0.044	0.037	-1.196
C6	0.099	0.035	2.810
C7	-0.159	0.036	-4.376
C1VOL	0.000	0.001	-0.274
C2VOL	-0.002	0.001	-2.627
C3VOL	-0.004	0.001	-3.212
C4VOL	-0.006	0.002	-3.315
C5VOL	0.003	0.002	1.243
C6VOL	-0.005	0.002	-2.982
C7VOL	0.002	0.002	1.281

Panel D. LIQ

	Estimate	SE	t-stat
constant	0.010	0.003	3.054
C1	-0.006	0.015	-0.429
C2	-0.008	0.018	-0.433
C3	0.010	0.017	0.576
C4	0.034	0.022	1.544
C5	-0.001	0.018	-0.065
C6	-0.006	0.026	-0.244
C7	-0.082	0.035	-2.365
C1LIQ	-0.093	0.093	-0.998
C2LIQ	-0.119	0.115	-1.037
C3LIQ	-0.253	0.152	-1.661
C4LIQ	-0.533	0.223	-2.388
C5LIQ	0.142	0.202	0.701
C6LIQ	-0.035	0.091	-0.389
C7LIQ	0.014	0.142	0.102

6.5 Conclusion

To conclude, this chapter analyses the impact of time-varying risk on the performance of time-series industry momentum. Except for macroeconomic risk factors, three other time-varying risk factors (i.e., HML, LIQ, and VOL) are introduced to standard macroeconomic models (i.e., TS, DS, TB, and DY) and factor analysis models as conditional variables to overcome the weakness of static beta model, in terms of the failure to address the variation of factor loadings with time-varying risk.

The findings in Jordan (2012) style conditional models show that though the introduction of market liquidity and value premium as conditional time-varying risk factors improves the Jordan (2012) style models' explanatory power, only the joint impact of macroeconomic risk and market liquidity helps to explain time-series industry momentum returns at the 5% level. However, factor analysis conditional models demonstrate that none of the time-varying risk factors help to explain time-series industry momentum returns, although the introduction of market liquidity and market volatility, respectively, as conditional time-varying risk factors to the factor analysis model improve the model explanatory power. These findings apply to time-series industry momentum returns under negative information discreteness. Therefore, it may be concluded that the time-series industry momentum effect is not an anomaly. It could be risk compensation for market liquidity risk, because time-series momentum returns substantially shrink when time-varying liquidity risk is examined.

The difference in results of the two methods may be due to the differing measuring scope of the macroeconomic risk proxies. Standard macroeconomic risk factors (i.e., TS, DS, TB, and DY) are more related to financial risk whereas the common processes derived from 128 macroeconomic risk factors are macro risk measures. Since the only consensus of the two methods are that only the introduction of market liquidity, among the time-varying risk factors examined, as a conditional factor, improves the explanatory power of the models. Accordingly, it is proposed that market liquidity is the most important factor for understanding the time-series industry momentum effect.

Prior cross-sectional momentum return improvement focuses on strategy specific volatility management or marketwise volatility management. The implication of the findings in this chapter for momentum studies is that the joint management of liquidity and macroeconomic standard factor may be a new angle to improve momentum returns. The implication for industry investors is that the joint impact of liquidity and standard macroeconomic factors needs to be considered when constructing sector rotation strategies. The implication for policy makers is that, when making policies to influence industry performance, macroeconomic policies being accompanied by marketwise liquidity management may generate more influence.

6.6 Appendices

Table 6a. 9 Jordan model for information discreteness grouped time-series industry momentum

Panel B. Positive ID time-series industry momentum (12-1 strategy)							
	M1	M2	M3	M4	M5	M6	M7
constant	0.006	0.006	0.005	0.005	0.007	0.004	0.005
t-stat	1.985	1.509	1.641	1.296	1.952	0.882	1.211
MKT		0.001		0.001	0.001	0.001	0.001
t-stat		0.712		0.700	0.639	0.664	0.586
JAN			0.010	0.009			0.007
t-stat			0.895	0.682			0.550
TS*MKT					0.004		0.004
t-stat					3.159		3.100
DS*MKT					-0.004		-0.004
t-stat					-1.670		-1.731
TB*MKT					0.002		0.002
t-stat					3.120		3.103
DY*MKT					0.000		0.000
t-stat					-0.187		-0.228
TS						0.004	0.001
t-stat						1.193	0.433
DS						0.008	0.006
t-stat						0.620	0.724
TB						0.001	0.000
t-stat						0.375	-0.081
DY						0.000	0.001
t-stat						-0.012	0.118

Table 6a.2 Panel B. reports 7 Jordan macroeconomic models. Positive information discreteness time-series industry momentum monthly returns for 12-month formation period and 1-month holding period are the dependent variable, and all the variables in the first column are the independent variables. The results are adjusted for heteroskedasticity and autocorrelation. MKT and JAN are at month t, TS, DS, TB, and DY are at month t-1. M1-M7 are the abbreviations for Model 1- Model 7.

Table 6a. 10 Jordan model for abnormal return volatility grouped time-series industry momentum

Panel A. Negative ARD time-series industry momentum (12-1 strategy)							
	M1	M2	M3	M4	M5	M6	M7
constant	-0.003	-0.002	-0.001	-0.001	-0.003	0.001	0.001
t-stat	-0.905	-0.787	-0.286	-0.189	-0.898	0.170	0.319
MKT		-0.001		-0.001	0.000	-0.001	0.000
t-stat		-0.551		-0.500	0.127	-0.602	0.170
JAN			-0.021	-0.021			-0.022
t-stat			-2.017	-2.262			-2.272
TS*MKT					-0.002		-0.002
t-stat					-1.839		-1.932

DS*MKT					0.001		0.000
t-stat					0.173		0.114
TB*MKT					-0.001		-0.001
t-stat					-1.404		-1.429
DY*MKT					0.002		0.002
t-stat					0.909		0.912
TS						-0.001	0.000
t-stat						-0.357	-0.060
DS						-0.003	-0.002
t-stat						-0.238	-0.178
TB						-0.001	0.000
t-stat						-0.415	-0.175
DY						0.006	0.005
t-stat						1.134	0.922

Table 6a.3 Panel A. reports 7 Jordan macroeconomic models. Negative abnormal return volatility time-series industry momentum monthly returns for 12-month formation period and 1-month holding period are the dependent variable, and all the variables in the first column are the independent variables. The results are adjusted for heteroskedasticity and autocorrelation. MKT and JAN are at month t, TS, DS, TB, and DY are at month t-1. M1-M7 are the abbreviations for Model 1- Model 7.

Panel B. Positive ARD time-series industry momentum (12-1 strategy)

	M1	M2	M3	M4	M5	M6	M7
constant	-0.001	-0.001	0.000	0.000	0.001	-0.001	0.002
t-stat	-0.208	-0.258	0.075	0.034	0.177	-0.184	0.332
MKT		0.001		0.001	-0.001	0.001	-0.001
t-stat		0.333		0.372	-0.337	0.350	-0.292
JAN			-0.010	-0.011			-0.005
t-stat			-0.770	-0.857			-0.413
TS*MKT					0.003		0.003
t-stat					2.225		2.217
DS*MKT					-0.006		-0.006
t-stat					-1.193		-1.259
TB*MKT					0.002		0.002
t-stat					2.897		2.882
DY*MKT					-0.004		-0.004
t-stat					-1.548		-1.592
TS						0.006	0.005
t-stat						1.173	1.153
DS						-0.011	-0.006
t-stat						-0.700	-0.412
TB						0.001	0.000
t-stat						0.187	0.043
DY						0.003	0.005
t-stat						0.346	0.592

Table 6a.3 Panel B. reports 7 Jordan macroeconomic models. Positive abnormal return volatility time-series industry momentum monthly returns for 12-month formation period and 1-month holding period are the dependent variable, and all the variables in the first column are the independent variables. The results are adjusted for heteroskedasticity and autocorrelation. MKT and JAN are at month t, TS, DS, TB, and DY are at month t-1. M1-M7 are the abbreviations for Model 1- Model 7.

