Faculty of Business

Momentum Profits and Herding Behaviour in Emerging Asian Equity Markets and Real Estate Investment Trusts

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DECLARATION

To the best of the author's knowledge and belief, this thesis contains no material previously published by any other person except where due acknowledgement has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Alpha anak Ngadan
18 October 2024

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Abstract

This study examines the presence of momentum profits and herding behaviour in emerging Asian markets for equities and real estate investment trusts (REITs) from 1990 to 2020. By utilising Statistical Analysis Software (SAS), daily and monthly closing prices were used to generate returns and then analysed to investigate the momentum through cross-sectional momentum (CSM) and time-series momentum (TSM). Meanwhile, herding behaviour was measured and examined via cross-sectional absolute deviation (CSAD) and quantile regression (QR). The findings revealed significant momentum across several markets, with significant CSM returns in Malaysia, South Korea and Thailand. Except for the Taiwan market, CSM has been more prominent in the markets that were analysed. The study also confirmed that TSM do exist in these markets albeit lower profitability compared to the South Korean market. Market states were found to influence momentum, with consistent market trends generating higher returns. Intriguingly, herding is prevalent in most markets (except Malaysia). Although QR analysis suggests a link between herding and momentum, strong herding does not necessarily enhance returns. The current findings support behavioural theories and challenge the weak efficient market hypothesis (EMH) in these markets. Market participants in these markets can potentially benefit from adopting the cross-sectional momentum portfolio strategies except for the Taiwan market.

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Chapter 1

Introduction

This chapter provides an overview of the research background and significance, study objectives and questions, research gaps, the structure of this empirical work and the research flowchart. The chapter concludes with a summary.

The current work aims to examine the momentum anomaly, namely cross-sectional (CS) (Jegadeesh & Titman, 1993) and time-series (Moskowitz et al., 2012) (hereafter TS), in emerging Asian markets (Malaysia, Taiwan, Thailand, and South Korea)[1] using individual stock data spanning 30 years (January 1990 - January 2020)[2].

Based on finance literature, the portfolio sorting strategy of buying recent winner stocks and selling recent loser stocks can generate significant and stable returns across time, country, financial instruments, and market dynamics (Griffin et al., 2003; Hung & Glascock, 2010; Jegadeesh & Titman, 1993, 2001).

[1] Markets selected are from the Morgan Stanley Capital International (MSCI) list of emerging Asian markets, which denote a reasonable number of REITs in their equity market. The selection of markets is also motivated by Hameed and Kusnadi (2002), who argued that the factors contributing to momentum returns in the U.S. are non-existent in Asian markets.

[2] The duration for the sample period is based on the availability of risk-free data, as retrieved from the Fama and French data library, which is only available from 1 January 1990.

The presence of momentum abnormal returns, which defies traditional pricing and market theories, continue to intrigue finance scholars (as cited by Fama, 1998).

Most studies have been based on CS (Brown et al., 2008; Conrad & Kaul, 1998; Fama & French, 2012; Jegadeesh & Titman, 2002; Lee & Swaminathan, 2000; Moskowitz & Grinblatt, 1999) following Jegadeesh and Titman (1993) introduction of momentum returns. Relevant scholars analyse momentum profits via buying (selling) the winning (losing) portfolio, where profitable (losing) stocks are sorted in the winning (losing) portfolio. Unlike traditional CS studies, Moskowitz et al. (2012) presented another type of momentum research termed time-series momentum (TSM) strategy. This approach involves documenting a plan of buying stocks based on the absolute return over a specific timeframe and holding them for several months (3, 6, 9, 12) to generate significant profit. The authors documented the robustness of TSM profits in all market types and (almost all) forms of asset classes in addition to equities.

Momentum strategies have been studied in numerous markets and conditions[3]. Recent works have investigated the difference between CS and

[3] See for example studies by Cooper et al. (2004) for market states; Lee et al. (2013) for industry herding and market states; Asness et al. (2013) pertaining to global individual stocks, global equity indices, currencies, global government bonds, commodity futures; Miffre and Rallis (2007), Shen et al. (2007), Menkhoff et al. (2012) and Narayan et al. (2015) for other studies pertaining to commodity and currencies among others.

TS and compared their performance in various markets and states. Nonetheless, more comprehensive research on this comparison remains lacking, specifically in emerging Asian markets (Moskowitz et al., 2012; He and Li, 2015; Cheema et al., 2017).

The current work highlighted the paucity of studies examining the relationship between market herding behaviour and momentum returns. To date, this study is the first of its kind in the context of emerging Asian markets. Herding and momentum in individual stocks and their potential correlation is a recent exploration. Lin et al. (2023) analysed U.S. stocks to delineate this relationship. Initial herding and momentum research by Grinblatt et al. (1995) examined the relationship in mutual funds, while Yan et al. (2012) and Demirer et al. (2015) explored industry level herding and CSM. Given the scarcity of literature in the Asian context, this study examined herding behaviour and conditioned it with momentum returns to justify the momentum and herding scenario in emerging Asian markets.

From a practitioner's perspective, the current work aimed to highlight the comparison between CSM and TSM strategies and the subsequent reaction towards herding, which allows potential inclusion (exclusion) in market participants' investment strategy. The following sections discuss studies on momentum and market herding and present the research objectives and questions, existing knowledge gaps, and overall thesis outline.

I.I Background

I.I.I Market Efficiency

The market efficiency in absorbing new information outwits market participants' attempts to beat the stock market. Introduced by Fama (1970), this phenomenon (known as EMH) involves rapidly disseminating available information on stock prices. Hence, investors are unable to earn significant profits for an extended period. Fama (1970) three forms of market hypothesis are presented as follows: (i) weak (share prices do not rely on historical price patterns); (ii) semi-strong (share prices are quickly adjusted to new and publicly available information); and (iii) strong-form (share prices reflect both private and public information).

Jegadeesh and Titman (1993) contradicted the EMH by proving that investors could profit from momentum returns by observing historical stock returns in the CS stock market. The authors demonstrated that the positive return stocks bought over three to 12 months and negative or declining return stocks sold from their stock portfolios potentially generate significant statistical profits. This strategy could generate an average compounded excess return of 12.01% per year.

I.I.2 Momentum Returns

Relevant scholars describe momentum as buying profitable stocks and selling those that are losing. The stocks are sorted into portfolios and categorised as winning (profitable) and losing (declining). Simply buying and selling stocks over three to 12 months generate annualised returns of approximately 12% the following year (Jegadeesh and Titman, 1993). This investment method, which defines the traditional market theory of EMH, appears to be contentious (Fama, 1970). A significant number of scholars have tested this anomaly following Jegadeesh and Titman (1993) initial work. Numerous CS - based momentum studies have been conducted on all market and asset types. Despite its prevalence on finance professions, momentum remains a mysterious phenomenon (Kelly et al., 2021).

Research on emerging markets is a relatively novel phenomenon. An early study by Naranjo and Porter (2007) disclosed robust momentum returns in a diversified momentum strategy when including emerging markets. Singh et al. (2022) examination of the risk-managed time-series momentum in the Indian equity market provided insights into the application of momentum strategies in an emerging economy. In re-examining momentum profits in the Vietnamese stock market, Duong and Bertrand (2022) examined momentum in specific regional contexts. Ahmad et al. (2021) suggested that momentum strategies are profitable in both developed and emerging markets, highlighting the importance

of momentum strategies in dynamic market conditions. Including emerging market stocks in a momentum portfolio offers more significant diversification benefits than adding those from developed markets.

Empirically, much of the significant diversification benefits stemmed from long-only portfolios. The results proved robust when controlling for the absence of short-selling in most emerging markets. Cakici et al. (2013), who used data from 18 emerging markets to examine momentum returns in emerging markets, highlighted the prevalence of momentum returns in emerging markets (excluding Eastern Europe). In using the latest classification of emerging markets by Morgan Stanley Capital International (MSCI), Butt et al. (2021) revealed positive and negative momentum returns in 13 and 6 markets, respectively. The current work focused on momentum and herding in Asian emerging markets.

Many studies included other financial instruments, such as equity index futures, government bonds, currencies, and commodity futures[4] in addition to different market types. The scholars also used REITs, which differ from traditional stocks, to examine momentum returns (Feng et al., 2014; Hao et al., 2016; Hung & Glascock, 2008). Feng et al. (2014) claimed that real estate returns, which are REITs' underlying asset, project strong autocorrelation and potentially generate momentum returns. Despite much research on the robustness of the momentum effect in the REIT market, no conclusive explanation has been proposed for momentum

[4] See Asness et al. (2013) for studies on various types of asset classes. For similar studies on commodities, see Miffre and Rallis (2007), Shen et al. (2007), and Narayan et al. (2015). For reviews on currencies, see Okunev and White (2003) and Menkhoff et al. (2012) among others.

profitability. For example, Hung and Glascock (2008) recorded higher momentum returns of REITs during up markets and explain their findings with the Johnson's risk-based dividend growth theory. And that higher returns do not accompany with higher risks. In contrast, Hao et al. (2016) provided evidence that the momentum return of REIT can be explained by the model based on investor confidence and biased self-attribution rather than the model based on dividend growth theory. Past studies did not directly address the role of overconfidence in justifying the momentum effect in the REIT market (Jensen & Turner, 2022). As such, this study employed REITs to analyse both CSM and TSM profits.

The TSM is a novel phenomenon that has garnered much interest. While traditional momentum studies involve buying and selling profitable and losing stocks, respectively, research on TSM entails observing its historical returns of securities (Moskowitz et al., 2012). Moskowitz et al. (2012) highlighted the prevalence of factors in behavioural and rational asset pricing theories in TSM returns (Ahn et al., 2003; Barberis et al., 1998; Berk et al., 1999; Daniel et al., 1998; Hong & Stein, 1999; Johnson, 2002; Liu & Zhang, 2008). The similarity among these theories lies in their emphasis on one risky asset. Moskowitz et al. (2012) constructed TSM portfolios with futures and commodities and documented robust returns in almost every instrument via TSM strategies. As the past price of security cannot determine the future price, the authors refuted the "random walk" theory.

To the best of the author's knowledge, no thorough study on TSM exists in the context of emerging Asian markets (Cheema et al., 2017; He & Li, 2015; Lim et al., 2018; Moskowitz et al., 2012). Emerging markets recorded more rapid growth compared to developed markets (Clarke, 2015). With the prevalence of TSM studies in more developed markets, the authors argue that this study will open a gateway for future studies as the market becomes more efficient and transparent. Many Asian markets are younger, may have less reliable data, exhibit lower levels of efficiency compared to developed markets, and have regulatory controls, among others. These factors provide opportunities for future research. This study compared the returns from TS using CS to determine whether the superior TS returns evidenced in the current literature holds in emerging Asian markets.

From a scholarly perspective, a market's state or dynamics can influence momentum profits. Researchers have categorised "UP" and "DOWN" market as two market types reflecting different momentum returns. In an earlier study, Cooper et al. (2004) denoted the link between market states and momentum returns. Scholars described the market as UP when the lagged three-year market return is positive or uptrend and DOWN when the three-year lagged market return is negative or on a downtrend. Short-run momentum returns were discovered in a UP market when conditioning market states with momentum returns. Following Asem and Tian (2010), momentum profits prevailed when the market is both UP and DOWN. Market reversals also impacted momentum profits. To achieve robustness, this study examined and conditioned market states with TSM and CSM returns.

1.1.3 Herding Behaviour and Momentum Returns

Scharfstein and Stein (1990) and Banerjee (1992) initially documented herding behaviour in stock markets. Based on these studies, herding is construed as a natural investor tendency or otherwise. Scholars posited that natural or rational herding depends on the principal-agent problem. Managers disregard their personal information to imitate the actions of others and maintain reputational capital in the market (Scharfstein & Stein, 1990). In this context, principals are mutual funds investors, while agents are fund managers. Institutional investors often analyse and emulate their peers' investment strategies to achieve similar results, which result in the market phenomenon of herding. Such imitation is a rational response to the competitive nature of the mutual funds industry. Nevertheless, Banerjee (1992) considered this view irrational. Investors who mimic external actions while neglecting their private information might risk going against their actual belief. Guo et al. (2020) recent work suggests that herding is inherent in fund management due to the principal-agent relationship.

The association between herding and momentum returns is a recent phenomenon (Demirer et al., 2015; Yan et al., 2012). Despite not directly examining momentum and herding, Komalasari et al. (2022) attributed foreign investors' herding tendency to momentum trading and informational advantage. Lin et al. (2023) recent work linked U.S. individual stocks

to herding and momentum trading. Meanwhile, Yan et al. (2012) and Demirer et al. (2015) employed industry momentum portfolios to examine this relationship. Demirer et al. (2015), whose research built on Moskowitz and Grinblatt (1999), highlighted the prominence of the momentum effect in industry portfolios compared to individual stock portfolios. Conversely, this study proposed the insufficiency of the industry momentum in explaining the profitability of momentum strategies (Grundy and Martin, 2001; Chordia and Shivakumar, 2002). Given the novelty of individual stock momentum and industry-based momentum, both entities must be treated as a separate phenomenon (Chordia & Shivakumar, 2002). The current work analyse the existence of CSM and TSM in these markets. At the same time, the study intends to unravel the asymmetric relationship between momentum and herding. Whether the existence of herding can influence the profitability of both momentum strategies.

1.1.4 Emerging Asian Markets

Asian markets have grown despite economic uncertainties. The capital markets of Malaysia, South Korea, Taiwan, and Thailand were valued at USD408.689 billion, USDl.092 trillion, USD818.49 billion, and USD277.732 billion, respectively, in 2010 and USD414.285 billion, USDl.644 trillion, USDl.448 trillion, and USD604.355 billion[5], respectively, in 2021.

The aforementioned countries demonstrate different levels of economic and financial development, political stability, financial architecture, and

[5] Data is collected from https://world-exchanges.org/

degree of integration with global economy and financial market. Cultural factors also influence the trading of these securities. Based on Chui et al. (2010), the momentum effect in the stock market is stronger in countries with a stronger degree of individualism. Such an effect implies that cultural factors affect trading behaviour. Galariotis and Karagiannis (2020) recently examined culture and economic policy uncertainty to explain their impact on momentum trading in emerging Asian markets (specifically equity markets), which constitute different cultural heritages and trading behaviours. Market frictions vary across time and countries and potentially hamper the attainment of an equilibrium relationship between cointegrated securities.

1.2 Research Gap

This study expands the current body of literature in four ways. Based on the literature review, much research has been conducted on CSM trading strategies. Despite extensive studies on TSM[6], empirical works on the equities and REITs of emerging Asian markets remain scarce. Emerging markets with less liquidity demonstrate stronger momentum returns (Erb & Harvey, 2006; Griffin et al., 2003; Rouwenhorst, 1998). Nevertheless, Jegadeesh and Titman (2023) highlighted the relatively weak empirical results supporting momentum in Asian markets. The first research contribution involves bridging the literature gap on TSM in emerging Asian markets.

[6] See studies on TSM; Cheema et al. (2017), Conover et al. (2017), Cheema et al. (2018), Goyal and Jegadeesh (2018), and Huang et al. (2020).

Second, this study investigated both CSM and TSM returns in Asian emerging markets, such as Malaysia, Taiwan, Thailand, and South Korea (Butt et al., 2021; Hanauer & Lauterbach, 2019) based on the emerging markets index of Morgan Stanley Capital International (MSCI) (MSCI n.d.). Existing research primarily focused on developed markets, such as Australia *(S&P200),* France *(CAC40),* Germany *(DAX),* Italy *(FTSE/MIB),* Japan *(TOPIX),* Netherlands *(AEX),* Spain *(IBEX35),* UK *(FTSElO0),* and the U.S. *(S&P500)* (Moskowitz et al., 2012; Cheema et al., 2017; Lim et al., 2018; Huang et al., 2020). The current work examined emerging Asian markets in place of countries with fully developed ones. Essentially, emerging markets have low exposure to global factors and little integration with Western economies (Aityan et al., 2010; Loh, 2010). The cultural differences drawn from Western individualism and Eastern cultures, which impact momentum returns, also motivated the selection of these countries. Chui et al. (2010) proposed that countries with a high Hofstede individualism score demonstrate higher monthly momentum returns. This suggestion coincides with prior studies, where investors from different individualistic cultures reflect distinct biases and construe information differently. Galariotis and Karagiannis (2020) recent study on culture and momentum denoted a strong association between different aspects of culture, economic policy uncertainty, and momentum trading in the global financial markets from 1999 to 2015.

Third, most TSM studies relied on datasets that include equity index, currency, bond futures, and commodities (Conover et al., 2017; Georgopoulou & Wang, 2016; Moskowitz et al., 2012). This research applied individual stocks and ascertained whether recent works on TS strategies made similar applications (Cheema et al., 2017; Fang et al., 2022; Goyal & Jegadeesh, 2017; Huang et al., 2020). Prior literature documenting the anomalies experienced by indices and assets classes did not extend to individual stocks and vice versa. The indices diversify studies on idiosyncratic risk, such as those performed by Menkhoff et al. (2012) and Asness et al. (2013).

This study examined the relationship between herding and momentum in emerging Asian markets, which is relatively underexplored to date. For example, the study by Lin et al. (2023) further supports studying herding and momentum returns. As they postulated, one of the challenges is to construct a herding measurement tool for individual firms. Christie and Huang (1995) and Chang et al. (2000) have introduced the herding tool to detect herding behaviour. However, Lin et al. (2023) further postulate that applying these measurements to individual firms can be challenging. Yan et al. (2012), Demirer et al. (2015); Demirer and Zhang (2019), and Lin et al. (2023) have evidenced significant links between herding and momentum. As past scholars only examined this relationship at the industry level via CSM, this study extended the current body of knowledge by conditioning TSM with herding behaviour using individual stocks.

Given the lack of information on TSM in existing finance literature, this study aimed to bridge the knowledge gap by developing and addressing six research questions.

1.3 Research Objectives

Despite extensive research on two market anomalies, momentum returns and herding behaviour, few scholars have examined their subsequent impact. The current work aimed to investigated momentum strategies and determine whether herding and market states influence the profit levels to narrow this literature gap. The study results could provide recommendations and guidelines to market participants and policymakers. The research objectives are presented as follows:

- To verify whether both CSM and TSM returns exist in emerging Asian stock markets and REITs.
- To determine whether TSM consistently exceeds CSM in emerging Asian markets.
- To evaluate whether market states influence momentum returns.
- To investigate whether herding behaviour exists in emerging Asian stock markets and REITs.
- To examine whether momentum returns depend on the level of herding behaviour.
- To ascertain whether REITs in emerging Asian markets generate CSM and TSM returns.

1.4 Research Questions

The research questions are presented as follows:

1. Do emerging Asian markets experience CSM and TSM?

   Hameed and Kusnadi (2002) initial work on Pacific Basin stock markets highlighted that the key catalysts for the United States (U.S.) CSM strategies are non-existent in Asian markets. In line with Chui et al. (2010), CSM returns proved to be weak in most East Asian countries. Butt et al. (2021) study involving 19 emerging markets revealed that overall momentum profits are lower in emerging markets. Meanwhile, Moskowitz et al. (2012) denoted the prevalence of TSM in almost all asset classes and markets. Huang et al. (2020) recently demonstrated that evidence of TSM does not hold statistically. Although the TSM strategy is deemed profitable, its performance resembles a similar strategy based on historical sample mean, which does not require predictability.

2. Do TSM returns exceed CSM returns in emerging Asian markets?

   Moskowitz et al. (2012) initial study disclosed that TSM is more profitable than that of CS, with an excess return of 76 basis points per month via regression in almost all asset classes and markets. Georgopoulou and Wang (2016), who included equity and commodity indices from developed and emerging markets, revealed that emerging

markets' TSM outperforms their developed counterparts. Based on Conover et al. (2017), TSM does not beat CSM in emerging market indices. Recent research by Pitkäjärvi et al. (2020) evidenced the unique ability of cross-asset TSM in outperforming the traditional single asset TSM. This study examined and compared the momentum returns for both CS and TS to determine whether TSM returns generally exceed those of CS in emerging Asian markets.

3. Do momentum returns depend on a market's state in emerging Asian markets?

   Cooper et al. (2004) argued that the profits yielded from CSM strategies depend on a market's state. Based on the authors, momentum profits are more statistically significant following UP rather than DOWN markets. While Moskowitz et al. (2012) asserted that TSM profits depend on the market condition in an extreme state, Wang and Xu (2015) recently claimed that loser stocks earn high returns owing to volatile down markets. Furthermore, the UP market state forecasts low returns on loser stocks. Tee et al. (2019) comparison between Islamic and conventional stocks revealed their association with market states. The current work aimed to investigate whether momentum profits exist during DOWN rather than UP states and whether transition states can generate momentum profits.

4. Do common stocks in emerging Asian markets exhibit herding behaviour?

This study advances the understanding of herding in equities and REITs in emerging Asian markets. It proves crucial to elaborate on herding in these markets, which vary in terms of efficiency, liquidity, and capitalisation. Much of the existing literature focuses on whether herding behaviour exists in the capital market. Such prioritisation results in underdeveloped research themes (Komalasari et al., 2022) on herding, which has yet to be systematically examined in REITs- oriented literature (Ro & Gallimore, 2014; Zhou & Anderson, 2013; Zhou, 2008).

5. Does herding behaviour induce momentum returns in emerging Asian markets?

   The relationship between herding and momentum returns continues to be underexamined. Yan et al. (2012) and Demirer et al. (2015) were some of the earliest works to be performed on this subject matter. Demirer and Zhang (2019) applied industrial portfolios to link herding and momentum, while Lin et al. (2023) applied individual stocks to analyse the relationship. The current work further enriches this body of knowledge.

6. Do REITs in emerging Asian markets generate CSM and TSM returns?

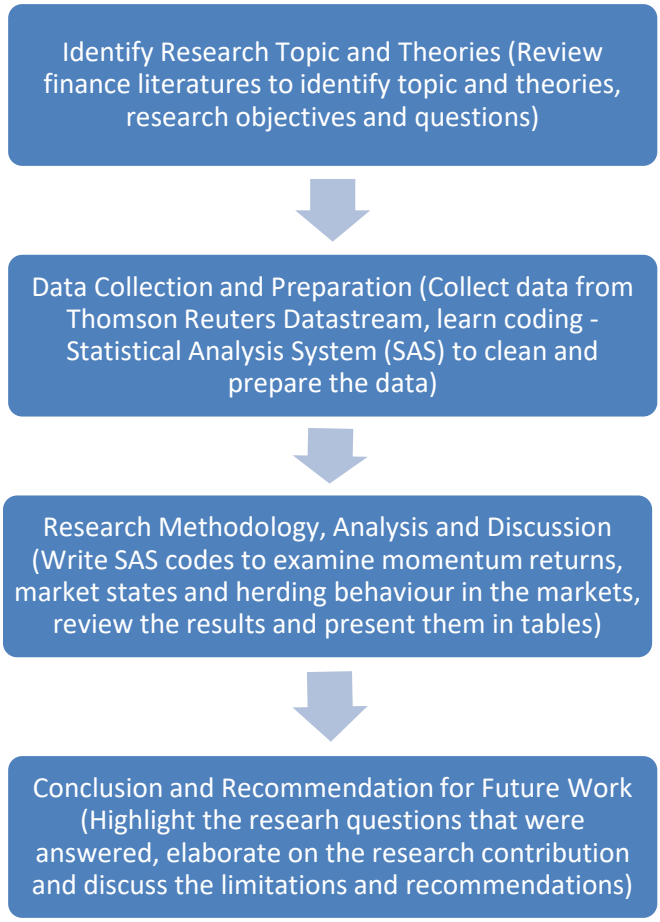
   This study provides a sound understanding of REITs and momentum returns. No study has yet to test the momentum returns of REITs in emerging Asian markets. Earlier works by Chui et al. (2003b) and Hung and Glascock (2010) studied momentum in the REITs of the U.S.

market. Zhang et al. (2023) recent work highlighted that momentum is positively related to the excess return of the REITs based on the its nature and the economic condition.

1.5 Thesis Structure

The study is organised as follows. In chapter two, the study conveys the broader context and importance of the research topic. Chapter three provides an in-depth review of the current and past literature. Next, the fourth chapter describes the data used in the study. Chapter five explains the methods applied to measure momentum and market herding. The sixth chapter details the analysis outcomes. Finally, the last chapter presents the research contribution regarding theory, practice, methodology, limitations and future research opportunities.

1.6 Research Flowchart



1.7 Chapter Summary

Chapter 1 provided an overview of the research background and areas of interest, followed by the research objectives. The literature gap highlighting the research scope was also clarified before presenting the research questions. This chapter concluded with the thesis outline.

Chapter 2

Background and Significance

This chapter presents the research background and significance, with emphasis on emerging Asian markets. Sections 2.1. 2.2 elaborate on behavioural theories, while Section 2.3 details the REITs. Section 2.4 concludes the chapter.

2.1 Emerging Asian Markets

Marketisation and the opening-up of emerging Asian markets has rendered them relevant to the global economy in the past few decades, specifically, during the Asian financial crisis (1997-1998). The Taiwanese stock market, one of the most prominent in Asia, was least affected by the 1997 financial crisis. The Thai stock market experienced economic crisis on 2 July 1997 with the devaluation of the Thai baht. This devaluation led to a decline in the Thai, Malaysian, and Korean markets by 29.3%, 44.8% and 49.5%, respectively, in the following six months. The Taiwanese market fell by a mere 9.3% (Titman & Wei, 1999).

Cultural factors play a role in the trading of securities. Chui et al. (2010) claim that the stock market's momentum effect is stronger in countries with a higher degree of individualism implies the effect of cultural factors on trading behaviour. The average monthly returns on a zero-cost momentum portfolio were more than 0.6% in countries with individualism indices in the top 30% than in counterparts with individualism indices in the bottom 30%. The individualism index for Malaysia, Korea, Taiwan, and Thailand is 27, 18, 40, and 19, respectively. Meanwhile, developed countries akin to the U.S., the United Kingdom, Germany, Switzerland, and Norway reflect an individualism index of 60, 76, 79, 79, and 81, respectively.

2.1.1 Malaysia

The Malaysian government aims to enhance the national capital market through the Malaysian stock exchange via Bursa Malaysia. With a history spanning more than 90 years, the private Singapore Stockbrokers Association was first established in 1930. Singapore was still under the federation of Malaysia at the time. The Malaysian stock market only accepted public trading on 9 May 1961 under the new name of Malayan Stock Exchange. The devolution of the stock market took effect following Singapore's exit from the federation. In this vein, the Malaysian Stock Exchange was officially formed in 1964. The Kuala Lumpur Stock

Exchange was established in 1994 and rebranded as Bursa Malaysia Berhad

in 2004 to become a public firm. The total market capitalisation of the Malaysian equity market was MYR722.04 billion (BNM n.d.) in 2004. The Malaysian capital market grew 49% to MYRl.078 trillion in 14 years (2004 to 2018) and stood at MYRl.776 trillion in August 2023 (Ceicmy n.d.).

2.1.2 South Korea

As one of the most developed economies in Asia, South Korea is renowned for its technology and electronics (Samsung, LG, Hyundai) and automotive (Hyundai, Kia) industries. The South Korean Stock Exchange (SKE) was initially launched as a government-run non-profit corporation, known as the Daehan Stock Exchange, on 3 May 1963. In 2005, the Korea Stock Exchange (SKE), Korea Futures Exchange, and KOSDAQ Stock Market were integrated to form KRX. Approximately 2400 stocks were listed in the exchange, with a market capitalisation of 1,955.85 USD (CEICKor n.d.) as of June 2024. Based on market capitalisation, South Korea ranks the seventh- largest stock market in Asia Pacific region (Statista, n.d.). Reportedly, South Korea demonstrates the highest stock market liquidity among emerging markets. Data from the World Bank revealed that the gross domestic product of the South Korean economy (USD 1647 billion) ranks 11th out of 264 countries as of 2020. The forecast Gross Domestic Product (GDP) projects an estimated 1924 billion USD in 2026 (Statista, n.d.).

The KOSDAQ market first introduced short-selling in in June 2002, with emphasis on small and medium-sized enterprises. This strategy was applied

to the KRX Main Board, which entails larger and more established companies, in May 2021 after only 18 years. Despite being a developing and vibrant stock market, Ryu et al. (2022) claimed that SKE is highly dominated by individual rather than institutional investors.

The Korean financial market, one of the largest and the most influential in terms of its economic scale and robustness of the financial system, is an emerging market susceptible to illegal or unjust acts. In examining the South Korean stock market based on geopolitical risks, Oloko et al. (2021) revealed the market's ability to provide a good hedge against global and South Korean geopolitical risks. This finding indicates the South Korean stock market's resilience and stability amidst various risks and uncertainties.