Table 6a. 11. Positive information discreteness time-series industry momentum returns

Panel A. Full model conditioning on HML (Strategy 12-1)

	Estimate	SE	t-stat
constant	0.003	0.004	0.629
MKT	0.002	0.002	1.039
HML	0.003	0.002	2.136
TS	0.005	0.004	1.485
DS	0.004	0.012	0.350
TB	0.002	0.002	0.834
DY	-0.001	0.005	-0.256
TS*HML	-0.001	0.002	-0.578
DS*HML	-0.008	0.002	-3.363
TB*HML	-0.001	0.001	-0.768
DY*HML	0.003	0.002	1.786

Panel B. Full model conditioning on VOL (Strategy 12-1)

	Estimate	SE	t-stat
constant	0.025	0.008	3.010
MKT	0.001	0.002	0.776
VOL	-0.001	0.001	-2.517
TS	0.001	0.006	0.192
DS	-0.022	0.016	-1.363
TB	-0.005	0.004	-1.084
DY	0.016	0.011	1.444
TS*VOL	0.000	0.000	0.440
DS*VOL	0.002	0.001	2.987
TB*VOL	0.000	0.000	1.384
DY*VOL	-0.001	0.001	-1.864

Panel C. Full model conditioning on LIQ (Strategy 12-1)

	Estimate	SE	t-stat
constant	0.004	0.005	0.888
MKT	0.001	0.002	0.726
LIQ	-0.005	0.021	-0.229
TS	0.004	0.004	1.038
DS	0.016	0.015	1.023
TB	0.000	0.002	0.215
DY	0.001	0.005	0.219
TS*LIQ	0.055	0.064	0.870
DS*LIQ	-0.342	0.188	-1.817
TB*LIQ	0.039	0.029	1.336
DY*LIQ	-0.037	0.040	-0.921

Table 6a.6 Panel A reports full Jordan model conditioning on HML. Panel B reports full Jordan model conditioning on VOL. Panel C. reports full Jordan model conditioning on LIQ. Positive information discreteness time-series industry momentum monthly returns for 12-month formation period and 1-month holding period are the dependent

variable, and all the variables in the first column are the independent variables. MKT, HML, VOL, and LIQ are at month t, TS, DS, TB, and DY are at month t-1. The results are adjusted for heteroskedasticity and autocorrelation.

Table 6a. 12. Negative ARD time-series industry momentum returns: conditional models (Strategy 12-1)

Panel A. HML

	Estimate	SE	t-stat
constant	0.003	0.004	0.678
MKT	-0.002	0.001	-1.526
HML	-0.004	0.002	-2.332
TS	-0.004	0.003	-1.144
DS	0.005	0.011	0.429
TB	-0.001	0.002	-0.540
DY	0.006	0.006	1.061
TS*HML	0.002	0.001	1.779
DS*HML	0.006	0.003	2.273
TB*HML	0.000	0.001	-0.751
DY*HML	-0.001	0.002	-0.516

Panel B. VOL

	Estimate	SE	t-stat
constant	-0.017	0.008	-2.117
MKT	-0.001	0.001	-0.540
VOL	0.001	0.001	2.135
TS	0.009	0.006	1.495
DS	-0.008	0.023	-0.352
TB	0.006	0.004	1.594
DY	-0.009	0.012	-0.716
TS*VOL	0.000	0.000	-1.407
DS*VOL	-0.001	0.001	-0.514
TB*VOL	0.000	0.000	-1.424
DY*VOL	0.001	0.001	1.243

Panel C. LIQ

	Estimate	SE	t-stat
constant	0.002	0.005	0.312
MKT	-0.001	0.001	-0.664
VOL	-0.033	0.020	-1.609
TS	-0.001	0.004	-0.327
DS	0.000	0.014	0.009
TB	0.000	0.002	-0.019
DY	0.004	0.006	0.573
TS*VOL	0.004	0.080	0.047
DS*VOL	-0.130	0.188	-0.690
TB*VOL	-0.019	0.037	-0.503
DY*VOL	0.127	0.067	1.885

Table 6a.7 Panel A reports full Jordan model conditioning on HML. Panel B reports full Jordan model conditioning on VOL. Panel C. reports full Jordan model conditioning on LIQ. Negative ARD time-series industry momentum

monthly returns for 12-month formation period and 1-month holding period are the dependent variable, and all the variables in the first column are the independent variables. MKT, HML, VOL, and LIQ are at month t, TS, DS, TB, and DY are at month t-1. The results are adjusted for heteroskedasticity and autocorrelation.

Table 6a. 13. Positive ARD time-series industry momentum returns: conditional models (Strategy 12-1)

Panel A. HML

	Estimate	SE	t-stat
constant	0.001	0.005	0.164
MKT	0.000	0.002	0.126
HML	-0.002	0.003	-0.711
TS	0.002	0.004	0.419
DS	-0.002	0.018	-0.114
TB	0.000	0.003	0.164
DY	0.003	0.007	0.365
TS*HML	0.003	0.002	1.350
DS*HML	-0.008	0.006	-1.390
TB*HML	0.000	0.001	-0.048
DY*HML	0.002	0.003	0.837

Panel B. VOL

	Estimate	SE	t-stat
constant	0.003	0.011	0.227
MKT	0.001	0.002	0.385
VOL	0.000	0.001	-0.369
TS	-0.003	0.007	-0.397
DS	-0.013	0.042	-0.303
TB	0.004	0.005	0.855
DY	-0.011	0.017	-0.691
TS*VOL	0.001	0.000	1.502
DS*VOL	0.000	0.003	0.028
TB*VOL	0.000	0.000	-0.566
DY*VOL	0.001	0.001	0.735

Panel C. LIQ

	Estimate	SE	t-stat
constant	-0.005	0.008	-0.560
MKT	0.001	0.002	0.483
LIQ	0.025	0.047	0.544
TS	0.005	0.005	0.851
DS	0.006	0.019	0.324
TB	0.001	0.003	0.239
DY	-0.001	0.011	-0.109
TS*LIQ	0.146	0.169	0.862
DS*LIQ	-0.558	0.340	-1.641
TB*LIQ	0.036	0.077	0.463
DY*LIQ	0.086	0.100	0.859

Table 6a.8 Panel A reports full Jordan model conditioning on HML. Panel B reports full Jordan model conditioning on VOL. Panel C. reports full Jordan model conditioning on LIQ. Positive ARD time-series industry momentum monthly returns for 12-month formation period and 1-month holding period are the dependent variable, and all the variables in the first column are the independent variables. MKT, HML, VOL, and LIQ are at month t, TS, DS, TB, and DY are at month t-1. The results are adjusted for heteroskedasticity and autocorrelation.

Table 6a. 14. Factor analysis (12-1 strategy)

Panel B. Positive ID

	Estimate	SE	t-stat
constant	0.006	0.003	1.807
C1	-0.007	0.013	-0.508
C2	0.012	0.018	0.637
C3	0.002	0.016	0.161
C4	0.004	0.019	0.194
C5	-0.003	0.020	-0.147
C6	0.010	0.022	0.465
C7	0.006	0.030	0.208

Panel C. Negative ARD

	Estimate	SE	t-stat
constant	-0.003	0.003	-0.915
C1	-0.006	0.011	-0.586
C2	-0.001	0.014	-0.088
C3	-0.003	0.013	-0.195
C4	-0.006	0.015	-0.407
C5	0.003	0.014	0.188
C6	-0.008	0.021	-0.374
C7	0.043	0.024	1.805

Panel D. Positive ARD

	Estimate	SE	t-stat
constant	-0.002	0.004	-0.465
C1	-0.015	0.017	-0.872
C2	0.002	0.021	0.095
C3	0.006	0.021	0.288
C4	-0.005	0.024	-0.209
C5	0.014	0.024	0.583
C6	-0.015	0.029	-0.540
C7	0.027	0.029	0.939

Table 6a.10 Panel A, B, C, D reports factor analysis on negative ID, positive ID, negative ARD and positive ARD time-series industry momentum with 12-month lookback period and 1-month holding period, respectively. The returns are dependent variables and the 7 common processes from the macroeconomic variables are independent variables.

Table 6a. 15. Factor analysis with interactive factors: Positive ID (12-1 strategy)

Panel A. MKT

	Estimate	SE	t-stat
constant	0.003	0.003	1.027
C1	-0.011	0.010	-1.049
C2	0.003	0.012	0.224
C3	0.016	0.017	0.902
C4	0.006	0.019	0.307
C5	-0.012	0.021	-0.562
C6	0.014	0.022	0.638
C7	-0.032	0.020	-1.605
C1MKT	-0.005	0.003	-1.874
C2MKT	-0.004	0.004	-1.140
C3MKT	-0.010	0.005	-2.156
C4MKT	0.009	0.005	1.914
C5MKT	0.003	0.006	0.489
C6MKT	0.006	0.007	0.783
C7MKT	-0.004	0.005	-0.788

Panel B. HML

	Estimate	SE	t-stat
constant	0.006	0.003	1.734
C1	-0.010	0.011	-0.868
C2	0.004	0.013	0.322
C3	0.003	0.016	0.202
C4	0.008	0.016	0.500
C5	-0.006	0.020	-0.326
C6	0.020	0.020	1.047
C7	-0.007	0.019	-0.388
C1HML	-0.004	0.004	-1.150
C2HML	-0.005	0.004	-1.396
C3HML	0.000	0.005	-0.068
C4HML	0.005	0.006	0.856
C5HML	-0.004	0.006	-0.602
C6HML	-0.011	0.007	-1.580
C7HML	-0.022	0.006	-3.433

Panel C. VOL

	Estimate	SE	t-stat
constant	0.004	0.003	1.111
C1	-0.017	0.014	-1.270
C2	0.002	0.020	0.100
C3	0.055	0.027	2.031

C4	0.111	0.030	3.641
C5	-0.023	0.034	-0.658
C6	-0.001	0.039	-0.036
C7	-0.115	0.040	-2.900
C1VOL	0.000	0.001	0.354
C2VOL	-0.001	0.001	-0.816
C3VOL	-0.002	0.001	-1.582
C4VOL	-0.005	0.001	-3.722
C5VOL	0.001	0.002	0.417
C6VOL	0.001	0.002	0.699
C7VOL	0.004	0.001	2.923

Panel D. LIQ

	Estimate	SE	t-stat
constant	0.007	0.003	2.063
C1	0.001	0.015	0.050
C2	0.013	0.020	0.648
C3	-0.001	0.018	-0.081
C4	0.008	0.021	0.395
C5	0.002	0.023	0.070
C6	0.015	0.025	0.618
C7	0.017	0.034	0.494
C1LIQ	-0.065	0.090	-0.722
C2LIQ	-0.041	0.123	-0.333
C3LIQ	0.105	0.125	0.841
C4LIQ	-0.165	0.159	-1.043
C5LIQ	-0.097	0.142	-0.681
C6LIQ	-0.066	0.095	-0.699
C7LIQ	-0.186	0.126	-1.472

Table 6a. 16. Factor analysis with interactive factors: Negative ARD (12-1 strategy)

Panel A. MKT

	Estimate	SE	t-stat
constant	-0.006	0.003	-2.148
C1	-0.014	0.009	-1.575
C2	-0.004	0.011	-0.346
C3	-0.001	0.012	-0.067
C4	-0.009	0.013	-0.651
C5	0.012	0.014	0.849
C6	-0.008	0.018	-0.432
C7	0.032	0.017	1.865
C1MKT	0.005	0.003	1.711
C2MKT	-0.003	0.002	-1.335

C3MKT	0.005	0.004	1.339
C4MKT	0.007	0.004	1.910
C5MKT	-0.007	0.005	-1.380
C6MKT	-0.003	0.005	-0.488
C7MKT	0.000	0.004	-0.123

Panel B. HML

	Estimate	SE	t-stat
constant	-0.002	0.003	-0.806
C1	-0.004	0.010	-0.378
C2	-0.012	0.012	-1.052
C3	-0.012	0.013	-0.928
C4	-0.006	0.013	-0.426
C5	-0.008	0.015	-0.564
C6	-0.007	0.018	-0.369
C7	0.041	0.019	2.180
C1HML	0.003	0.003	0.960
C2HML	-0.001	0.004	-0.337
C3HML	0.010	0.005	2.189
C4HML	0.007	0.005	1.517
C5HML	0.010	0.007	1.431
C6HML	-0.002	0.006	-0.314
C7HML	-0.013	0.007	-1.901

Panel C. VOL

	Estimate	SE	t-stat
constant	-0.006	0.003	-2.030
C1	-0.028	0.019	-1.477
C2	-0.027	0.021	-1.243
C3	-0.037	0.028	-1.284
C4	-0.004	0.027	-0.137
C5	0.075	0.038	1.982
C6	-0.114	0.045	-2.512
C7	-0.004	0.035	-0.120
C1VOL	0.001	0.001	0.872
C2VOL	0.001	0.001	1.644
C3VOL	0.002	0.001	1.370
C4VOL	0.000	0.001	0.054
C5VOL	-0.004	0.002	-2.316
C6VOL	0.006	0.002	2.620
C7VOL	0.003	0.002	1.347

Panel D. LIQ

	Estimate	SE	t-stat
constant	-0.002	0.003	-0.674
C1	-0.008	0.013	-0.638
C2	-0.001	0.014	-0.058
C3	-0.008	0.015	-0.532
C4	-0.030	0.018	-1.719
C5	0.010	0.016	0.620
C6	-0.005	0.023	-0.231
C7	0.053	0.025	2.113
C1LIQ	0.059	0.089	0.668
C2LIQ	-0.090	0.128	-0.705
C3LIQ	0.139	0.156	0.890
C4LIQ	0.537	0.200	2.688
C5LIQ	-0.194	0.182	-1.062
C6LIQ	-0.150	0.138	-1.088
C7LIQ	-0.004	0.136	-0.031

Table 6a. 17. Factor analysis with interactive factors: Positive ARD (12-1 strategy)

Panel A. MKT

	Estimate	SE	t-stat
constant	-0.001	0.004	-0.318
C1	-0.009	0.013	-0.689
C2	0.004	0.019	0.217
C3	0.007	0.018	0.370
C4	0.010	0.020	0.517
C5	0.014	0.021	0.657
C6	-0.002	0.027	-0.081
C7	0.013	0.025	0.526
C1MKT	-0.010	0.003	-3.688
C2MKT	-0.002	0.004	-0.431
C3MKT	0.003	0.004	0.602
C4MKT	-0.002	0.005	-0.388
C5MKT	0.002	0.006	0.301
C6MKT	-0.004	0.008	-0.514
C7MKT	0.001	0.005	0.172

Panel B. HML

	Estimate	SE	t-stat
constant	-0.002	0.004	-0.405
C1	-0.013	0.012	-1.078
C2	-0.004	0.019	-0.186
C3	0.007	0.019	0.387
C4	0.003	0.022	0.133

C5	0.005	0.024	0.193
C6	0.002	0.024	0.100
C7	0.012	0.024	0.499
C1HML	0.000	0.004	-0.031
C2HML	-0.006	0.006	-0.872
C3HML	0.005	0.006	0.843
C4HML	0.002	0.007	0.284
C5HML	-0.005	0.007	-0.622
C6HML	-0.028	0.010	-2.923
C7HML	-0.016	0.009	-1.861

Panel C. VOL

	Estimate	SE	t-stat
constant	-0.001	0.004	-0.153
C1	0.010	0.024	0.432
C2	-0.020	0.034	-0.567
C3	0.101	0.042	2.413
C4	0.103	0.034	3.079
C5	-0.003	0.045	-0.058
C6	0.137	0.045	3.052
C7	-0.012	0.044	-0.271
C1VOL	-0.001	0.001	-0.921
C2VOL	0.000	0.002	-0.086
C3VOL	-0.004	0.002	-1.990
C4VOL	-0.005	0.002	-2.659
C5VOL	0.001	0.003	0.506
C6VOL	-0.007	0.003	-2.772
C7VOL	-0.001	0.002	-0.384

Panel D. LIQ

	Estimate	SE	t-stat
constant	-0.002	0.005	-0.333
C1	-0.014	0.023	-0.616
C2	0.019	0.021	0.909
C3	0.009	0.022	0.397
C4	0.013	0.026	0.488
C5	0.000	0.027	0.016
C6	0.005	0.032	0.146
C7	0.024	0.032	0.758
C1LIQ	-0.078	0.136	-0.577
C2LIQ	-0.492	0.302	-1.625
C3LIQ	-0.021	0.262	-0.081
C4LIQ	-0.256	0.356	-0.718

C5LIQ	0.377	0.352	1.072
C6LIQ	-0.216	0.253	-0.853
C7LIQ	-0.027	0.226	-0.120

Table 6b. 1. Jordan macroeconomic models for time-series industry momentum

Panel B. 6-1 strategy

	M1	M2	M3	M4	M5	M6	M7
constant	0.007	0.006	0.007	0.006	0.007	0.005	0.008
t-stat	2.582	2.155	2.640	2.332	2.841	1.540	2.573
MKT		0.002		0.002	0.001	0.002	0.001
t-stat		1.071		1.081	0.560	1.113	0.571
JAN			-0.006	-0.007			-0.006
t-stat			-0.586	-0.636			-0.661
TS*MKT					0.005		0.005
t-stat					3.981		4.033
DS*MKT					-0.008		-0.008
t-stat					-2.906		-2.945
TB*MKT					0.002		0.002
t-stat					3.247		3.257
DY*MKT					-0.004		-0.004
t-stat					-1.991		-1.976
TS						0.002	-0.001
t-stat						0.502	-0.365
DS						-0.005	0.000
t-stat						-0.479	0.060
TB						0.001	0.000
t-stat						0.751	-0.010
DY						-0.003	0.001
t-stat						-0.615	0.183