2.1.3 Taiwan

The Taiwan Stock Exchange (TWSE) was established on 23 October 1961 and began operating on 9 February 1962 (Twseh, n.d.). Four of the largest governmental enterprises' stock and land bond certificates have been traded in the secondary market since 1953 following the implementation of the land tiller policy. The TWSE aimed to manage unsound and unregulated brokers with liquid securities and vibrant markets to service the securities market and inject momentum into the national economy. Developing the securities market can strengthen the channel between private savings and business investments while improving economic growth. Following its vision, TWSE

strives to achieve a dual mission by "providing expedient fundraising processes for the enterprises and ensuring a secure investing environment for the public".

The TWSE aims to expand the securities market functions and develop a trading system and investment environment based on global standards with the three following strategies: "more transparent corporate information, fairer trading mechanisms, and more diversified financial products". These measures ensure market safety and discipline while accelerating the financial product innovation to meet diversified investment needs. In the long run, the TWSE's focus and challenge in the current macro environment of economic stagnation lies in injecting momentum into the Taiwanese economy and developing new growth opportunities.

The total market capitalisation of TWSE exceeding NT$60 trillion (US$2 trillion) as of February 2024 renders it the 10th largest stock exchange in the world (visualcapitalist, n,d). This report indicates the significant size and value of the Taiwanese stock market. Wang and Wang (2010) depicted the intraday volatility patterns in the Taiwanese stock market and their impact on volatility forecasting, which indirectly influences the market capitalisation dynamics. Teng et al. (2021) examination involving the role of financial flexibility in the sustainable development of the enterprises listed on TWSE during the COVID-19 pandemic shed light on the factors affecting the listed companies' performance and capitalisation.

2.1.4 Thailand

The Thailand stock exchange was established in July 1962 in the form of a limited partnership and registered as a limited company in 1963, with its name changed to the Bangkok Stock Exchange Co., Ltd. (BSE)(thaihistory, n.d.).

Despite providing a good venue for trading shares, the BSE garnered limited attention, with an annual turnover of only THB 160 million and THB 114 million in 1968 and 1969, respectively. Trading volumes continued to decline to THB 46 million and THB 28 million in 1970 and 1971, respectively. While the turnover in debentures reached THB 87 million in 1972, the stocks continued to demonstrate poor performance. The BSE turnover hit an all-time low of only THB 26 million and eventually ceased operations in the early 1970s (thaihistory, n.d.).

Low government support and Thai people's limited understanding of the equity market are they factors contributing to BSE's failure. Notwithstanding, the concept of establishing a well-regulated stock market with adequate government support garnered much public interest. Hence, the Second National Economic and Social Development Plan (1967-1971) proposed launching a capital market with appropriate measures and tools to facilitate securities trading.

As recommended by the World Bank, the Thai government appointed Professor Sidney M. Robbins from Columbia University in 1969 to study

the Thai capital market development. Professor Robbins had previously served as Chief Economist at the United States Securities and Exchange Commission. The Bank of Thailand also formed a working group on capital market development in the same year to establish the stock market. In 1970, Professor Robbins produced a comprehensive report entitled "A Capital Market in Thailand", which became the master plan for the Thai capital market' future development (thaihistory, n.d.).

Known for its tourism industry, agriculture, and manufacturing sector, Thailand is one of the largest economies in Southeast Asia with a steady economic growth and foreign investments in recent years. The Thailand equity market accounted for 559.223 USD billion in July 2023. The data reached an all-time high of 621.517 USD billion in January 2023 and a record low of 17.411 USD billion in Aug 1998 (Thailand Market Capitalization, n.d.).

The Thai stock market significantly influences the national economy and attracts international investors, not unlike those of other Southeast Asian countries (Hussaini et al., 2016). This free-market economy aims to attract foreign direct investment in all sectors (Hussaini et al., 2016). Based on Prilitaningtyas and Prasetyo (2019) research on Thailand's Islamic stock market, scholarly debates on the efficiency of the Thai stock market remains inconclusive. Global factors exert much influence on the country's stock market. The empirical results presented by Tharavanij (2015) denotes the

strong performance of technical trading rules in Thailand's emerging stock market. Regardless, the technical trading rules in the Thai stock market has generated profitability (to some extent) post-adjustment for transaction costs (Yu et al., 2013).

The Thai stock market is a key component of the national economy. Despite evidence of market mispricing and inefficiency, Thailand's stock market attracts international investors and is influenced by global factors, exchange rate fluctuations, and integration with other ASEAN countries.

2.2 Other Behavioural Finance Theories and Momentum

Underreaction to news: investors who underreact to news may cause stock prices to not fully reflect the true value of the underlying assets. This situation can also lead to momentum profits for investors who can correctly identify past winners and losers (Jegadeesh & Titman, 1993).

Overreaction to news: Investors who overreact to news about individual stocks or sectors may cause stock prices to move in either extreme. This situation can lead to momentum profits for investors who buy and sell past winners and losers, respectively (Reddy et al., 2021).

2.2.1 Underreaction

Underreaction is a market anomaly that occurs when stock prices fail to fully reflect a company's fundamental value. Under behavioural theory, investor overconfidence, conservatism, and herding behaviour are some of the reasons that can cause this anomaly.

Much research has evidenced the presence of underreaction in stock markets. For example, Jegadeesh and Titman (1993) well-known research on underreaction reported that stock prices continue to rise for several months following unexpected positive earnings.

Underreaction can be a profitable investment strategy. Investors who

identify underpriced stocks can buy and hold them until their prices adjust to their fundamental value (See for example Chung et al., 2020). As the market may only partially recognise the stock's fair value, underreaction may also be a risky strategy.

Recent research on underreaction has focused on identifying the factors contributing to the anomaly. Research on behavioural finance, which suggests that investor biases may cause underreaction, is one of the most promising research avenues (De Bondt, 2020; De Bondt & Thaler, 1985; Mohrschladt & Langer, 2018). Investors may require more confidence in their ability to value stocks or focus on recent news instead of long-term fundamentals.

Research on underreaction in different market environments is another area of active research (Fama, 1998). Based on Spyrou et al. (2007), underreaction is more pronounced in medium and small-cap stock portfolios during market shocks. In a more recent study, Sinha (2016) posited that in the US stock market, underreaction is not limited to small-cap stocks, stocks with limited analyst attention, stocks with more retail holders, or losing stocks. Nevertheless, existing evidence suggests that underreaction is a natural phenomenon that can be exploited by market participants to gain profit.

2.2.2 Overreaction

Overreaction or momentum investing is a form of investing strategy based on the following idea: investors who overreact to news events tend to cause stock prices to deviate from their intrinsic value (Reddy et al., 2021). This overreaction can create profitable opportunities for investors who buy stocks that have fallen in price due to bad news and sell those that have increased in price following good news.

Investors who receive new information about a company often react in an exaggerated manner. Given the company's underlying fundamentals, stock prices can fluctuate more than they should. Stock prices can become mispriced, as overreaction leads to mispricing. Hence, stock prices do not reflect the company's value. Exploiting stock mispricing can result in momentum profits. For example, investors can profit from overreaction by buying oversold stocks due to bad news and selling overbought stocks due to good news.

2.3 Real Estate Investment Trusts (REITs)

The REITs are entities in the form of corporations or trusts that focus their investment strategies on owning direct real estate assets or real estate securities (interests in other REITs or mortgages). These trusts are characterised by their low risk, low volatility, moderate returns, and high

liquidity for investors (Brounen & De Koning, 2012).

The REITs originated from the establishment of the Massachusetts Trusts, which began in 19th-century New England, the U.S., and resemble modern REITs (Chan et al., 2003). It was developed in the 1960s in the U.S. and operated under the Real Estate Investment Trust Act of 1960, which exempts REITs from paying tax. This tax-exempt status provides an attractive legal structure for real estate companies. The trusts encounter several operational and policy-related restrictions amidst industrial progress. These restrictions have since been improved to popularise REITs as real estate investment vehicles (Brounen et al., 2009). Essentially, REITs imply the securitisation of real estate (properties or mortgages) traded in the stock market.

2.3.1 Malaysian REITS

In Malaysia, the regulatory body of Security Commission (SC) stipulates that an REIT "is an investment vehicle that proposes to invest at least 50 per cent of its total assets in real estate, whether through direct ownership or through a single purpose company, whose principal asset comprises of real estate" (SCMalaysia, n.d.). Investors in Malaysia are presented with equity and mortgage as two REIT choices. Equity REITs, which involves owning physical property and managing the portfolio, primarily generate income

through rents. Mortgage REITs borrow money at a lower rate, invest the proceeds in higher-rate mortgage-backed securities, and generate income between the interest paid and received.

2.3.2 South Korean REITS

South Korea introduced the concept of REITs in in July 2001, which renders it one of the first REIT markets in Asia. The total market capitalisation of South Korean REITs (K-REITs) proved significantly smaller than those of Japan, Hong Kong, and Singapore despite an early start and a sizable economy (Jin & Kim, 2017). Nevertheless, substantial growth has been recorded over the years. The recent data for 2022 reported a combined total asset of K-REITs exceeding 80 trillion won ($59 billion) 20 years after the country introduced the real estate investment system (South Korean REITs, n.d.). Consequently, the South Korean public REITs' market capitalisation increased from 198.1 billion won at the end of 2016 to over 70 trillion won at the end of 2021. The statistics documents a nearly 60% increase by 4.4 trillion won at the end of 2020 (Yoon et al., 2022).

2.3.3 Taiwan REITs

Taiwan released the first REIT guidelines in July 2003. The Fubon No. 1 REIT, the first Taiwan REIT, was only listed in 2005 (Ooi et al., 2006). As companies that own and operate income-producing real estate, REITs are required to distribute at least 90% of their taxable income to shareholders.

These trusts benefit investors in terms of diversification, income, transparency, and tax.

Essentially, REITs expose investors to a diversified portfolio of real estate assets for risk mitigation and distribute at least 90% of their taxable income to shareholders. These aspects render them an attractive source of income. In addition to the listing requirements, REITs are subject to strict reporting. Such prerequisites present REITs as relatively transparent investment systems. In Taiwan, REITs are exempt from corporate income tax. This exemption attracts tax-conscious parties make investments.

The Taiwanese REIT market has grown steadily following its inception in 2007. A total of 7 REITs were listed on TWSE as of December 2022 (Victor et al., 2023), with a market capitalisation of approximately EUR3,528 million (European Public Real Estate Association, 2020). Several factors have influenced the growth of the Taiwanese REIT market and economy.

2.3.4 Thailand REITs

Thailand introduced REITs in 2014 to provide investors with a transparent and accessible means of investing in real estate assets (Jamar, 2016). This introduction was part of a broader effort to develop the nation's capital market and attract more foreign investment. The first Thai REIT, Impact Growth Real Estate Investment Trust (IMPACT), was listed on SET in 2014. The Thai REIT market has since grown steadily, with the total market capitalisation approximating USD 5.9 billion in December 2023 (Kelly, 2024).

The two main types of REITs in Thailand are (i) equity, which entails directly owning and operating real estate properties, and (ii) mortgage, which involves investing in mortgages and other debt instruments secured by real estates.

2.4 Chapter Summary

Chapter 2 elaborated on the emerging markets in Asia and the significant need to investigate the subject matter. The research background and behavioural finance theories were established in detail. Finally, REITs were discussed in the context of emerging markets.

Chapter 3

Literature Review

This chapter discusses the empirical evidence of momentum returns in stock markets and the contrast between CSM and TSM. Section 3.1 denotes the prevalence of momentum returns in financial markets, while Section 3.2 highlights the presence of momentum in REITs. Meanwhile, Section 3.3 outlines the evidence of momentum in emerging markets. Sections 3.4 depicts the existence of herding behaviour on momentum, Section 3.5 reviews the source of momentum returns, and Section 3.6 summarises the chapter.

3.1 Momentum Returns in Financial Markets

3.1.1 Cross-sectional Momentum Returns

Jegadeesh and Titman's (1993, 2001) research on the U.S. stock market disclosed that constructing a portfolio comprising past winners and selling loser stocks generate significant returns. Consequently, momentum profits were evident in most stock markets worldwide. Rouwenhorst (1998)

discovered momentum returns in 12 European markets, including Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom, with the Deutsche Mark to calculate monthly total returns. The author claimed that company size and common unpriced industrial factors potentially drive momentum returns. Furthermore, investors who use a globally diversified relative strong portfolio that invests in medium-term winners and sells past medium-term losers could earn approximately 1% per month. Although the return continuation was stronger for small rather than large firms, the momentum returns proved consistent in all the 12 markets holding across size deciles. Risk theories fail to explain the outperformance, which lasts for approximately one year. Conclusively, European momentum returns correlate with those of the U.S. Chan et al. (2000) implemented momentum strategies on international stock market indices to highlight the factors underlying robust momentum returns. Traders' behaviour, such as underreaction to the information described by Chan et al. (1996) and Hong and Stein (1999), and the existence of herding in the market are some of the contributing factors (Grinblatt et al., 1995; Lakonishok et al., 1992).

Chordia and Shivakumar (2002), who employed a conditional forecasting model to explain momentum profits in 16 markets, highlighted that macroeconomic variables[7] could explain momentum profits in the U.S.

[7] The model used historical momentum profits onto lagged values of four instruments, the market dividend yield, the difference between the average yield on treasury bonds with more than 10

Meanwhile, Griffin et al. (2003) focused on macroeconomic risk[8] by documenting statistically significant momentum profits in 40 countries experiencing both good and bad economic states (see Chen et al., 1986 for similar studies in factors affecting stock price). In line with Griffin et al. (2003), these macroeconomic factors do not explain pricing and time series in the momentum strategy in the U.S. and abroad. Asian stock markets demonstrated the weakest momentum returns among 39 international markets.