Table 6b. 2. Jordan macroeconomic models for information discreteness grouped time-series industry momentum

Panel C. Negative ID time-series industry momentum (6-1 strategy)

	M1	M2	M3	M4	M5	M6	M7
constant	0.008	0.007	0.009	0.008	0.008	0.008	0.010
t-stat	2.877	2.307	2.948	2.494	2.979	2.104	3.041
MKT		0.002		0.002	0.002	0.002	0.002
t-stat		1.181		1.191	0.864	1.219	0.871
JAN			-0.007	-0.008			-0.008
t-stat			-0.673	-0.726			-0.787
TS*MKT					0.004		0.004
t-stat					3.035		3.097
DS*MKT					-0.009		-0.009
t-stat					-3.043		-3.093
TB*MKT					0.002		0.002

	M1	M2	M3	M4	M5	M6	M7
t-stat					2.593		2.620
DY*MKT					-0.004		-0.004
t-stat					-1.774		-1.774
TS						0.000	-0.002
t-stat						-0.023	-0.843
DS						-0.008	-0.001
t-stat						-0.730	-0.134
TB						0.001	0.000
t-stat						0.454	-0.241
DY						-0.001	0.003
t-stat						-0.233	0.624

Panel D. Positive ID time-series industry momentum (6-1 strategy)

	M1	M2	M3	M4	M5	M6	M7
constant	0.003	0.003	0.002	0.002	0.004	-0.002	-0.001
t-stat	1.059	0.899	0.626	0.516	1.136	-0.466	-0.278
MKT		0.001		0.001	0.000	0.001	0.000
t-stat		0.766		0.737	0.209	0.750	0.187
JAN			0.015	0.014			0.015
t-stat			1.340	1.167			1.369
TS*MKT					0.003		0.003
t-stat					2.724		2.783
DS*MKT					-0.001		-0.001
t-stat					-0.229		-0.249
TB*MKT					0.002		0.002
t-stat					2.545		2.533
DY*MKT					0.000		0.000
t-stat					0.008		-0.012
TS						0.006	0.003
t-stat						1.914	1.173
DS						0.010	0.006
t-stat						0.943	0.739
TB						0.002	0.001
t-stat						1.106	0.609
DY						-0.005	-0.005
t-stat						-1.067	-1.114

Table 6b. 3. Jordan macroeconomic models for abnormal return volatility grouped time-series industry momentum

Panel C. Negative ARD time-series industry momentum (6-1 strategy)

	M1	M2	M3	M4	M5	M6	M7
constant	0.004	0.004	0.005	0.005	0.004	0.004	0.004
t-stat	1.803	1.663	1.967	1.806	1.509	1.174	1.050
MKT		0.000		0.000	0.002	0.000	0.001
t-stat		0.487		0.510	1.568	0.327	1.426

	M1	M2	M3	M4	M5	M6	M7
JAN			-0.007	-0.008			-0.009
t-stat			-0.836	-0.932			-1.159
TS*MKT					-0.002		-0.002
t-stat					-3.155		-3.076
DS*MKT					-0.001		-0.001
t-stat					-0.563		-0.606
TB*MKT					-0.001		-0.001
t-stat					-2.065		-2.014
DY*MKT					0.001		0.001
t-stat					1.181		1.164
TS						-0.006	-0.004
t-stat						-2.064	-1.630
DS						0.008	0.010
t-stat						1.018	1.308
TB						-0.004	-0.003
t-stat						-2.485	-2.214
DY						0.001	0.001
t-stat						0.263	0.165

Panel D. Positive ARD time-series industry momentum (6-1 strategy)

	M1	M2	M3	M4	M5	M6	M7
constant	0.005	0.004	0.004	0.003	0.005	0.000	0.001
t-stat	1.871	1.487	1.570	1.246	1.946	-0.041	0.176
MKT		0.002		0.002	0.001	0.002	0.001
t-stat		1.615		1.602	0.764	1.544	0.662
JAN			0.007	0.006			0.008
t-stat			0.771	0.599			0.770
TS*MKT					0.002		0.002
t-stat					2.205		2.215
DS*MKT					-0.003		-0.003
t-stat					-1.054		-1.206
TB*MKT					0.001		0.001
t-stat					2.210		2.256
DY*MKT					-0.003		-0.003
t-stat					-1.714		-1.771
TS						0.001	0.000
t-stat						0.358	-0.156
DS						0.008	0.013
t-stat						0.633	1.585
TB						-0.001	-0.002
t-stat						-0.678	-1.423
DY						-0.005	-0.003
t-stat						-1.114	-0.720

Table 6b. 4. Jordan conditional model for time-series industry momentum returns

Panel A. Full model conditioning on HML (Strategy 6-1)			
	Estimate	SE	t-stat
constant	0.004	0.003	1.327
MKT	0.003	0.001	2.007
HML	0.003	0.003	1.326
TS	0.004	0.003	1.113
DS	-0.013	0.009	-1.488
TB	0.003	0.002	1.597
DY	-0.004	0.004	-0.786
TS*HML	-0.001	0.002	-0.795
DS*HML	-0.013	0.003	-4.390
TB*HML	0.000	0.001	-0.307
DY*HML	0.002	0.003	0.755

Panel B. Full model conditioning on VOL (Strategy 6-1)			
	Estimate	SE	t-stat
constant	0.028	0.010	2.638
MKT	0.002	0.001	1.422
VOL	-0.001	0.001	-1.985
TS	-0.002	0.006	-0.397
DS	-0.015	0.015	-0.972
TB	-0.003	0.004	-0.775
DY	0.009	0.012	0.741
TS*VOL	0.000	0.000	0.523
DS*VOL	0.001	0.001	1.424
TB*VOL	0.000	0.000	1.128
DY*VOL	-0.001	0.001	-1.133

Panel C. Full model conditioning on LIQ (Strategy 6-1)			
	Estimate	SE	t-stat
constant	0.003	0.005	0.661
MKT	0.002	0.002	1.201
LIQ	0.025	0.015	1.694
TS	0.002	0.004	0.498
DS	0.002	0.012	0.144
TB	0.001	0.002	0.498
DY	-0.003	0.005	-0.516
TS*LIQ	0.060	0.056	1.064
DS*LIQ	-0.255	0.148	-1.729
TB*LIQ	0.044	0.028	1.560
DY*LIQ	-0.070	0.056	-1.251

Table 6b. 5. Jordan conditional model for negative ID Time-series industry momentum returns

Panel A. Full model conditioning on HML (Strategy 6-1)			
	Estimate	SE	t-stat

constant	0.007	0.004	1.925
MKT	0.003	0.002	2.149
HML	0.003	0.003	1.177
TS	0.002	0.003	0.547
DS	-0.017	0.009	-1.908
TB	0.002	0.002	1.262
DY	-0.002	0.005	-0.400
TS*HML	-0.001	0.002	-0.659
DS*HML	-0.013	0.003	-4.363
TB*HML	0.000	0.001	-0.085
DY*HML	0.002	0.003	0.773

Panel B. Full model conditioning on VOL (Strategy 6-1)

	Estimate	SE	t-stat
constant	0.028	0.009	3.008
MKT	0.002	0.002	1.389
VOL	-0.001	0.001	-2.017
TS	-0.003	0.005	-0.504
DS	-0.022	0.014	-1.512
TB	-0.003	0.004	-0.793
DY	0.010	0.011	0.856
TS*VOL	0.000	0.000	0.322
DS*VOL	0.001	0.001	1.753
TB*VOL	0.000	0.000	1.113
DY*VOL	-0.001	0.001	-1.190

Panel C. Full model conditioning on LIQ (Strategy 6-1)

	Estimate	SE	t-stat
constant	0.004	0.005	0.933
MKT	0.003	0.002	1.324
LIQ	0.030	0.015	1.984
TS	0.000	0.004	0.041
DS	0.001	0.013	0.117
TB	0.000	0.002	0.235
DY	-0.002	0.005	-0.339
TS*LIQ	0.079	0.061	1.281
DS*LIQ	-0.351	0.151	-2.318
TB*LIQ	0.058	0.031	1.863
DY*LIQ	-0.070	0.060	-1.158

Table 6b. 6. Jordan conditional model for positive ID Time-series industry momentum returns

Panel A. Full model conditioning on HML (Strategy 6-1)

	Estimate	SE	t-stat
constant	-0.003	0.004	-0.668
MKT	0.001	0.001	0.857

HML	0.003	0.002	1.324
TS	0.008	0.003	2.153
DS	0.009	0.011	0.785
TB	0.003	0.002	1.353
DY	-0.007	0.005	-1.311
TS*HML	-0.002	0.002	-1.046
DS*HML	-0.007	0.004	-1.810
TB*HML	-0.001	0.001	-0.890
DY*HML	0.002	0.003	0.706

Panel B. Full model conditioning on VOL (Strategy 6-1)

	Estimate	SE	t-stat
constant	0.021	0.011	1.985
MKT	0.001	0.001	0.763
VOL	-0.002	0.001	-2.032
TS	-0.002	0.005	-0.394
DS	0.011	0.018	0.629
TB	0.001	0.005	0.224
DY	-0.001	0.011	-0.099
TS*VOL	0.000	0.000	1.527
DS*VOL	0.000	0.001	0.496
TB*VOL	0.000	0.000	0.191
DY*VOL	0.000	0.001	-0.679

Panel C. Full model conditioning on LIQ (Strategy 6-1)

	Estimate	SE	t-stat
constant	0.003	0.006	0.563
MKT	0.001	0.001	0.695
LIQ	-0.002	0.022	-0.103
TS	0.006	0.004	1.748
DS	0.006	0.012	0.511
TB	0.002	0.002	1.229
DY	-0.001	0.006	-0.241
TS*LIQ	-0.116	0.085	-1.367
DS*LIQ	0.256	0.179	1.431
TB*LIQ	-0.068	0.043	-1.604
DY*LIQ	-0.063	0.063	-1.007

Table 6b. 7. Negative ARD Time-series industry momentum returns: conditional models (Strategy 6-1)

Panel A. HML

	Estimate	SE	t-stat
constant	0.004	0.004	1.059
MKT	0.000	0.001	0.148
HML	-0.001	0.001	-0.396

TS	-0.006	0.003	-2.092
DS	0.009	0.007	1.257
TB	-0.004	0.002	-2.532
DY	0.001	0.005	0.229
TS*HML	0.000	0.001	0.306
DS*HML	0.002	0.002	0.984
TB*HML	0.000	0.000	0.146
DY*HML	0.000	0.001	0.126

Panel B. VOL

	Estimate	SE	t-stat
constant	0.013	0.008	1.560
MKT	0.000	0.001	0.526
VOL	0.000	0.001	-0.885
TS	-0.012	0.005	-2.307
DS	-0.003	0.013	-0.253
TB	-0.005	0.003	-1.881
DY	0.024	0.009	2.652
TS*VOL	0.000	0.000	1.089
DS*VOL	0.000	0.001	0.695
TB*VOL	0.000	0.000	0.421
DY*VOL	-0.001	0.001	-2.063

Panel C. LIQ

	Estimate	SE	t-stat
constant	0.007	0.004	1.863
MKT	0.000	0.001	0.402
LIQ	0.018	0.019	0.948
TS	-0.008	0.003	-2.736
DS	0.006	0.010	0.623
TB	-0.005	0.002	-2.921
DY	0.007	0.005	1.359
TS*LIQ	0.045	0.055	0.810
DS*LIQ	0.015	0.143	0.105
TB*LIQ	0.011	0.028	0.383
DY*LIQ	-0.145	0.057	-2.524

Table 6b. 8. Positive ARD time-series industry momentum returns: conditional models (Strategy 6-1)

Panel A. HML

	Estimate	SE	t-stat
constant	-0.002	0.004	-0.440
MKT	0.003	0.001	2.551
HML	0.004	0.002	2.103
TS	0.001	0.003	0.469

DS	0.007	0.008	0.936
TB	-0.001	0.002	-0.793
DY	-0.006	0.005	-1.276
TS*HML	0.000	0.001	-0.144
DS*HML	-0.013	0.003	-4.227
TB*HML	0.000	0.001	0.615
DY*HML	0.003	0.002	1.505

Panel B. VOL

	Estimate	SE	t-stat
constant	0.023	0.010	2.436
MKT	0.002	0.001	1.640
VOL	-0.001	0.001	-2.127
TS	-0.018	0.005	-3.649
DS	0.011	0.023	0.495
TB	-0.007	0.004	-1.666
DY	0.020	0.012	1.646
TS*VOL	0.001	0.000	3.924
DS*VOL	0.000	0.001	0.213
TB*VOL	0.000	0.000	1.179
DY*VOL	-0.001	0.001	-2.025

Panel C. LIQ

	Estimate	SE	t-stat
constant	0.001	0.005	0.230
MKT	0.002	0.001	1.733
LIQ	0.043	0.022	1.967
TS	-0.002	0.003	-0.555
DS	0.012	0.015	0.802
TB	-0.002	0.002	-1.277
DY	-0.001	0.005	-0.130
TS*LIQ	0.119	0.077	1.553
DS*LIQ	-0.202	0.210	-0.963
TB*LIQ	0.046	0.039	1.179
DY*LIQ	-0.185	0.078	-2.364

Table 6b. 9. Factor analysis (6-1 strategy)

	Estimate	SE	t-stat
constant	0.007	0.003	2.549
PC1	-0.002	0.010	-0.192
PC2	-0.014	0.011	-1.215
PC3	-0.001	0.014	-0.091

PC4	-0.005	0.016	-0.316
PC5	0.008	0.013	0.659
PC6	0.006	0.021	0.275
PC7	-0.032	0.022	-1.429

Table 6b. 10. Factor analysis (6-1 strategy)

Panel A. Negative ID

	Estimate	SE	t-stat
constant	0.008	0.003	2.838
PC1	0.000	0.011	0.031
PC2	-0.012	0.014	-0.844
PC3	-0.009	0.014	-0.632
PC4	-0.012	0.018	-0.665
PC5	0.010	0.014	0.690
PC6	-0.002	0.022	-0.089
PC7	-0.035	0.027	-1.311

Panel B. Positive ID

	Coefficient	Standard Error	t-value
constant	0.003	0.003	1.049
PC1	-0.006	0.011	-0.528
PC2	0.005	0.014	0.334
PC3	0.026	0.013	1.984
PC4	0.010	0.018	0.540
PC5	-0.018	0.017	-1.069
PC6	0.044	0.021	2.161
PC7	-0.015	0.023	-0.635

Panel C. Negative ARD

	Estimate	SE	t-stat
constant	0.004	0.002	1.801
PC1	0.005	0.007	0.725
PC2	0.028	0.009	3.000
PC3	0.024	0.011	2.256
PC4	-0.010	0.011	-0.896
PC5	-0.004	0.013	-0.322
PC6	-0.008	0.013	-0.620
PC7	0.027	0.017	1.589

Panel D. Positive ARD

	Coefficient	Standard Error	t-value
constant	0.005	0.002	2.059
PC1	0.002	0.012	0.195
PC2	0.008	0.009	0.915
PC3	0.028	0.013	2.167

PC4	-0.006	0.014	-0.457
PC5	0.006	0.013	0.494
PC6	-0.006	0.017	-0.382
PC7	-0.018	0.016	-1.097

Table 6b. 11. Factor analysis with interactive factors (6-1 strategy)

Panel A. MKT

	Estimate	SE	t-stat
constant	0.011	0.002	4.716
PC1	0.012	0.007	1.708
PC2	-0.004	0.012	-0.329
PC3	-0.004	0.010	-0.359
PC4	0.019	0.014	1.378
PC5	-0.002	0.013	-0.134
PC6	0.029	0.017	1.759
PC7	-0.029	0.017	-1.771
PC1MKT	-0.013	0.002	-5.864
PC2MKT	0.001	0.003	0.503
PC3MKT	0.003	0.004	0.609
PC4MKT	-0.006	0.004	-1.424
PC5MKT	0.002	0.005	0.477
PC6MKT	-0.012	0.005	-2.359
PC7MKT	0.002	0.004	0.651

Panel B. HML

	Estimate	SE	t-stat
constant	0.006	0.003	2.479
PC1	-0.004	0.008	-0.444
PC2	-0.007	0.012	-0.583
PC3	0.009	0.012	0.742
PC4	-0.003	0.015	-0.208
PC5	0.013	0.014	0.935
PC6	0.014	0.020	0.699
PC7	-0.039	0.024	-1.607
PC1HML	-0.005	0.003	-1.994
PC2HML	-0.005	0.004	-1.318
PC3HML	-0.008	0.005	-1.547
PC4HML	-0.004	0.005	-0.882
PC5HML	-0.009	0.008	-1.112
PC6HML	-0.014	0.006	-2.356
PC7HML	0.001	0.008	0.147