Earlier Asian studies by Hameed and Kusnadi (2002) recorded insignificant momentum returns in Malaysia, South Korea, Taiwan and Thailand from 1981 to 1994. In their study, the factors contributing to the United States' momentum are not prevalent in these markets. For example, applying unrestricted momentum trading strategies that involves long positions on previous winners and short positions on previous losers. In another Asian study, Brown et al. (2008) examined the Asian markets of Hong Kong, Korea, Singapore, and Taiwan to determine their value and momentum returns. Individual stock prices were applied to seek momentum returns. Excluding Taiwan, the Asian markets disclosed significant momentum returns. However, the momentum returns are relatively low for both equal weighted and value weighted strategies recording 1.33% and 1.53% respectively. The authors, believe Taiwanese companies consistently exhibited value discounts, while the other countries documented value premiums. This reason potentially justifies the insignificant momentum returns in Taiwan. Similarly, Du et al. (2009) recorded more DOWN markets

in Taiwan, asserting that this is the reason for the lack of momentum in the Taiwan market. The authors postulate that the weakness in momentum returns in emerging markets may be due to the market dynamics of these markets. In linking both market dynamics and momentum profits, Lin et al. (2016) denoted the profitability of the momentum strategy when considering the effect of market dynamics. Momentum profits are positively significant when the market remains in the same state. The authors justified the research results based on the overconfidence hypothesis, whereby significant positive momentum returns were concentrated in stocks that attract more investor attention.

Asness et al. (2013) revealed consistent value and momentum returns across eight diverse markets and asset classes. The study involved stocks from four major stock markets (mainly the U.S. the United Kingdom, continental Europe, and Japan), equity indices from 18 developed equity markets, currencies and government bonds from 10 developed markets, and 27 commodity futures. A global three-factor model was structured to explain returns across asset classes. Resultantly, liquidity risk was positively associated with global momentum.

Asness et al. (2014) disproved the myths surrounding momentum returns by listing 10 myths and denoting supporting studies to refute them. Intriguingly, many of the myths stem from value investors who invalidate momentum trading. The authors highlighted that both value and momentum complement one another.

Narayan and Phan (2017) discovered significant momentum profits in Islamic stocks, which generated significant momentum returns of 10.56% per annum compared to non-Islamic stocks (8.88% per annum). Stock characteristics, market states, and the January effect significantly influence these returns.

Chou et al. (2019) recently introduced style momentum strategy to seek momentum profits based on asset growth (AG) and size. The authors adopted Cooper et al. (2004) method to measure AG. Resultantly, the AG in this study predicted CS stock returns better than counterparts in past research. The strategy's average monthly profit is significant and robust, irrespective of the formation period between six and 12 months. It is also insensitive to the holding periods of one, three, six, and 12 months.

3.1.2 Time-series Momentum Returns

Most empirical studies on the momentum effect focus on Jegadeesh and Titman's (1993) initial work. Essentially, momentum studies were cross-sectional up to 2012. Moskowitz et al. (2012) empirically tested a momentum portfolio strategy focusing on the security's historical returns by taking a long position in securities with recent positive returns (winners' portfolio) and a short position in securities with negative returns (losers' portfolio). This momentum strategy was termed TSM.

Based on the authors, the common behavioural and rational asset pricing theories also apply to TSM returns (Ahn et al., 2003; Barberis et al., 1998;

Berk et al., 1999; Daniel et al., 1998; Hong & Stein, 1999; Johnson, 2002; Liu & Zhang, 2008). These theories emphasise a single risky asset similar to TSM. The study entailed 24 commodities, 12 cross-currency pairs, nine developed equity indices, and 13 developed government bond futures over 25 years to construct TSM portfolios. The significant TSM returns identified in almost every instrument revealed the TSM's contradiction of the random walk theory, where the historical price of a security does not determine the future direction of the price.

Recent articles refute the superiority of the TSM strategy. Kim et al. (2016) suggested that volatility-scaling drives the TSM strategy rather than the short-term momentum effect, indicating no scientific evidence of the TSM strategy, refuting earlier claims of TSM superiority. Another study by Huang et al. (2020) also refutes the weakness of the TSM strategy. Their study shows that the evidence for TSM is statistically weak in asset-by-asset time series regressions and a pooled regression accounting for size distortions. Furthermore, the study shows that the performance of the TSM strategy may be due to the differences in mean returns, not predictability.

Moskowitz et al. (2012) examination of eight equity indices in Australia, Germany, Spain, France, Italy, Japan, the Netherlands, the UK, and the U.S. (S&P500) implied that TSMOM profits should be widely applied to individual stocks. In support of Moskowitz et al. (2012) findings, but using individual common stocks, Fang et al. (2022) found weak TSM profits in their full sample. However, after selecting stocks that meet strict market conditions and specific types of stocks (lower information transparency and investor

attention), the TSM returns are, on average, 5.09% per month.

Despite the recent increase in TSM[9], most of them emphasised developed markets. Recent works have discovered higher TSM returns in emerging rather than developed markets (Georgopoulou & Wang, 2016). Regardless, Georgopoulou and Wang (2016) contended that the TSM profits in emerging markets are of a shorter duration. Emerging market returns are quicker to dissipate than those in developed markets. Arguably, the short- term duration of emerging markets changed when the currency component is controlled. The return period becomes similar in both emerging and developed markets.

To date, comprehensive research on TSM returns remains lacking in the context of emerging Asian markets. This study examined the momentum returns from TS and subsequently compared it against that from CS to determine whether the TSM consistently exceeds CSM in these markets. The current work also analysed market states and herding and their impact on both types of momentum returns.

[9] See studies by Zakamulin (2014), He and Li (2015), Georgopoulou and Wang (2016), Goyal and Jegadeesh (2017), Cheema et al. (2017), Lim et al. (2018), Pitkajarvi et al. (2020), and Fama and French (2020).

3.1.3 Cross-sectional vs. Time-series Momentum Returns

Momentum-oriented research has examined many various types of conditions and financial instruments[10] following the initial study of Jegadeesh and Titman (1993). Nevertheless, a significant number of the studies were predominantly based on CS. Moskowitz et al. (2012) examined the variation between CSM and TSM by building on the foundation of behavioural and rational asset pricing theories. Based on futures prices from 58 financial instrument types, TSM demonstrates a positive and significant alpha of 76 basis points per month. The TS factors could predict the TS model returns, while the CSM could not explain that of TS.

Goyal and Jegadeesh (2015) compared the excess returns of TSM and CSM strategies and documented an annualised return of -5.09% for CS when ranking stocks based on the one-month prior returns and holding period (1 x 1 strategy) following Jegadeesh (1990) short-horizon contrarian profits. The study also conjectured an excess return of 4.03% when using the 1 X 1 TS strategy.

One crucial difference discussed by prior literature is the strategy used to select stocks when forming portfolios (Cheema et al., 2017; Cheema et al., 2018; Goyal & Jegadeesh, 2017). In a CS strategy, stocks are ranked based on their prior returns (winner or loser) and included in the winning (losing)

[10] See Moskowitz and Grinblatt (1999) on CS in industries; Asness et al. (2013) on equity indices, currencies, commodities, and other futures contract.

portfolio. This categorisation results in an equal number of stocks in the winner and losing portfolios. The CS strategy results in a net position of zero with an equal number of stocks in both portfolios (Cheema et al., 2017). In the TS strategy, stocks are selected based on their prior absolute returns. Stocks with positive returns and negative returns are sorted into the winner and loser portfolios, respectively. Portfolios in the TS strategy would reflect more positive (negative) return stocks in a bull (bear) market. This condition leads to a net long (short) position (Cheema et al., 2017; Cheema et al., 2018).

Goyal and Jegadeesh (2017) corroborated Moskowitz et al. (2012), in which TS strategy outperforms CS following its net long position. With more UP than DOWN states, the market resulted in a net long position for the TS strategy. Moskowitz et al. (2012) regressed excess returns of CS with TS and vice versa to determine the significance of the intercept in these regressions. Insignificant alphas were achieved when CS profits were regressed against TS profits. Comparatively, significant positive alphas were reported when TS profits were regressed against CS profits. Goyal and Jegadeesh (2017) extended the aforementioned study by including holding periods equal to ranking periods. When TS excess returns were regressed against CS returns, the results were positive alphas that proved significant in the short and long horizons. Although this finding coincided with that of Moskowitz et al. (2012), the results were significant and negative when CS excess returns were regressed with TS excess returns in short and long horizons.

Asness et al. (2013) claimed that Moskowitz et al. (2012) TS strategy outperformed Jegadeesh and Titman (1993) CS strategy due to the stock selection process. Based on Goyal and Jegadeesh (2017), the TS strategy outperformed the CS following the net long position. This strategy involves integrating a zero-net investment strategy and a net long investment with risky assets (Goyal and Jegadeesh, 2017). Literature on CS is an entirely zero-cost strategy. Net long investment in securities enhances the TS strategy performance. Given the presence of more UP than DOWN markets, the market timing is deemed crucial (Cheema et al., 2017).

3.1.4 Market States and Momentum Returns

Cooper et al. (2004) applied market conditions to explain the source of momentum returns. In this vein, market states were divided into two scenarios: (i) UP state when the three-year lagged market return is non-negative and (ii) DOWN state when the three-year lagged market return is negative. Moreover, short-run momentum profits are only prevalent following the UP market.

Cooper et al. (2004) examination of market states and momentum demonstrated the presence of momentum profits during UP markets and the absence of momentum profits during DOWN markets. Following Cooper et al. (2004), Asem and Tian (2010) summarised that market reversals reduce momentum profits owing to both market states. Regardless, momentum

profits were evident in the UP market and continued to exist in the DOWN market, albeit with lower profit levels. The reason underlying low returns following the DOWN market stems from offsetting the losses when the market reverses to UP states against the profits when they continue in the DOWN state.

While many researchers disclosed non-existent momentum profits in Japan (Chui et al., 2010; Gong et al., 2015; Griffin et al., 2003), Hanauer (2014) inclusion of market states revealed the presence of momentum returns in the country. Unlike CS, the stock market often switch states and leads to this anomaly in the Japanese market. As investors would gain profits if the market continues in the same state, Japan reflects no momentum returns. Regardless, frequent market reversals eliminate the gains.

Cheema et al. (2017) echoed the relationship between market states and momentum profits levels, specifically Goyal and Jegadeesh (2015) the net long position in TS strategy. Similar to the methods employed by Asem and Tian (2010), both momentum strategies reacted similarly when conditioned with market states. The TS strategy only outperformed that of CS strategy when the market is in a continuation state. This strategy instigated substantial losses during market transitions.

Past research disclosed a significant link between market states and momentum profits, albeit with little emphasis on the market states and momentum returns in emerging Asian markets. For completeness, this study examined CSM and TSM returns contingent upon emerging Asian market

states.

3.2 Momentum Returns in Real Estate Investment Trusts

Researchers documented the extent of momentum returns in REITs, whose novelty lies in the strong autocorrelation returns and a favourable environment for momentum (Feng et al., 2014). Chui et al. (2003a) documented strong momentum profits in REITs stocks compared to non-REITs ones. In examining the CS determinants of anticipated REIT returns, Chui et al. (2003b) contended that momentum effect varies over time. Momentum, size, turnover, and analyst coverage predicted REIT returns in the pre-1990 period, while momentum significantly predicted REIT returns in the post-1990 period. In considering the individualism factor, Chui et al. (2003a) revealed that REITs demonstrate a momentum effect over a six-month holding period.

Momentum returns for REITs may depend on market state. Hung and Glascock (2010) research on the U.S. REIT momentum returns posited that the gains are contingent upon market dynamics, specifically those generated from a UP market. Derwall et al. (2009) performed a comprehensive study on REIT using the capital asset pricing model (CAPM), the Fama-French three-factor models, and Carhart (1997) four-factor model. Resultantly, the momentum effect explained returns in REIT. The findings

also confirmed that common stock factors did not influence the returns of REIT momentum portfolios. Arguably, the REIT momentum results from CS variation in the REIT fund performance.

Titman and Warga (1986) reported that risk-adjusted REIT returns are generally higher under CAPM, including a value-weighted stock market proxy, than under a multi-index model extracted from factor analysis. The REIT returns can be driven by factors that are not determined by aggregate stock market dynamics. Chan et al. (1990) and Karolyi and Sanders (1998) explained the CS of REIT returns by recommending the multi-factor models in the tradition of Merton (1973) intertemporal CAPM (ICAPM) and Ross (1976) arbitrage pricing theory (APT).

Hung and Glascock (2010) used a GARCH-in-mean model that incorporates liquidity risk into the asset-pricing model to examine how time-varying idiosyncratic risk influences momentum returns in REITs. Four factors were yielded from the study outcomes. First, momentum returns displayed asymmetric volatility when REIT momentum returns are higher for greater volatility. Second, losers reflect a higher level of idiosyncratic risk than winners. Although the outcome contradicted the traditional risk- return tradeoff theory, Ang et al. (2006) and Guo and Savickas (2006) reported the negative correlation between idiosyncratic risks and stock returns. Third, the difference in losers' and winners' idiosyncratic risks was positively related to momentum returns. This outcome highlighted the significance of idiosyncratic risk in explaining momentum returns. Fourth,

a definite link was identified between momentum returns and liquidity risk. The results corroborated the traditional risk-return theory, where higher liquidity risk leads to higher momentum returns.

This study examined REITs due to the rapid economic growth of emerging Asian countries, which has increased stock and real estate prices, and momentum profits in relation to herding behavior in REITs and the stock markets.

3.3 Momentum Returns in Emerging Markets

This study aimed to expand the current body of work on momentum profits in emerging markets. To the researcher's knowledge, Hameed and Kusnadi (2002) pioneered the examination of the U.S. CSM anomaly from the perspective of Pacific Basin markets, followed by Griffin et al. (2003) study on Asian markets, and Brown et al. (2008). As these studies covered a broad range that included emerging and developed markets based on CSM. Hence, the current work examined CSM and TSM in emerging Asian markets.

Cakici et al. (2013) study on CSM in emerging markets examined a broad sample of emerging markets[11]. The authors reported a unique finding that explains asset pricing theory. Portfolios from emerging markets recorded

[11] The study by Cakici et al. (2013) covered Asia (China, India, Indonesia, South Korea, Malaysia, the Philippines, Taiwan, and Thailand), Latin America (Argentina, Brazil, Chile, Colombia, and Mexico), and Eastern Europe (Czech Republic, Hungary, Russia, Poland, and Turkey).

superior returns compared to CS factors.

Butt et al. (2021) recent work on momentum trading strategies in emerging markets highlighted the relatively lower momentum returns in these markets. This poor performance could be attributed to the inverse relationship between momentum profits and market factors during DOWN market states.

Prior studies have outlined the distinct features of emerging Asian markets compared to other counterparts. Aityan et al. (2010) and Loh (2010) highlighted the low exposure to global factors as one distinct feature. The cultural differences described by Chui et al. (2010) is another factor determining the selection of emerging Asian markets. Building on Hofstede (2001) theory of individualism, Chui et al. (2010) claimed that countries with a high individualism index demonstrate significant momentum returns. Compared to the high individualism index in the U.S. (91), the countries examined in this study, such as Malaysia (26), South Korea (18), Taiwan (17), and Thailand (20)[12] revealed a lower index.