Panel C. VOL

	Estimate	SE	t-stat
constant	0.008	0.003	2.937
PC1	0.014	0.014	1.049
PC2	0.006	0.016	0.371
PC3	0.062	0.025	2.447
PC4	0.104	0.033	3.191
PC5	-0.045	0.030	-1.506
PC6	0.112	0.029	3.844
PC7	-0.081	0.033	-2.437
PC1VOL	-0.001	0.001	-0.937
PC2VOL	-0.002	0.001	-2.574
PC3VOL	-0.003	0.001	-2.585
PC4VOL	-0.005	0.002	-3.469
PC5VOL	0.003	0.002	1.886
PC6VOL	-0.005	0.002	-3.034
PC7VOL	0.001	0.002	0.554

Panel D. LIQ

	Estimate	SE	t-stat
constant	0.006	0.003	2.188
PC1	0.002	0.014	0.145
PC2	-0.008	0.013	-0.630
PC3	0.010	0.016	0.580
PC4	0.020	0.018	1.094
PC5	0.007	0.015	0.444
PC6	0.015	0.023	0.654
PC7	-0.041	0.026	-1.599
PC1LIQ	-0.096	0.095	-1.017
PC2LIQ	-0.071	0.098	-0.725
PC3LIQ	-0.173	0.123	-1.411
PC4LIQ	-0.493	0.209	-2.357
PC5LIQ	0.117	0.167	0.702
PC6LIQ	-0.036	0.083	-0.435
PC7LIQ	0.016	0.128	0.124

Table 6b. 12. Factor analysis with interactive factors: Negative ID (6-1 strategy)

Panel A. MKT

	Estimate	SE	t-stat
constant	0.013	0.003	4.843
PC1	0.015	0.008	1.917
PC2	-0.004	0.013	-0.284
PC3	-0.013	0.011	-1.227

PC4	0.016	0.015	1.095
PC5	0.000	0.015	-0.015
PC6	0.031	0.018	1.706
PC7	-0.036	0.018	-1.982
PC1MKT	-0.014	0.002	-6.129
PC2MKT	0.000	0.003	0.034
PC3MKT	0.004	0.004	1.029
PC4MKT	-0.007	0.004	-1.880
PC5MKT	-0.001	0.006	-0.157
PC6MKT	-0.017	0.005	-3.234
PC7MKT	0.000	0.004	-0.070

Panel B. HML

	Estimate	SE	t-stat
constant	0.008	0.003	2.817
PC1	-0.002	0.009	-0.219
PC2	-0.005	0.014	-0.380
PC3	0.003	0.012	0.213
PC4	-0.009	0.017	-0.562
PC5	0.015	0.015	1.032
PC6	0.007	0.021	0.332
PC7	-0.043	0.027	-1.599
PC1HML	-0.005	0.003	-1.970
PC2HML	-0.006	0.004	-1.380
PC3HML	-0.008	0.005	-1.605
PC4HML	-0.005	0.005	-1.031
PC5HML	-0.010	0.008	-1.188
PC6HML	-0.015	0.006	-2.287
PC7HML	-0.001	0.009	-0.123

Panel C. VOL

	Estimate	SE	t-stat
constant	0.009	0.003	3.048
PC1	0.016	0.014	1.117
PC2	0.006	0.017	0.378
PC3	0.066	0.028	2.356
PC4	0.113	0.033	3.380
PC5	-0.042	0.035	-1.215
PC6	0.102	0.032	3.214
PC7	-0.108	0.033	-3.230
PC1VOL	-0.001	0.001	-0.953
PC2VOL	-0.002	0.001	-2.680
PC3VOL	-0.003	0.001	-2.658

PC4VOL	-0.006	0.002	-4.000
PC5VOL	0.003	0.002	1.540
PC6VOL	-0.005	0.002	-2.684
PC7VOL	0.002	0.001	1.205

Panel D. LIQ

	Estimate	SE	t-stat
constant	0.007	0.003	2.323
PC1	0.005	0.014	0.377
PC2	-0.005	0.016	-0.304
PC3	0.004	0.017	0.244
PC4	0.017	0.020	0.825
PC5	0.009	0.017	0.508
PC6	0.008	0.024	0.338
PC7	-0.049	0.031	-1.572
PC1LIQ	-0.123	0.097	-1.271
PC2LIQ	-0.094	0.108	-0.873
PC3LIQ	-0.222	0.131	-1.695
PC4LIQ	-0.542	0.222	-2.442
PC5LIQ	0.139	0.167	0.829
PC6LIQ	-0.034	0.088	-0.387
PC7LIQ	0.077	0.131	0.590

Table 6b. 13. Factor analysis with interactive factors: Positive ID (6-1 strategy)

Panel A.

	Estimate	SE	t-stat
constant	0.005	0.003	1.633
PC1	-0.002	0.009	-0.206
PC2	0.000	0.012	0.007
PC3	0.034	0.014	2.544
PC4	-0.003	0.016	-0.173
PC5	-0.028	0.016	-1.815
PC6	0.024	0.018	1.279
PC7	-0.017	0.019	-0.875
PC1MKT	-0.004	0.003	-1.153
PC2MKT	0.001	0.003	0.371
PC3MKT	-0.012	0.005	-2.636
PC4MKT	0.002	0.004	0.401
PC5MKT	0.013	0.005	2.376
PC6MKT	0.018	0.006	2.910
PC7MKT	0.005	0.004	1.241

Panel B. HML

	Estimate	SE	t-stat
constant	0.003	0.003	0.964
PC1	-0.006	0.010	-0.641
PC2	0.000	0.014	0.026
PC3	0.024	0.014	1.652
PC4	0.011	0.019	0.565
PC5	-0.021	0.018	-1.122
PC6	0.049	0.021	2.383
PC7	-0.020	0.024	-0.862
PC1HML	-0.001	0.005	-0.107
PC2HML	-0.002	0.005	-0.522
PC3HML	-0.001	0.005	-0.294
PC4HML	0.008	0.007	1.098
PC5HML	0.007	0.006	1.120
PC6HML	0.003	0.008	0.434
PC7HML	-0.003	0.009	-0.357

Panel C. VOL

	Estimate	SE	t-stat
constant	0.004	0.003	1.184
PC1	-0.002	0.016	-0.114
PC2	-0.002	0.027	-0.062
PC3	0.002	0.027	0.083
PC4	0.038	0.039	0.983
PC5	-0.026	0.030	-0.888
PC6	0.073	0.035	2.067
PC7	0.008	0.044	0.184
PC1VOL	0.000	0.001	-0.316
PC2VOL	0.000	0.001	0.275
PC3VOL	0.001	0.001	0.906
PC4VOL	-0.001	0.002	-0.700
PC5VOL	0.000	0.002	0.308
PC6VOL	-0.002	0.002	-0.959
PC7VOL	-0.001	0.002	-0.543

Panel D. LIQ

	Estimate	SE	t-stat
constant	0.005	0.003	1.452
PC1	-0.006	0.014	-0.428
PC2	0.003	0.015	0.176
PC3	0.020	0.016	1.281
PC4	0.012	0.021	0.586
PC5	-0.026	0.019	-1.381

PC6	0.045	0.022	2.023
PC7	0.000	0.027	0.018
PC1LIQ	0.029	0.082	0.353
PC2LIQ	0.089	0.115	0.774
PC3LIQ	0.133	0.129	1.029
PC4LIQ	-0.173	0.211	-0.818
PC5LIQ	0.059	0.146	0.405
PC6LIQ	-0.027	0.107	-0.252
PC7LIQ	-0.274	0.132	-2.084

Table 6b. 14. Factor analysis with interactive factors: Negative ARD (6-1 strategy)

Panel A. MKT

	Estimate	SE	t-stat
constant	0.004	0.003	1.691
PC1	0.005	0.007	0.637
PC2	0.028	0.009	3.078
PC3	0.025	0.011	2.349
PC4	-0.010	0.011	-0.947
PC5	-0.001	0.013	-0.062
PC6	-0.005	0.013	-0.350
PC7	0.028	0.017	1.651
PC1MKT	0.002	0.002	1.386
PC2MKT	-0.001	0.002	-0.242
PC3MKT	-0.001	0.003	-0.307
PC4MKT	0.000	0.003	0.017
PC5MKT	0.001	0.004	0.213
PC6MKT	-0.005	0.004	-1.160
PC7MKT	-0.003	0.004	-0.768

Panel B. HML

	Estimate	SE	t-stat
constant	0.004	0.002	1.748
PC1	0.004	0.007	0.481
PC2	0.024	0.008	2.935
PC3	0.028	0.011	2.618
PC4	-0.007	0.010	-0.723
PC5	-0.003	0.011	-0.316
PC6	-0.004	0.014	-0.269
PC7	0.021	0.017	1.237
PC1HML	0.004	0.001	2.605
PC2HML	-0.005	0.003	-1.914
PC3HML	-0.002	0.003	-0.791
PC4HML	0.007	0.004	1.854

PC5HML	0.002	0.004	0.510
PC6HML	-0.001	0.004	-0.279
PC7HML	-0.008	0.005	-1.514

Panel C. VOL

	Estimate	SE	t-stat
constant	0.004	0.002	1.860
PC1	0.019	0.011	1.763
PC2	-0.007	0.015	-0.464
PC3	-0.030	0.022	-1.340
PC4	-0.027	0.018	-1.473
PC5	0.006	0.034	0.183
PC6	-0.027	0.027	-0.997
PC7	-0.008	0.027	-0.315
PC1VOL	-0.001	0.000	-1.800
PC2VOL	0.002	0.001	2.573
PC3VOL	0.003	0.001	2.572
PC4VOL	0.001	0.001	1.233
PC5VOL	-0.001	0.002	-0.474
PC6VOL	0.001	0.001	0.876
PC7VOL	0.002	0.001	1.529

Panel D. LIQ

	Estimate	SE	t-stat
constant	0.004	0.002	1.841
PC1	0.019	0.007	2.889
PC2	0.023	0.011	2.142
PC3	0.012	0.010	1.168
PC4	-0.012	0.012	-0.989
PC5	-0.026	0.013	-1.975
PC6	-0.002	0.013	-0.131
PC7	0.035	0.019	1.837
PC1LIQ	-0.217	0.063	-3.420
PC2LIQ	0.020	0.129	0.154
PC3LIQ	-0.029	0.126	-0.232
PC4LIQ	0.058	0.111	0.521
PC5LIQ	0.449	0.113	3.961
PC6LIQ	-0.026	0.076	-0.338
PC7LIQ	-0.061	0.076	-0.800

Table 6b. 15. Factor analysis with interactive factors: Positive ARD (6-1 strategy)

Panel A. MKT

	Estimate	SE	t-stat
constant	0.009	0.003	3.535
PC1	0.015	0.011	1.361
PC2	0.009	0.010	0.907
PC3	0.029	0.012	2.410
PC4	0.002	0.013	0.119
PC5	-0.002	0.013	-0.170
PC6	0.004	0.015	0.286
PC7	-0.013	0.017	-0.753
PC1MKT	-0.008	0.002	-3.438
PC2MKT	0.002	0.002	0.937
PC3MKT	-0.004	0.003	-1.166
PC4MKT	-0.006	0.003	-1.897
PC5MKT	0.005	0.005	1.026
PC6MKT	-0.003	0.004	-0.719
PC7MKT	0.000	0.003	0.096

Panel B. HML

	Estimate	SE	t-stat
constant	0.005	0.002	1.997
PC1	0.005	0.011	0.495
PC2	0.009	0.010	0.862
PC3	0.042	0.014	3.098
PC4	-0.009	0.014	-0.675
PC5	0.017	0.016	1.109
PC6	-0.004	0.016	-0.278
PC7	-0.021	0.017	-1.186
PC1HML	-0.004	0.003	-1.101
PC2HML	0.002	0.004	0.521
PC3HML	-0.008	0.004	-1.766
PC4HML	0.001	0.005	0.192
PC5HML	-0.013	0.006	-2.242
PC6HML	-0.010	0.005	-2.029
PC7HML	0.000	0.005	0.055

Panel C. VOL

	Estimate	SE	t-stat
constant	0.008	0.002	3.214
PC1	0.037	0.018	2.066
PC2	0.008	0.017	0.456
PC3	0.033	0.026	1.265

PC4	0.043	0.029	1.502
PC5	-0.044	0.030	-1.475
PC6	0.148	0.034	4.383
PC7	-0.061	0.032	-1.866
PC1VOL	-0.001	0.001	-1.404
PC2VOL	-0.001	0.001	-0.542
PC3VOL	0.000	0.001	0.087
PC4VOL	-0.002	0.001	-1.710
PC5VOL	0.003	0.002	1.882
PC6VOL	-0.007	0.002	-4.224
PC7VOL	0.001	0.001	0.559

Panel D. LIQ

	Estimate	SE	t-stat
constant	0.005	0.002	1.898
PC1	0.013	0.011	1.157
PC2	0.014	0.010	1.393
PC3	0.026	0.014	1.779
PC4	0.020	0.016	1.218
PC5	-0.015	0.016	-0.914
PC6	0.002	0.018	0.107
PC7	-0.027	0.019	-1.440
PC1LIQ	-0.203	0.095	-2.143
PC2LIQ	-0.204	0.106	-1.914
PC3LIQ	-0.066	0.113	-0.584
PC4LIQ	-0.510	0.160	-3.193
PC5LIQ	0.472	0.143	3.307
PC6LIQ	-0.023	0.083	-0.274
PC7LIQ	0.059	0.106	0.558

Table 6b. 16. Components[4] of the common processes

PC1	PC2	PC3	PC4	PC5	PC6	PC7
PAYEMS	CUSR0000SAC	AAAFFM	GS1	T1YFFM	AWHMAN	S&P 500
USGOOD	DNDGRG3M086SBEA	T10YFFM	GS5	TB6SMFFM	CES0600000007	S&P: indust
IPMANSICS	CUSR0000SA0L2	BAAFFM	AAA	T5YFFM	S&P PE ratio	S&P div yield
INDPRO	CPIAUCSL	T5YFFM	TB6MS	TB3SMFFM	UEMP15OV	UMCSENTx
MANEMP	CUSR0000SA0L5	TB3SMFFM	GS10	PERMIT	ACOGNO	S&P PE ratio
IPFPNSS	CPITRNSL	TB6SMFFM	BAA	PERMITW	S&P div yield	VXOCLSx
DMANEMP	PCEPI	T1YFFM	CP3Mx	HOUSTW	UEMP27OV	IPCONGD
CUMFNS	CPIULFSL	HOUST	TB3MS	T10YFFM	ISRATIOx	IPFINAL
IPFINAL	WPSFD49502	HOUSTMW	TWEXMMTH	HOUST	S&P 500	IPDCONGD
IPDMAT	WPSFD49207	HOUSTNE	S&P div yield	PERMITMW	S&P: indust	IPNCONGD

[4] The definition of the abbreviations can be found on the website of Research Division of Federal Reserve Bank of St. Louis by Michael W. McCracken

Chapter 7 Conclusion and limitations

7.1 Introduction

Time-series momentum returns are linked to information diffusion in Moskowitz et al. (2012) in the futures market. However, no specific elements of information diffusion are constructed to test the relationship to understand what elements of information diffusion are relevant/irrelevant in the relationship. To fill this gap, the first empirical chapter deals with the relationship between information diffusion and the time-series momentum effect at the global asset class level, by adopting three different elements of information diffusion (i.e., information discreteness, abnormal return volatility, and abnormal turnover).

The time-series momentum effect is initially studied in broad asset classes, and only recently it has been extended to individual stocks (Goyal and Jegadeesh, 2018; Lim et al., 2018). Before the current study, no time-series momentum studies occur at the industry level. Since industry as an analysis unit is important in corporate finance literature, and in literatures for practitioners, the second empirical chapter focuses on the existence of the time-series industry momentum and the influence of information diffusion on time-series industry momentum.

The correlation among industry returns and time-series industry momentum returns indicates potential common processes that drive the co-movement. Therefore, the third empirical chapter deals with the influence of time-varying risk on time-series industry momentum returns.

7.2 Research scope

The objectives of this study are to: 1) to examine the impact of information diffusion on time-series momentum returns; 2) to examine the existence of the time-series industry momentum effect; and 3) to study the influence of time-varying risk on time-series industry momentum. To fulfil these objectives, the following aspects are studied.

First, the three elements of information diffusion (i.e., information discreteness, abnormal return volatility, and abnormal turnover) are adopted to study the influence of information diffusion on time-series momentum returns. Information discreteness captures whether information arrives in small pieces or large chunks, abnormal return volatility captures the noise level of the information, and abnormal turnover captures investor attention to information.

Second, the data from 49 US industries are collected to study the time-series industry momentum effect. Since there are a lot of common movements of firms within an industry, the study on the existence of the time-series industry momentum effect may provide hints for time-series individual stock momentum researchers on whether they should include the industry components in future studies. This uncovers whether it is the industries, the individual firms, or the mutual influence of the two, that leads to time series momentum effect at the individual stock level. In addition, the study of time-series industry momentum may provide potential asset tactical allocation methods for fund managers. Furthermore, compared to cross-sectional industry momentum, time-series industry momentum strategies are a more direct application of mainstream behavioural theories. This is because the time-series strategies do not involve cross-industry comparisons, which directly match the prediction of behavioural models, demonstrating that investor underreaction to prior asset price information, induced by slow information diffusion, leads to momentum returns. Since the US market leads global market, it is a good starting point to study the existence of the time-series industry momentum effect. The strategy returns under good and bad market states defined in NBER business cycle are also shown.