Galariotis and Karagiannis (2020), who recently underscored the significance of culture and momentum returns, denoted a strong association between cultural dimensions, economic policy uncertainty, and momentum portfolio strategy in global financial markets.

This study enriches their research on emerging markets by analysing

[12] Individualism index is available on https://www.hofstede-insights.com/countrycomparison/

TSM and herding behaviour.

3.4 Evidence of Herding Behaviour on Momentum Returns

Investors may profit from the stock market by trading against the herd[13] in addition to using momentum strategies. Herding behaviour entails performing the same action due to the influence of other participants, to the extent of even contradicting their personal information (Banerjee, 1992). In the context of financial markets, Nofsinger and Sias (1999) characterised herding as the tendency to emulate other people's actions by disregarding personal beliefs and understanding. This anomaly occurs when market participants, particularly traders, buy (sell) together with the market while discounting personal information. Herding, which primarily results from hearsay, disrupts the market price discovery process. In line with Nofsinger and Sias (1999), herding could induce mispricing, price momentum, and risk.

Herding behaviour, which intensifies during a DOWN market, potentially threatens financial stability during economic crises or market uncertainties

[13] See Chen and Demirer (2018) for profitability herding in the Taiwanese market.

(Chiang et al., 2007; Demirer & Kutan, 2006; Zhou & Anderson, 2013). This phenomenon also leads to correlated trades that boost co-movement among asset returns. Hence, investors fail to reduce their risk exposure by diversifying their portfolios (Baur, 2006; Chang et al., 2000; Chiang & Zheng, 2010; Morelli, 2010).

Christie and Huang (1995) measured dispersion, the CS standard deviation of returns, and detected herding in the U.S. market. Empirically, dispersion measures the proximity of the average returns to the mean. They were close to zero when all the returns move in tandem with the market. The dispersion potentially increases as returns began varying from the market return. Christie and Huang (1995) summarised that herding is less palpable in UP markets.

From a scholarly perspective, herding behaviour is more prevalent in emerging markets[14]. Chang et al. (2000) examined herding behavior in global markets, particularly the U.S., Hong Kong, Japan, South Korea, and Taiwan. Both the U.S. and Hong Kong did not demonstrate herding, while Japan disclosed partial evidence. Based on the study, herding was more prevalent in DOWN than UP markets. Christie and Huang (1995) applied cross-sectional standard deviation to detect herding. Meanwhile, Chang et al. (2000) used the CSAD of asset returns.

[14] See studies on herding in emerging markets; Demirer and Kutan (2006), Tan et al. (2008), and Chiang and Zheng (2010).

Chiang and Zheng (2010) examination of market dynamics with a large sample of 18 markets found herding to be present in both UP and DOWN markets. Contrary to past works, the authors disclosed that Asian markets demonstrated herding during a CP market[15]. Demirer et al. (2015) analysis of herding behaviour in four southern European markets (Economou et al., 2011) found institutional and market issues to be the key determinants of Herding effects in emerging markets.

In researching the U.S. REITs, Philippas et al. (2013) highlighted the link between herding behaviour and the weakening of investor sentiments regarding market conditions and adverse implications on REIT funding conditions. In contrast to past research, the recent financial crisis did not appear to instigate herding.

Chen (2013) detected herding in 69 sample countries with data derived from 35,328 stocks. Three methods[16] by Christie and Huang (1995), Chang et al. (2000), and Hwang and Salmon (2004) were employed. Chen (2013) denoted the prevalence of herding in all markets. Notably, Chen's finding contradicted those of prior studies, where herding was more apparent in developed than emerging markets. Developed markets with more efficient information flow engage in more rapid market trading decision- making (as cited by Chen, 2013).

[15] See herding in down markets by Chang et al. (2000).

[16] The methods employed by Chen (2013) to detect herding are Christie and Huang's (1995) linear model, Chang et al.'s (2000) non-linear model, and Hwang and Salmon's (2004) state-space model.

Following recent research, the level of herding in an industry can contribute to profitable investment strategy (Chen & Demirer, 2018). In cases where past performance forecasts future returns, Chen and Demirer (2018) conjectured that integrating the herding level with past performance could improve profits, regardless of the formation and holding periods.

Yan et al. (2012) claimed that investors' extent of herding behaviour induces asset price movement toward fundamentals, improves market efficiency, and reduces the momentum effect. Based on the study, the momentum strategy proved effective and generated significant returns during a low industry herding level. Demirer et al. (2015) corroborated Yan et al. (2012) and affirmed that the profitability of industry momentum strategies depends on the herding level in an industry. In seeking momentum returns through industry portfolios, the authors posited that the approach of buying winner industries with a high herding level and selling losing industries in a low herding level could generate positive returns for the next one, two, and three months. This herding and momentum return relationship is deemed the key catalyst for profitable zero-cost momentum strategies.

Demirer and Zhang (2019) further amplified this unique relationship. In this context, the level of herding significantly affects momentum returns performance. The authors also revealed the momentum strategies' weak performance during high market uncertainty. Resultantly, market participants can apply momentum strategies during periods of market crisis.

The aforementioned studies applied industry portfolios to examine the

momentum-herding relationship. Notwithstanding, this study highlighted the insufficiency of the industry momentum in explaining the profitability of momentum strategies (Chordia & Shivakumar, 2002; Grundy & Martin, 2001). Given the novelty and directness of individual stock and industry-based momentums, both elements should be treated as distinctive phenomena. The current work examined herding behaviour to determine the association between momentum and herding.

3.5 Sources of Momentum Returns

Relevant scholars have strived to identify the sources of momentum returns. Prior literature proposed two schools of thought. One school argued that momentum results from the risk as to the contributor to the anomaly. For example, the traditional CAPM estimated the expected return and systematic risk of a portfolio (Lintner, 1965; Mossin, 1966; Sharpe, 1964). This model assumes that all investors hold the market portfolio in equilibrium relative to the market. Hence, the investors had eliminated the idiosyncratic risk. The CAPM only incorporates systematic risk measured by beta (β). If β equals one, the portfolio reflects the same risk as the market. A β exceeding one indicates that the portfolio fluctuates more than the market, thus implying higher risk. Meanwhile, a β less than one denotes the opposite. Fama and French (1993) reported that β did not fully determine the CS returns on stock portfolios. The authors added market capitalisation and book-to-market

measures to explain differences in returns, known as the Fama-French three-factor model. Carhart (1997) extended the Fama and French (1993) model by including momentum factor. Regardless, the models failed to justify the presence of momentum returns (Griffin et al., 2003; Grundy & Martin, 2001; Jegadeesh & Titman, 1993; Moskowitz & Grinblatt, 1999). Derwall et al. (2009) also failed to explain momentum returns in REITs using CAPM, modified CAPM, and the three-factor and four-factor models.

Regarding risk as a contributor to momentum, Park and Kim (2014) found compelling evidence of risk-based momentum when applying Lo and MacKinlay (1990) approach spanning three areas: (i) the first-order serial covariance of market returns, (ii) the average of first-order serial covariances of all individual assets, and (iii) the CS dispersion in the unconditional mean returns of individual assets. The authors suggested that the profit from momentum would be the sum of -(1) + (2) + (3). The behavioural aspect would be derived from the first two components, while the risk component would result from the third component. Overall, countries with higher CS dispersion in unconditional mean returns tend to generate higher momentum profits. Investors can profit from momentum returns, a phenomenon that risk models fail to explain.

Another argument pertained to behavioural models. Past scholars referred to Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999), who examined the models' association with the momentum phenomenon and

stock price underreaction and overreaction upon receiving favourable (or unfavourable) information. Based on Daniel et al. (1998), momentum profits result from overconfident investors who tend to overreact to new information. Hong and Stein (1999) concurred with Daniel et al. (1998), but added that overreaction is a delayed response to the slow diffusion of private information. Jegadeesh and Titman (1993) initial study attributed momentum profits to the delayed price reactions to information.

Cheema et al. (2017) and Cheema et al. (2018) have empirically documented these behavioural traits. Specifically, investor behaviours of representativeness, conservatism, overconfidence, and self-attribution contribute to momentum profits.

Although behavioural biases drive momentum, considering the influence of investor psychology may (partially) justify the prevalence of momentum profits or enhance the returns of a momentum strategy. No universal definition exists for 'behavioural finance'. Regardless, some issues are underpinned by non-traditional investor preferences or beliefs, retail versus institutional investors, or market-wide sentiment.

The behavioural approach gained much traction following the advent of Fama and French (1996) three-factor model and the failure of beta, firm size, and value effect to explain short-term momentum returns. Consequently, Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999) developed robust models based on various investor psychology attributes.

These models lay the foundation for many empirical momentum tests from the behavioural finance perspective.

The fact that slow information diffusion among market participants can lead to momentum is one of the key insights derived from the Hong and Stein (1999) model. For example, Hong et al. (2000) underscored the prevalence of momentum in small stocks. Chen and Lu (2017) analysed option markets, the potential trading venue for informed traders, to infer the speed of information diffusion. Resultantly, momentum was more pronounced in stocks that demonstrate notable shifts in option implied volatility. Information is more likely to be incorporated into the option rather than the stock market and reflect stronger momentum than those demonstrating small changes in the implied volatility.

A stock's return pattern or price path (including large price movements) or the absence of significant price movements has been shown to lead to the continuation of momentum in returns. Perceivably, investors may not have efficiently impounded information from stock prices. Recent research (Atilgan et al., 2020) highlighted the complexity of this scenario for downward price movements, where investors appear to underreact to potential risks of further price declines.

First documented by George and Hwang (2004), the 52-week high effect (inextricably linked to momentum), implies that firms trading near the highest point over the previous year tend to continue upwards. Grinblatt and Han (2005) proposed that stocks near the 52-week high fall under the

domain of gains for investors with prospect-theoretic preferences. Also known as the disposition effect, investors' preference to sell winners impose uninformed selling pressure and possible return continuation. This scenario supports the contention of underreaction or delayed reaction driving momentum.

The issue of who 'creates' momentum is deemed a behavioural issue. Institutional investors appear to trade 'with' momentum strategies, unlike most other asset pricing anomalies (Edelen et al., 2016). Following Grinblatt and Han (2005) predictions, the counterparties tend to be individual investors who sell out winners before an increase in price and similarly buy losers. Kaniel et al. (2008) contended that individuals are compensated for providing liquidity in the short term but tend to underperform at longer horizons.

The final issue in this section involves investor sentiment. Recent attempts to operationalise behavioural finance have led to the development of 'top-down' sentiment indices (Baker & Weurgler, 2006). These indices integrate specific factors, such as initial public offering (IPO) first-day returns that potentially indicate excessive optimism or pessimism, to capture excessive mispricing (over- or under-valuation). Stocks that are challenging to value or arbitrage are most likely to load positively on a sentiment index.

Momentum strategies appear profitable during periods of high rather than low sentiments (Antoniou et al., 2013; Stambaugh et al., 2012). Arguably,

this phenomenon is driven by investor preferences and liquidity.

Another study analysed how cross-country cultural differences are positively associated with momentum profits and how behavioural biases generate the momentum effect with global data. The authors investigated whether momentum returns are more significant in countries where investors tend to display the psychological traits covered in behavioural finance research. The authors focused on what psychologists' call 'individualism', which, Hofstede (2001) describes as the degree to which people prioritise their internal characteristics (skills) to distinguish themselves from others. Hofstede (2001) individuality index was employed based on the survey data derived from 50 countries. Notably, the individualism index and other cultural norms have gained widespread acceptance in financial literature.

3.6 Chapter Summary

This chapter presented the evaluation of two types of momentum trading strategies and highlighted the merits of each one. Studies on REITs, momentum trading, and emerging markets were also extensively discussed.

Following past works, herding significantly influences momentum trading strategies from the perspective of industrial momentum. The literature review highlighted the need to complement the momentum strategies with market herding. Overall, risk factors and behavioural finance could be the key determinants of momentum.

Chapter 4

Data Analysis

Chapter 4 presents the data employed to test and analyse the momentum returns, the two aforementioned momentum strategies, market dynamics, and herding behaviour. As this study solely employed secondary data, its accuracy and quality significantly influence the research quality. This chapter delineates the process of data cleaning and filtering. Section 4.1 details the type of data collected for the analysis, while Section 4.2 describes the Datastream issues. Section 4.3 concludes the chapter.

4.1 Data Retrieved

Thomson Datastream is one of the widely-used sources of international data for finance research. Researchers have extensively employed Datastream as a robust financial TS database containing broad categories of data. Ince and Porter (2006) denoted the breadth and depth of the information derived from Datastream. From a scholarly viewpoint, no other data source is as inclusive when it comes to global data.

This study similarly employed Datastream to gather stock price data from 1990 to 2020. Following Cakici et al. (2013) data collection method, the derived information is unaffected by the survivorship bias. The Datastream sample includes both active and inactive firms. The emerging markets observed in this study were based on the MSCI emerging Asian markets of South Korea, Malaysia, Taiwan, and Thailand with REITs.

Based on relevant literature (Cakici et al., 2013; Fama & French, 2012), returns were computed in U.S. dollars. Excess returns were calculated relative to the one-month U.S. Treasury bill (T-bill) rate. This study disregarded exchange rate risk, in which purchasing power parity (PPP) is assumed. Regardless, this exclusion may become a study limitation if PPP does not hold or the portfolio returns correlate with the exchange-rate risks (Cakici et al., 2013).

The following list of data was used to test the research questions:

- **Adjusted Price of Each Stock**

  Monthly (daily) adjusted stock prices and monthly (daily) market index prices were retrieved from emerging Asian markets (Malaysia, Taiwan, Thailand, and South Korea).

- **Volume of Trading**

  The trading volume of individual stocks and all market indices were collected. Trading volume was included to determine whether the stocks remain active. Meanwhile, market index was incorporated to ascertain whether the index was traded or the price was merely brought forward due to public holidays.

- **Market Capitalisation of Each Stock**

  The market capitalisation of each stock was included to determine the market capital and screen small capital stocks following Fama and French (2012).

- **Risk-free Rate**

  The one-month T-bill rate retrieved from French's data library[17].