Finally, value premium, market volatility, and market liquidity, the three risk factors that are related to market equity risk premium, are introduced as conditional time-varying risk factors to Jordan (2012) style CAPM conditional macroeconomic models, to examine the influence of time-varying risk on time-series industry momentum. Compared to prior studies on time-series momentum, a wider range of factors, that cover broad macroeconomic common processes and cover narrow macroeconomic factors that are related to financial risk, are included in this study.

7.3 Key Research Questions

7.3.1 Research question 1: Is time-series momentum effect influenced by information diffusion?

Chapter 4 (empirical chapter 1) examines the relationship between the time-series momentum effect and information diffusion in global equity indices and commodity indices. Three different elements of information diffusions are adopted. These are: information discreteness, which captures whether the information comes in small pieces or large chunks; abnormal return volatility, which captures the noise level of information; and abnormal turnover, which captures investor attention shocks.

7.3.2 Research question 2: Does time-series industry momentum effect exist? If it exists, what is the impact of information diffusion on time-series industry momentum?

Chapter 5 (empirical chapter 2) examines the existence of the time-series industry momentum effect, and the relationship between information diffusion and time-series industry momentum. Due to industry data availability, only information discreteness and abnormal turnover are adopted as two elements of information diffusion.

7.3.3 Research question 3: What is the role of time-varying risk in time-series industry momentum?

Chapter 6 (empirical chapter 3) examines the relationship between time-varying risk and time-series industry momentum. Value premium, market volatility, and market liquidity are risk factors that are related to market equity premium and economic growth. Therefore, they are candidates for time-varying risks in this study, and they are novel time-varying risks that are introduced to time-series momentum literature.

7.4 Key Findings

7.4.1 Chapter 4 (empirical chapter 1)

The main findings for the first empirical chapter on the relationship between the time-series momentum effect and information diffusion at the global asset class level are that: 1) TSM profits are clustered in a continuous information environment, and they disappear in a discrete information environment; 2) it is the enhanced long position TSM returns, and more negative short position TSM returns, that leads to the overall enhanced TSM returns under information continuity; and 3) abnormal return volatility and abnormal turnover have an insignificant influence on time-series momentum returns. The findings indicates that investors treat asset index information that arrives in small pieces differently from other information that is contained in prior asset index changes, whereas they treat the noises in asset indices in the same way as other information that is contained in asset index changes.

7.4.2 Chapter 5 (empirical chapter 2)

The key findings for the second empirical chapter on the existence of the time-series industry momentum and the influence of information diffusion on time-series industry momentum are that: 1) time-series industry momentum returns are significant in all ranking period and holding period horizons; 2) time-series industry momentum returns are enhanced in up markets and weakened in down markets; 3) time-series industry momentum returns are clustered in a continuous information environment and disappear in a discrete information environment; and 4) abnormal return volatility has an insignificant influence on time-series industry momentum returns. The findings indicate that industry investors underreact to prior industry price information, and that this underreaction is influenced by market states and information continuity. Investors underreact more to prior price information in up markets and in a continuous information environment. Industry investors treat industry level noises in the same way as other information that is included in the prior industry price changes.

7.4.3 Chapter 6 (empirical chapter 3)

The major findings in the third empirical chapter are that: 1) market liquidity, together with standard macroeconomic factors (i.e., term spread, default spread, T-bills, and dividend yield, which are the narrow macroeconomic factors that are related to financial risk compared to the common macroeconomic processes adopted in the factor analysis), may explain time-series industry momentum returns; and 2) broad macroeconomic common processes do not help to explain time-series industry momentum returns. The findings indicate that time-series industry momentum could be compensating for market liquidity risk rather than an anomaly.

7.5 Contribution and implications

7.5.1 Chapter 4 (empirical chapter 1)

By demonstrating the significant influence of negative information discreteness on time-series industry momentum on global equity indices and commodity indices, and identifying the insignificant influence of abnormal return volatility and abnormal turnover, this work contributes to prior time-series momentum literature by specifying what information diffusion elements are important for time-series momentum returns. That is, investors treat asset level information that arrives in small pieces differently from other information contained in asset prior price changes, but they treat noise in the prior asset price information similarly to other information that is contained in the prior asset price changes. That is, investors tend to be less attentive to the information arrival scale, but they react promptly to the noises contained in the prior asset price changes.

For global fund managers, the implication is that the predictability of asset indices makes it not necessary to diversify across assets to reduce risk, instead, they may manage portfolio risk by constructing ID-neutral portfolios, or they may add a low information discreteness dimension to a specific asset class following time-series momentum strategies in their portfolios, to increase alpha.

7.5.2 Chapter 5 (empirical chapter 2)

To the best of my knowledge, this chapter is the first to examine the existence of the time-series industry momentum effect, and it contributes to the industry momentum literature and time-series momentum literature by demonstrating that: 1) time-series momentum is not confined to broad asset classes and individual stocks; 2) time-series industry momentum exists, which is demonstrated in the significantly positive returns in all horizons reported; 3) investors process industry information that arrives in small pieces differently from other information that is contained in prior industry price changes, which is reflected by the better time-series industry momentum performance under low information discreteness; and 4) investors process industry noise information in a similar way to other information contained in prior industry price changes, this is reflected by the insignificant influence of abnormal return volatility on time-series industry momentum returns.

The implications for researchers are that future research can focus on other information diffusion elements and priced risk factors to further analyse the existence of the time-series industry momentum effect.

The implications for fund managers are that it is unnecessary for them to allocate capital to all industries to diversify industry-specific risk. Instead, they are recommended to utilise negative information discreteness time-series industry momentum strategies to predict industry returns. Since the main driver of the strategy returns are the long positions, the managers are advised to construct the long portfolios by using the strategies, and construct short portfolios by using cross-sectional momentum strategies, for the main profit driver of cross-sectional momentum strategies are the short positions.

7.5.3 Chapter 6 (empirical chapter 3)

The findings in this chapter contribute to time-series momentum literature by demonstrating that the time-series industry momentum effect is not an anomaly. It could be risk compensation for market liquidity risk, because time-series momentum returns substantially shrink when time-varying liquidity risk is examined.

The implication for cross-sectional momentum literature is that the joint management of liquidity and macroeconomic standard factors may be a new angle to improve momentum returns. This is because prior cross-sectional momentum return improvement focuses on strategy specific volatility management or marketwise volatility management. The implication for industry investors is that the joint impact of liquidity and standard macroeconomic factors needs to be considered when constructing sector rotation strategies. The implication for policy makers is that, when making policies to influence industry performance, macroeconomic policies being accompanied by marketwise liquidity management, may generate more influence.

7.6 Limitations

There are two main limitations of this study. First, the commodity turnover data is unavailable, making the test of the influence of abnormal turnover on the time-series momentum effect not feasible. In addition, the industry turnover data are also not available to examine the influence of abnormal turnover on the time-series industry momentum effect. Abnormal turnover tests will be added once this data problem is resolved.

Second, the present data ends in March 2019, and does not include the recent Covid-19 V-shaped trajectory in global equity markets. The occurrence of Covid-19 has had significant influence on the market information uncertainty, which is relevant to the current study. This is the area that requires further investigation.

7.7 Future research

This section is on the recommendations for future time-series momentum and cross-sectional industry momentum research. Three recommendations for future research are given.

Firstly, empirical chapter 1 and 2 demonstrates that abnormal return volatility and abnormal turnover have an insignificant influence on time-series momentum returns and time-series industry momentum returns. However, Connolly and Stivers (2003) findings show that the two elements are related to return autocorrelation in weekly equity indices. The reasons for this could be that the impact of the two elements on momentum is short lived, and that this study is at monthly horizon. Therefore, future research can adopt weekly horizons to study the relationship between the two information diffusion elements and the time-series momentum effect. In addition, future research can also add the impact of abnormal return turnover on the time-series momentum effect in commodity indices.

Secondly, it is demonstrated in empirical chapter 3 that time-series industry momentum is likely to be compensating for market liquidity risk rather than an anomaly. Future research can focus on exploring other information diffusion elements or risk factors to further analyse the existence of the time-series industry momentum effect.

Finally, the existence of the time-series industry momentum effect may of interest to cross-sectional industry momentum researchers, to examine the extent to which cross-sectional industry momentum returns can be explained by the time-series industry momentum effect. The rationale is that time-series industry momentum profits are mainly driven by industry return sign continuation, whereas cross-sectional industry momentum returns are influenced by both the return sign continuation and the relative industry return scale continuation.

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