4.2 Issues with Data from Datastream

Despite its breadth and depth, several issues underpin the information derived from Datastream. Some of the challenges are presented as follows:

- issues related to de-listed firms
- problems related to non-trading days
- problems primarily related to small stocks, such as small-cap stocks
- data recording errors (high spurious returns)

Overall, the raw data from Datastream could not be directly analysed.

This study employed methods similar to those of Cheema et al. (2017) to screen irrelevant data. Some bias in the sample may remain undetected

[17] The data is accessible from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

post-screening and filtering, albeit with a low.

The following section elaborates on the screening of the four aforementioned issues.

4.2.1 Screening for Delisted Firms

Past works on Datastream observed the continuous repetition of the price of dead stocks as the last valid trade price before delisting through to the end of the sample. The trading volume served to determine whether the firm is delisted or not traded on a particular day. The presence of a volume on that day while the price remains the same implies that the stock is traded but remains the same price. Otherwise, zero return was deleted.

4.2.2 Testing for Non-trading Days

Trading volume was examined in this study. Datastream typically records the closing price from the previous trading day on a public holiday. As the price remains unchanged on non-trading days, it would result in zero return. Meanwhile, a stock price might remain the same for two or more consecutive trading periods and generate zero return. Chui et al. (2010) methods were employed to address this issue. A stock with zero return would be retained in the presence of trading volume or otherwise excluded.

4.2.3 Screening for Small-cap Stocks

Small capital stocks reflect a more significant deviation of returns compared

to their bigger counterparts. Such occurrences may compromise the final study outcomes. Thus, the current work excluded small capital stocks with Fama and French (2012) methods. Small capital stocks accounting for 10% of the total market capitalisation were identified and excluded based on the portfolio formation date. Naturally, the remaining 90% constituted big capital stocks.

4.2.4 Screening for Highly Spurious Returns

This screening process involved setting returns more (less) than 100% (-95%) to 100% (-95%). The returns not within this range were excluded. As such, this process allows for the omission of extreme stock returns and the inclusion of a notable number of stocks to form momentum portfolios (minimum of 30 stocks in any month during the specified period).

4.3 Chapter Summary

This chapter detailed the data necessary to perform this study. The secondary data derived from Datastream were seriously considered. Section 3.2 explains the rigorous screening process, which involves addressing issues of delisted firms, non-trading days, small-cap stocks, and highly spurious returns. Empirical data in terms of price, volume, market capital for daily and monthly, and market index prices were collected for analysis.

Chapter 5

Research Methodology

This chapter outlines the methodology used to empirically test the research questions. Section 5.1 presents the returns equation, while Section 5.2 describes the formation of momentum portfolios. Meanwhile, Section 5.3 details the methods employed to calculate market states. Section 5.4 denotes the methodology used to detect herding behaviour in the market. Lastly, Section 5.5 concludes the chapter.

5.1 Returns

Similar to relevant literature on momentum returns, the daily (monthly) returns for each stock i are calculated as follows:

$$R_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1 \qquad (5.1)$$

Where $\boldsymbol{R_{i,t}}$ is the return on stock i for days (months) $\boldsymbol{t}$ and $\boldsymbol{P_{i,t}}$ is the adjusted close price for stock i for days (months) $\boldsymbol{t}$.

Daily returns served to calculate the herding behavior (Chen & Demirer, 2018; Choi & Yoon, 2020; Demirer & Zhang, 2019), while monthly returns were used to calculate the momentum portfolios.

5.2 Formation of Portfolios - Momentum Strategies

5.2.1 Cross-sectional Momentum Strategy

Finance literature applied Jegadeesh and Titman (1993) methodology to calculate CSM returns by sorting portfolios. Stock returns were initially calculated based on the closing price of the past 12 months. The stocks were subsequently ranked following their previous J-month return (J = 3, 6, 9, 12). This study primarily aimed to compare between the CSM and TSM returns by applying Goyal and Jegadeesh (2017) methods via simple equal weighting. Three portfolios of winner, loser, and winner minus loser were formed.

The CSM used stocks that are value-weighted in each portfolio, while, TSM was equal-weighted and held for h subsequent months (H = 3, 6, 9, 12)[18]. Notably, the portfolios were not rebalanced during these periods. As this study employed monthly data, the holding period returns are bound to

[18] This equal-weighted strategy is preferred for TS as the value-weighted returns is not suitable. See for example Narayan and Phan (2017) and Cheema et al. (2018) since the results are also robust.

overlap. Jegadeesh and Titman (1993) proposed using the monthly average return of **j** strategies and disregarding the first month. Based on past literature, the issue of short-term reversals might occur. The study also applied the one-month gap between ranking and holding periods[19].

This study adopted the methods used by Goyal and Jegadeesh (2017), where stocks are categorised into two equal-weighted winner (loser) portfolios following their excess return from the CS average. Winner portfolios encompassed stocks exceeding the CS average, while loser portfolios comprised of stocks below the CS average. The returns depended on their lagged three, six, nine, 12-month (t - 12 to t - 1) returns. Notably, the CS strategy invested $1 each month on both the long and short sides.

The CS strategy equation is expressed as follows:

$$CSMOM_t = \frac{1}{N+}\sum_{R_{it-1}\geq \bar{R}_{t-1}} R_{it} - \frac{1}{N-}\sum_{R_{it-1}<\bar{R}_{t-1}} R_{it} \qquad (5.2)$$

The CSM returns for month **t** is ***CSMOMt***, while the formation period return of stock **i** is $\mathbf{R_{it-l}}$, the CS average of the formation period return is $\mathbf{R_{t-i}}$, and the ***N*+ (N-)** denotes the number of stocks with returns higher (lower) than the CS average formation period returns. Additionally, these portfolios are held for three, six, nine, and 12 months (t + 1 to t + 12).

[19] See for example Lo and MacKinlay (1990); Jegadeesh (1990); and Lehmann (1990).

5.2.2 Time-series Momentum Strategy

The current work also replicated Goyal and Jegadeesh (2017) approach for TS. Essentially, stocks were sorted based on their prior raw returns excess of the risk-free rate (excess return). The stocks were long (winner portfolio) when the excess-return was more than zero and stocks were shortened (loser portfolio) when the excess return was less than zero. Goyal and Jegadeesh (2017) added the numerator two in the equation below to render the momentum strategies comparable. In this vein, the TS strategies' total winner plus loser positions (or the total active position) are $2, which is equivalent to CS strategies. If the number of stocks with positive and negative ranking period excess returns are equal, factor two would ensure that the TS strategy invests $1 each month on the winner and loser sides.

The TS equation is expressed as follows:

$$TSMOM_t = \frac{2}{N}(\sum_{Rit-1\geq 0} R_{it} - \sum_{Rit-1<0} R_{it}) \qquad (5.3)$$

Where $(\Sigma_{R_{it-1}\geq 0} R_{it})$ denotes the returns of the stocks bought and $(\Sigma_{R_{it-1}<0} R_{it})$ relates to the returns of the stocks sold. The ***TSMOMt*** applies to the average monthly momentum returns at time ***t*** for TS strategy where holding periods can be three, six, nine, and 12 months. The quantity of stocks with positive and negative excess returns determines whether TS strategies take long or short positions in the market. The excess returns for the holding period are applicable if the number of stocks in

winner and loser portfolios are unequal. Assumably, borrowing occurs at a risk-free rate. The proceeds gained from selling the stocks will be invested at the risk-free rate.

5.3 Market States

This study applied Asem and Tian (2010) methodology to measure market states. This method is commonly used to identify uptrend (UP) and downtrend (DN) market states (Cheema et al., 2017; Cheema et al., 2018; Hanauer, 2014). Finance literature classified market state as UP/UP (DN/DN) if the lagged 12-month (from t - 11 to t) and subsequent month (t+ 1) market returns prove positive (negative). Furthermore, the market states were categorised as UP/DN (DN /UP) if the lagged 12-month returns prove positive (negative) and those of the subsequent month are negative (positive).

5.4 Detecting Herding Behaviour in Markets

Relevant literature documented two types of herding detection methods in the market. One method involved applying stock returns to determine the link between stock market movements and the individual stocks' CS behaviour (Chang et al., 2000; Christie & Huang, 1995). The other method involved analysing investors' holdings or transaction records (Celiker et al., 2015; Choi & Sias, 2009; Lakonishok et al., 1992; Nofsinger & Sias, 1999). The current work incorporated the first method via the return-based test to detect herding. The second test, which depends on investors' holding details, may be incomplete or unavailable in many cases. Such data seldom comes in high frequency (daily or intra-daily). From a scholarly perspective, the first approach provided a better argument for herding (Demirer et al., 2015).

This study applied Chang et al. (2000) CSAD to measure herding behaviour. Based on this approach, individual stock returns will converge with market returns in the wake of herding. As such, herding causes a small difference in individual versus market returns. The CSAD is the average value obtained by taking an absolute value for the difference between individual stock and market returns:

$$CSAD_t = \frac{1}{n}\sum_{i=1}^{n}\left|R_{i,t} - R_{m,t}\right| \qquad (5.4)$$

Where ***n*** is the total number of stocks on a day, ***Ri, t*** is the company returns

at time ***t,*** and ***Rm, t*** is the average market returns[20]. Upon calculating the absolute difference, Christie and Huang (1995) improved version of CSAD was incorporated to measure stock returns dispersion and herding behaviour:

$$CSAD_t = \beta_0 + \beta_1 . R_{M,t} + \beta_2 . |R_{M,t}| + \beta_3 . \left(R_{M,t} - \overline{R_M}\right)^2 + \beta_4 . CSAD_{t-1} + \varepsilon_t \quad (5.5)$$

The CSAD measures the dispersion of stock returns. The β_1 coefficient measures the sensitivity of the market portfolio's volatility, while β_2 detects the sensitivity of the dispersion to the market movements' magnitude. Notably, $\boldsymbol{R_{M,t}}$ = the market return at time ***t*** and $\overline{\boldsymbol{R_M}}$ denotes the arithmetic mean of $\boldsymbol{R_{M,t}}$. Following Yao et al. (2014), a one-day lag variable was added to mitigate the autocorrelation and multicollinearity between variables. This inclusion is denoted by $\boldsymbol{CSAD_{t-1}}$. Lastly, β_3 was anticipated to be negative and statistically significant in the wake of herding behaviour in the market.

This study included the QR analysis to thoroughly detect herding. Following past research, herding often occurs during periods of market uncertainty. While the traditional herding behaviour detection model uses ordinary least square (OLS), QR proves more suitable to clearly depict

[20] As proxies for the market portfolios the study uses historical daily data for KLCI, KOSPI, TWSE and SET50 Index from 2nd January 1990, to 31st December 2020.

herding in different quantiles of the distribution (Aharon, 2020; Pochea et al., 2017; Zhou & Anderson, 2013). As this study involved analysing returns dispersion in the distribution tails, Barnes and Hughes (2002) highlighted the appropriacy of QR over OLS.

The quantile ($\boldsymbol{\tau}$) regression equation for estimating the $\boldsymbol{CSAD}_t$ and explanatory variables (V_t) is expressed as follows:

$$Q_\tau(\tau|V_t) = \beta_{0,\tau} + \beta_{1,\tau}.R_{M,t} + \beta_{2,\tau}.|R_{M,t}| + \beta_{3,\tau}.\left(R_{M,t} - \overline{R_M}\right)^2 + \beta_{4,\tau}.CSAD_{t-1} + \epsilon_{t,\tau} \quad (5.6)$$

Lastly, Demirer and Zhang (2019) methods served to compare herding and momentum returns. The equation to calculate CSAD resembles that of Equation 5.4, excluding market returns. Rather than using the market index as proxies, market returns were calculated based on the average of all stocks at time $\boldsymbol{t}$. The quadratic model below facilitates herding detection at specific holding periods in the momentum strategies.

$$CSAD_t = \beta_0 + \beta_1.|R_{M,t}| + \beta_2.R_{m,t}^2 + \epsilon_t \quad (5.7)$$

Herding is identified when the (β_2) is negative and statistically significant.

5.5 Chapter Summary

Chapter 5 presented the equation to calculate monthly and daily returns, followed by the formation of CSM and TSM portfolios. The following chapter outlines the methodology used to calculate market states and detect herding behaviour in the markets.

Chapter 6

Results and Discussion

This chapter presents the empirical results and plausible explanation for the derived outcomes. The following section presents the calculation of both daily and monthly returns. Section 6.2 discusses the results of CSM returns in emerging Asian stock markets, while Section 6.3 details the results of TSM returns. Section 6.4 denotes the conditioned CSM and TSM returns with market states. Meanwhile, Section 6.5 highlights the herding behaviour conditioned with momentum returns. Section 6.6 compares between CSM and TSM returns, Section 6.7 elaborates on the REITs in emerging Asian markets, and Section 6.8 concludes the chapter.

6.1 Returns

Table 1 tabulates the raw and screened data on market returns and the maximum and minimum daily and monthly returns pre- and post-data filtering. For each market, information on the listed and delisted firms was derived from Datastream between 1990 and 2020. Following Ince and Porter

(2006), the data were filtered for de-listed firms and non-trading days. The stocks were subsequently screened for outliers and spurious returns by limiting returns (losses) to 100% (-95%) for the monthly (daily) returns.

The study also recorded the average returns for daily and monthly observations during the period of interest (see Table 2). Raw returns were positive for both daily and monthly periods. All the markets' average return were mostly negative post-screening, except for the daily returns for Thailand (0.02%). Overall, emerging Asian markets recorded more negative returns compared to positive returns during the specified period.

This study analysed the Asian REIT as one big Asian market following the smaller number of available REITs in Asian markets compared to their developed counterparts. The mean and standard deviation of REITs' monthly stock returns across the four markets are duly summarised.

6.2 Cross-sectional Momentum Returns

6.2.1 Malaysia

The current work ran the CSM codes with stocks from Bursa Malaysia using Goyal and Jegadeesh (2017) methods (see Table 5) . This study complied with the strict screening process for spurious returns, confined to only 90% of market capital limitation and limit returns 100% (-0.95%).

Table 1: Raw and Screened Returns (%) of Asian Emerging Markets

Raw monthly return

Country	N	Mean	Minimum	Maximum
Malaysia	268262	6.82	-99.51	407300
Korea	326196	88	-100	5765859
Taiwan	233224	5.82	-99.81	385913
Thailand	194979	13.74	-100	425000

Raw daily return

Country	N	Mean	Minimum	Maximum
Malaysia	5796393	0.40	-99.26	407300
Korea	7083957	27	-2830	49752080
Taiwan	233224	0.27	-99.68	32503
Thailand	4243111	0.70	-100	556569

Screened monthly return

Country	N	Mean	Minimum	Maximum
Malaysia	167813	0.27	-95	100
Korea	163970	-11.56	-95	100
Taiwan	192984	0.56	-86.92	100
Thailand	94574	0.33	-94.64	100

Screened daily return

Country	N	Mean	Minimum	Maximum
Malaysia	2871403	-0.53	-0.95	100
Korea	4397197	-12.00	-95	100
Taiwan	1375941	-1.08	-95	100
Thailand	1696459	0.04	-92.86	100

Table 2: Mean Returns (%) of Asian Emerging Markets

	Average raw returns		**Average screened returns**	
	Days	Months	Days	Months
Malaysia	0.76	6.82	-0.12	-1.05
Korea	27	88	-11.56	-27.24
Taiwan	0.24	5.82	-2.36	0.56
Thailand	0.70	13.74	0.02	-3.86

Table 3: Monthly Returns for Asian REITs

REIT	Raw monthly returns				Screened monthly returns			
Country	N	Mean	Minimum	Maximum	N	Mean	Minimum	Maximum
Malaysia	1431	0.45	-42.04	386.36	1392	0.18	-42.04	96.72
Korea	1518	10.18	-97.27	8746.15	617	-0.23	-78.55	58.95
Taiwan	626	89.83	-96.64	13153.14	501	-9.60	-93.38	99.32
Thailand	3669	15.29	-89.78	640.74	3173	-0.23	-62.89	90.40

Notes: This table reports the raw and screened returns (%) of REITs

Table 4: Market Indices Returns and US Treasury Bill Rates (1990-2020)

Country	N	Mean	Minimum	Maximum
Malaysia (KLCI)	372	0.005019	-0.3199	0.3995
Korea (KOSPI)	372	0.006071	-0.2725	0.5077
Taiwan (TAIEX)	372	0.004743	-0.3806	0.5283
Thailand (SETI)	372	0.004833	-0.2741	0.4885
UST-Bill	372	0.002177	0	0.0069

Notes: This table reports the market returns and the US T-Bill rate.

Three distinct portfolios, winners (W), losers (L), and winners minus losers (WML), were formed. The W portfolio comprised of stocks with returns exceeding the CS average, while the L portfolio encompassed stocks below the CS average. Statistically significant results were yielded for all holding and look-back periods upon running the codes. The W portfolio returns increased exponentially from 30.80% in the lower formation 3-3 period to 240.25% in the 12-12 formation period. Additionally, the L portfolios recorded significant positive returns and increased with the extension of the formation period to the longer time frame. The WML momentum returns decreased from a high of 25.89% recorded in the shorter formation to only 18.62% in the extended formation period. This decrease was attributed to the stock overreaction documented in Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999).

As information becomes available at a later period, the decrease in stock returns will rectify mispricing and momentum reverses. The periods of interest recorded significant statistical results at the 1% level using the Newey and West (1987) standard errors with three lags. These findings corroborate with May et al. (2018), who documented the positive returns of momentum strategies on the Malaysia market. The CSM from the table also highlights short-term momentum.

6.2.2 South Korea

Table 6 presents the analysis outcomes for the South Korean market. This study recorded high W portfolio returns in all portfolio formations with significance at the 1% level. The South Korean market recorded a 9.39% average return at the 3-3 formation period, with the positive returns continuing to rise

Table 5: Malaysia Cross-sectional Momentum Returns

Formation (J-K)	3-3	6-6	9-9	12-12
Winners (W)	30.79	79.8	147.18	240.25
	(37.05)***	(39.07)***	(37.81)***	(33.12)***
Losers (L)	4.90	54.92	128.56	221.63
	(5.99)***	(28.48)**	(34.45)***	(33.15)***
WML	25.89	24.88	18.62	18.62
	(20.52))***	(11.91)***	(10.79)***	(8.89)***

Note: This table reports the subsequent returns (%) for winner, loser, and winner minus loser portfolios. Winners (W) comprise stocks with returns above the CS average, whereas losers (L) encompass the total stocks with returns lower than the CS average. The portfolio formation and holding period is based on 3, 6, 9, and 12 months. The t-statistics is based on Newey and West (1987) standard errors (%), with **3** lags reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

in the other formation periods. The L portfolios also increased as the stocks were held longer. On another note, the mean WML portfolios (CSM returns) for all formation periods (3-3, 6-6, 9-9, and 12-12) were 7.05%, 3.07%, 1.29%, and 0.87%, respectively. The WML returns, specifically concerning the 3-3 and 6-6 holding and formation periods, proved significant at the 1% level. Regardless, these returns were not sustainable over the longer formation periods. Returns from the CSM strategy dipped more than 50% for the 6-

6 and the 9-9 formation and more than 60% for the 12- 12 period. Known as short-term momentum, this occurrence has been recently evidenced by Chiang et al. (2021), Gökçen and Post (2018), and Zaremba et al. (2019).

Table 6: Korea Cross-sectional Momentum Returns

Formation (J - K)	3-3	6-6	9-9	12-12
Winners (W)	9.39	11.65	12.95	13.02
	(13.64)***	(12.00)***	(11.65)***	(12.01)***
Losers (L)	2.34	8.58	11.12	12.32
	(2.58)**	(8.16)***	(10.74)***	(10.70)***
WML	7.05	3.07	1.29	0.87
	(7.98)***	(4.10)***	(1.54)	(1.55)

Nate: This table reports the subsequent returns (%) for winner, loser and winner minus loser portfolios. Winners (W) comprised stocks that have returns above the cross-sectional average, whereas losers (L) total stocks that have returns lower than the cross-sectional average. The portfolio formation and holding period was based on 3, 6, 9 and 12 months. The t-statistics were based on Newey and West (1987) standard errors (%) with 3 lags reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

6.2.3 Taiwan

Table 7 details the Taiwanese market CSM returns. No momentum profits (non-significant statistically) were found in the Taiwan market upon running the CSM codes. The findings align with Lin et al. (2020), who claimed that the Taiwanese market did not generate any momentum profits due to the extreme absolute strength of stocks in this market. The shorter formation period of 3-3 and 6-6 recorded profitable but low statistically significant results for the W portfolio. Meanwhile, the more extended formation period 9-9 and 12-12 documented negative profits. Only the L portfolio in those formation periods recorded weak significant returns. The

small mean returns of the W portfolios and larger mean returns of the L portfolio instigate such weak momentum returns. The empirical evidence for the Taiwan market is in support of the nonexistent momentum returns in this market as postulated by Du et al. (2009), Lin et al. (2016) and Butt et al. (2021). Du et al. (2009) and Lin et al. (2016) have suggested market dynamics as one of the plausible reasons. In contrast, Jegadeesh and Titman (2023) suggested the sample selection as the reason behind not earning momentum profits.

Table 7: Taiwan Cross-sectional Momentum Returns

Formation (J-K)	3-3	6-6	9-9	12-12
Winners (W)	0.12	0.08	0.03	0.05
	(2.52)**	(1.92)*	(0.60)	(1.63)
Losers (L)	0.04	0.03	0.05	0.06
	(0.92)	(0.97)	(1.78)*	(1.80)*
WML	0.08	0.05	-0.02	-0.002
	(1.10)	(0.88)	(-0.47)	(-0.05)

Note: This table reports the subsequent returns (%) for winner, loser, and winner minus loser portfolios. Winners (W) comprise stocks with returns above the CS average, whereas losers (L) encompass the total stocks with returns lower than the CS average. The portfolio formation and holding period is based on 3, 6, 9 and 12 months. The t-statistics is based on Newey and West (1987) standard errors (%), with 3 lags reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.2.4 Thailand

The Thailand market data results highlight the profitability of the CSM strategy. All portfolios in the formation periods recorded high statistically significant results. The W portfolio gradually increased from 1.58% to 5.09%. Though significant, the L portfolio demonstrated a gradual rise from

-0.93% to -2.22%. This contrast of returns from the W and L portfolios led to higher CSM returns. The Thai market recorded the highest momentum profit (WML) during the 12-12 formation period a t 7.37%. This return proved higher than only investing in W. The market was subject to conservatism and representativeness biases, which led them to update their beliefs and, subsequently, underreaction in the short run (Barberis et al., 1998).

Table 8: Thailand Cross-sectional Momentum Returns

Formation (J-K)	3-3	6-6	9-9	12-12
Winners (W)	1.58	3.37	4.29	5.09
	(7.27)***	(6.52)***	(8.43)***	(8.25)***
Losers (L)	-0.93	-1.32	-1.67	-2.22
	(-8.55)***	(-4.47)***	(-3.59)***	(-3.74)***
WML	2.51	4.70	5.97	7.37
	(9.98)***	(9.31)***	(11.17)***	(10.22)***

Note: This table reports the subsequent returns (%) for winner, loser, and winner minus loser portfolios. Winners (W) comprise stocks with returns above the CS average, whereas losers (L) encompass the total stocks with returns lower than the CS average. The portfolio formation and holding period is based on 3, 6, 9 and 12 months. The t-statistics is based on Newey and West (1987) standard errors (%), with 3 lags reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.3 Time-series Momentum Returns

6.3.1 Malaysia

The study ran the time-series momentum (TSM) codes for Bursa Malaysia stocks via Goyal and Jegadeesh (2017) methods. Table 9 presents the associated outcomes. The TSM returns (based on Newey and West, 1987 standard errors with three lags) proved significant for all four formation periods. Regardless, the TSM returns were low (less than 1%) for all the formation periods. The longer holding and formation period of 12-12 recorded the highest average returns at 0.35% (t-value = 23.88), followed by that of 9-9 at 0.34% (t-value = 26.02), 6-6 at 0.32% (t-value = 28.22), and 3-3 at 0.25% (t-value = 42.11). Conclusively, the Malaysian market can generate small TSM returns that increase minimally as the formation period extends to the longer period. Similar to the CSM returns, stock overreaction contributes to the mild increase in returns over the longer time frame (Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999). Meanwhile, only buying winner stocks that generate returns above the U.S. T-bill rate proved more profitable than applying the traditional TSM strategy (buying winners and shorting losers). Another plausible explanation of this weak TSM returns is due to the differences in mean returns and not predictability as denoted by Huang et al. (2020). The evidence provided weak TSM in asset-by-asset time series regression and pooled regression.

Table 9: Malaysia Time-series Momentum Returns

Formation (J - K)	3-3	6-6	9-9	12-12
Winner (W)	45.64	46.63	46.09	45.99
	(51.63)***	(38.94)***	(37.32)***	(31.63)***
Losers (L)	-41.33	-36.26	-32.50	-30.67
	(-68.87)***	(-41.79)***	(-32.19)***	(-28.11)***
WML	0.25	0.32	0.34	0.35
	(42.11)***	(28.22)***	(26.02)***	(23.88)***

Note: This table reports the subsequent returns (%) for winner, loser and winner minus loser portfolios. Winners (W) comprised stocks that have returns above zero, whereas losers (L) total stocks that have returns less than zero. The portfolio formation and holding period were 3, 6, 9 and 12 months. The t-statistics were based on Newey and West (1987) standard errors (%) with 3 lags reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

6.3.2 South Korea

The TSM strategy proved superior in the South Korean market (see Table 10). The South Korean market recorded the highest TSM returns during the extended formation period. The winners' portfolio increased from 34.77% to 42.55% during the 3-3 and 12-12 periods, respectively. Meanwhile, the losers' portfolio gradually decreased from -41.17% to -26.14% during the 3-3 and 12-12 periods. The study reported an increase in significant statistical TSM returns even as the holding period is extended after 12 months (see appendices for results of the extended periods). This result contradicts the outcomes elicited in traditional momentum literature, where momentum returns are short-term. This result resembles the Thai market when applying the CSM strategy.

Table 10: Korea Time-series Momentum Returns

Formation (J - K)	3-3	6-6	9-9	12-12
Winner (W)	34.77	36.64	40.29	42.55
	(27.95)***	(21.44)***	(16.89)***	(20.19)***
Losers (L)	-41.17	-31.40	-27.64	-26.14
	(-42.65)***	(-25.51)***	(-20.67)***	(-18.58)***
WML	2.60	8.61	16.79	22.59
	(8.45)***	(8.60)***	(8.12)***	(7.86)**

Note: This table reports the subsequent returns (%) for winner, loser and winner minus loser portfolios. Winners (W) comprised stocks that have returns above zero, whereas losers (L) total stocks that have returns less than zero. The portfolio formation and holding period were 3, 6, 9 and 12 months. The t-statistics were based on Newey and West (1987) standard errors (%) with 3 lags reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

6.3.3 Taiwan

The Taiwanese market shared similar TSM returns with the Malaysian market. The winners' portfolio increased from 14.53% to a high 32.47% during the 3-3 and 12-12 formations, respectively. While Newey and West's (1987) t-statistics was at the 1% level, the relatively small TSM returns were less than 1% on the average per formation period. Likewise, the losers' portfolios gradually increased from -12.10% to -22.75% during the 3-3 and 12-12 formation periods. The increase in winners' portfolios and a simultaneous increase in losers' portfolios led to a slight increase in TSM returns over the specified years. This finding corroborates the South Korean market, where TSM returns continue to rise with the extension of the formation period.

Table 11: Taiwan Time-series Momentum Returns

Formation (J - K)	3-3	6-6	9-9	12-12
Winner (W)	14.53	21.46	27.19	32.47
	(10.27)***	(10.26)***	(10.45)***	(10.58)***
Losers (L)	-12.10	-16.53	-19.77	-22.75
	(-11.72)****	(-12.40)***	(-13.00)***	(-13.49)***
WML	0.10	0.15	0.18	0.22
	(19.98)***	(20.10)***	(19.74)***	(19.57)***

Note: This table reports the subsequent returns (%) for winner, loser and winner minus loser portfolios. Winners (W) comprised stocks that have excess-returns above zero, whereas losers (L) total stocks that have excess-returns less than zero. The portfolio formation and holding period were 3, 6, 9 and 12 months. The t-statistics were based on Newey and West (1987) standard errors (%) with 3 lags reported in parentheses.
***,**,and* denote statistical significance at the 1%, 5%, and 10% level, respectively.

6.3.4 Thailand

The study documented low TSM returns that were statistically significant at the 1% level. The returns were slightly above those of the Malaysian and Taiwanese markets but far below those of the South Korean market. The performance of TSM returns was also similar to the other markets. Essentially, the returns gradually rose as the formation of portfolios was extended from the 3-3 to 12-12 periods. Holding on to the winners' portfolio generated gains of 23.74% in the 3-3 period, which increased to 48.53% in the 12-12 period. Summarily, holding on to the winners' portfolios can produce high returns, while applying the TSM strategy only generates average returns of 0.75% for the 12-12 period.

Table 12: Thailand Time-series Momentum Returns

Formation (J-K)	3-3	6-6	9-9	12-12
Winner (W)	16.64	21.75	27.19	30.76
	(60.88)***	(62.27)***	(60.79)***	(51.10)***
Losers (L)	-22.45	-27.56	-31.73	-35.56
	(-109.73) ****	(-132.21)***	(-116.84)***	(-89.30)***
WML	0.28	0.35	0.42	0.47
	(110.63)***	(137.30)***	(124.51)***	(146.31)***

Note: This table reports the subsequent returns (%) for winner, loser, and winner minus loser portfolios. Winners (W) comprise stocks with excess-returns above zero, whereas losers (L) encompass total stocks with returns less than zero. The portfolio formation and holding period is 3, 6, 9 and 12 months. The t-statistics is based on Newey and West (1987) standard errors (%) with 3 lags reported in parentheses.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.4 Comparison between Cross-sectional Momentum and Time-series Momentum

Relevant research outlines the formation of momentum strategies. Stocks were categorised based on their aggregate returns above (below) the CS average (zero). The winner portfolio entails stocks that perform better in some prior period, above the CS average (zero). Conversely, the selling portfolio contains stocks that perform lower than the CS average (zero) over the same period. These methods coincide with those of Goyal and Jegadeesh (2017) and Cheema et al. (2017).

The difference between CSM and TSM strategies lies in how the stocks are included in winner and loser portfolios. All stocks under the CSM strategy are categorised into winning (losing) portfolios if their returns are above (below) the CS average based on their performance over some predefined period. The TSM strategy shares similarity the CSM strategy, excluding the excess returns above (below) zero.

In comparing the returns from CSM and TSM, this study revealed mixed results (see Table 13). Analysis of the Malaysian market disclosed higher average monthly returns (CSM supersedes TSM) for the shorter formation periods of 3-3 and 6-6 at 25.64% and 24.56%, respectively. Concurrently, the difference begins significantly dissipating from the 9-9 formation

onwards. A decrease of 25.16% to 18.62% was recorded for the 9-9 and 12-12 formation periods. The current work highlighted similar evidence of short-horizon contrarian profits in the Malaysian market following Jegadeesh (1990) and Hameed and Ting (2000). The CSM strategy in the South Korean market proved slightly more profitable than TSM during the shorter formation period. Meanwhile, the TSM strategy was more profitable during the extended formation period. The CSM traders tend to overreact to information, whereas their TSM counterparts underreact to information.

Table 13: Difference between the Cross-sectional Momentum Returns Compared to Time-series Momentum Returns for Each Market from 1990 to 2020

Country	**Portfolio Strategy (J-K)**	**CSM**	**TSM**	**Difference CSM-TSM**
Malaysia	3-3	25.89	0.25	25.64
	6-6	24.88	0.32	24.56
	9-9	18.62	0.34	18.28
	12-12	18.62	0.35	18.27
Korea	3-3	7.05	2.89	4.16
	6-6	3.07	8.02	-4.95
	9-9	1.29	14.90	-13.61
	12-12	0.87	17.03	-16.16
Taiwan	3-3	0.08	0.10	-0.02
	6-6	0.05	0.15	-0.10
	9-9	-0.02	0.18	-0.20
	12-12	-0.002	0.22	-0.222
Thailand	3-3	2.51	0.28	2.23
	6-6	4.70	0.35	4.35
	9-9	5.97	0.42	5.55
	12-12	7.37	0.47	6.90

Note: This table reports the average returns (%) for winner minus loser portfolios (WML).

The portfolio formation and holding period is based on 3, 6, 9 and 12 months. Almost all the markets and holding periods record statistical significance at the 1% level for the TSM returns. Only Malaysia and Thailand record statistical significance for CSM at the 1% level. South Korea only records statistical returns during the 3-3 and 6-6 formation periods, Taiwan does not record any significant statistical returns. The significance is based on Newey and West (1987) standard errors (%) with 3 lags.

The Taiwanese market analysis led to different outcomes. Both the CSM and TSM strategies resulted in weak momentum returns. The highest average returns of 0.22% was recorded during the 12-12 formation for TSM. Additionally, all the periods documented almost zero average returns. This finding aligns with that of Lin et al. (2020), where stocks with extreme absolute strength are highly volatile and reduces the momentum profitability in Taiwan.

The Thai market analysis outcome supports those of Moskowitz et al. (2012), Goyal and Jegadeesh (2017), and Cheema et al. (2017), where TSM supersedes CSM in all the observed periods. Overall, market participants tend to underreact to both CSM and TSM strategies.

6.5 Momentum Returns Conditioned with Market States

Table 14 presents the momentum returns in the Asian emerging markets reacting differently in various market conditions. In running the CSM codes conditioned with the various market states, the Malaysian market performed positively, excluding the DN/DN market state. No result was generated for the aforementioned market. This absence led to the disproportionate number of stocks that meet the criteria of either long or short portfolios. Similarly, the programme failed to generate any result for the DN/UP market. Regarding the TSM returns, all the market conditions could generate statistically significant positive results, except for the DN market. Despite being positive, the mean returns were less than 1%. The TSM strategy generated statistically significant results for the South Korean market, while that of CSM conditioned with market states recorded weak significance. The highest returns in the South Korea market were recorded at 22.84% (t-value = 7.46**) when the market transitioned UP/DN, via CSM strategy. The lowest returns were recorded at -47.83% (t-value = -8.21***) in the DN/DN market via TSM strategy. This empirical evidence supports the CSM strategy conditioned with market states as the ideal strategy to earn positive returns in the Taiwanese market. Only a market that maintains the same condition (UP/UP and DN/DN) can generate significant positive results. The UP/DN market can also generate

returns. Despite generating statistically significant results in the Taiwanese market, the returns generated via TSM strategy were under 1% in all the market states.

The Thailand market recorded the lowest results for both CS and TS strategies in all market states. The highest positive and statistically significant results were recorded in the UP/UP market and CS strategy. Thailand's TSM strategy performed poorly in all the market conditions. Only significant profits were recorded with CSM strategy when the market was UP (DOWN) and continued to be so in the following month. Based on empirical evidence, investors can only apply the CSM strategy when the market state does not change in the Thai market.

Table 14: Momentum Returns conditioned with Market States.

Markets	Cross-section Momentum Returns				
	UP	DOWN	UP/UP	DN/DN	UP/DN
Malaysia	23.24	13.40	19.48	-9.64	-1.15
t-stat	(11.25)***	(2.18)**	(6.04)***	(-2.37)**	(-0.75)
N	58	14	13	18	28
Korea	8.14	1.59	35.34	-8.34	20.68
t-stat	(1.72)*	(0.62)	(2.04)*	(-2.35**)	(3.16)*
N	144	85	20	10	3
Taiwan	4.06	5.15	19.57	19.25	14.86
t-stat	(7.99)***	(8.03)***	(8.69)***	(9.35)***	(8.64)***
N	144	70	15	9	9
Thailand	2.41	1.82	5.84	2.92	0.17
t-stat	(7.56)***	(3.84)***	(6.66)***	(2.89)**	(0.16)
N	157	70	21	12	4

Markets	Time-series Momentum Returns				
	UP	DOWN	UP/UP	DN/DN	UP/DN
Malaysia	0.04	0.02	-0.01	0.04	0.04
t-stat	(13.50)***	(1.3)	(-1.43)	(5.89)***	(7.16)**
N	58	14	13	14	3
Korea	2.57	1.59	0.04	3.04	2.56
t-stat	(5.64)***	(0.62)	(7.09)***	(2.87)***	(3.66)*
N	144	85	13	10	3
Taiwan	0.16	0.21	0.04	0.06	0.06
t-stat	(7.41)***	(8.89)***	(10.61)***	(13.28)***	(5.46)***
N	144	70	144	9	9
Thailand	0.004	0.006	0.03	0.009	0.01
t-stat	(2.01)**	(1.76)*	(1.61)	(1.14)	(0.71)
N	157	70	6	12	4

Note: This table reports the average returns (%) of the portfolios of winners minus losers (WML) conditioned with market states. At the beginning of month t + 1, positive (negative) market index returns over the past 12 (t - 1 to t) months and market index subsequent returns over the holding period t + 1 are used to define UP /UP, UP /DN and DN /DN market states. If lagged and subsequent market returns are positive (negative), the market state is defined as UP/UP (DN/DN). If lagged market returns are positive (negative), and subsequent market returns are negative (positive), then the market state is defined as UP /DN (DN/UP). The sample period ranges from January 1990 to December 2020. The t-statistics are based on Newey and West (1987) standard errors (%) with three lags. ***,**,and* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.6 Herding Behaviour in Emerging Asian Markets

This study aimed to determine the presence of herding in stock markets. Table 15 presents the non-linear regression results based on Equation 5.5 and the signs at the various quantiles. Pochea et al. (2017) approach and Christie and Huang (1995) updated version of CSAD were used to measure stock returns dispersion. The current work ran the QR following Equation 5.6 to identify any significance in the data quantiles to check for robustness. A significant negative coefficient of β_3 potentially signifies the presence of herding. First, the linear regression of CSAD was implemented. Although Malaysia recorded a coefficient of -0.0000183, the result proved statistically insignificant. The market participants in Malaysia are more rational and trade based on their knowledge rather than the crowd. This result corroborates with another domestic herding study by Mand et al. (2021). The South Korean market recorded a coefficient of -0.13667 with a t-value of -34.22, which proved significant at the 1% level. Based on the study outcomes, the market participants in South Korea are prone to herding. The Taiwanese market recorded the highest level of herding, with a coefficient of -0.20812 and t-value -16.60 at the 1% significant level. Meanwhile, the Thai market only registered -0.0003668 and t-value -7.02, which also proved significant at the 1% level. Excluding Malaysia, the remaining three markets

recorded significant negative coefficients.

Table 13 denotes the sign of β_3 of the CSAD of returns in a QR to better understand market herding. The analysis did not result in any negative coefficient when only run with CSAD to identify herding in the Malaysian market. Upon running QR, the Malaysian market resulted in a negative coefficient at the 10% and 25% quantiles. Regardless, they were insignificant. The remaining quantiles in the Malaysian market were positive, which implied no herding. Although the South Korean market resulted in negative coefficients at the 10% and 90% quantiles, the remaining quantiles revealed positive coefficients. The Taiwanese market recorded more negative coefficients, where all the negative β_3 coefficients (excluding the 90% quantile, which proved positive) were reported. Negative β_3 coefficients were only detected at 10%, 25% and 50% in the Thai market.

Table 15: Estimates of Herding Behaviour in Emerging Asian Markets

Methodology Herd coefficient	OLS β_3	Q (T = 10%) β_3	Q (*T* = 25%) β_3	Q (T = 50%) β_3	Q (*T* = 75%) β_3	Q(T=90%) β_3
Malaysia	-0.0000183	(-)	(-)	(+)	(+)	(-)
Korea	-0.1367***	(-)	(+)	(+)	(+)	(-)
Taiwan	-0.2081***	(-)	(-)	(-)	(-)	(+)
Thailand	-0.00037***	(-)	(-)	(-)	(+)	(+)

Notes: This table reports the sign and statistical significance of herding coefficients in Asian emerging markets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The method of showing coefficient results of either near zero or just signs (- or +) are similar to QR studies by Mallek et al. (2022), Kannadhasan and Das (2020), and Pochea et al. (2017).

6.7 Momentum Returns and Herding Behaviour

The current work applied Equation 5.7, conditioned with the holding period, to compare the herding level and momentum returns. As previously mentioned, market herding would lead stock returns to display greater

directional similarity, particularly during periods of large price movements. The CSAD was computed based on the holding periods of 3, 6, 9, and 12 months. Subsequently, the QR was run following Equation 5.5 to calculate the coefficient β_3 for the respective holding periods.

Table 16 presents the herding level in the sample markets and holding periods. The Malaysian market recorded in significant results for herding and the relationship between herding and both CSM and TSM. Regressing CSM and TSM momentum proved different for the South Korean market. Thus, herding can influence CSM returns with a t-value of 3.11 at the 5% significance level. Regardless, the f-value was non-significant and implied no relationship when TSM and herding were subjected to regression. The study also ran the regression for herding on Taiwanese and Thai markets. Only the Thai market recorded significant momentum profits for CS, albeit almost at 0% average returns for TS. The Taiwanese market portrayed the highest negative coefficient among the sample countries. Unfortunately, the result was non-significant with p values > 5% when momentum returns was regressed with herding. Although substantial momentum profits are associated with market herding, strong market herding does not enhance momentum returns.

Table 16: Impact of Herding on Momentum Portfolios

Country	Portfolio Strategy (J-K)	Herding Level	Herding Coefficient	CSM	TSM
Malaysia	3-3	High	-4.54	25.89	0.25
			(-4.03)***	(37.05)***	(42.11)***
	6-6	Low	-0.67	24.88	0.32
			(-0.50)	(18.96)***	(28.22)***
	9-9	Low	0.17	18.62	0.34
			(0.16)	(16.83)***	(26.02)***
	12-12	Low	-0.14	18.62	0.35
			(-0.20)	(14.04)***	(23.88)***
Korea	3-3	Low	-0.53	7.05	2.89
			(-0.69)	(7.98)***	(8.40)***
	6-6	Low	0.48	3.07	8.02
			(0.39)	(4.10)***	(8.79)***
	9-9	Low	0.47	1.29	14.90
			(0.32)	(1.54)	(8.82)***
	12-12	Low	0.71	0.87	17.03
			(0.43)	(1.55)	(8.23)**
Taiwan	3-3	Low	59.94	0.08	0.10
			(0.87)	(1.10)	(19.98)***
	6-6	Low	429.76	0.05	0.15
			(1.85)*	(0.88)	(20.10)***
	9-9	Low	635.09	-0.02	0.18
			(1.35)	(-0.47)	(19.74)***
	12-12	Low	990.68	-0.002	0.22
			(1.46)	(-0.05)	(19.57)***
Thailand	3-3	Low	6.66	2.51	0.28
			(0.87)	(9.98)***	(110.63)***
	6-6	Low	11.94	4.70	0.35
			(1.85)*	(9.31)***	(137.30)***
	9-9	Low	7.84	5.97	0.42
			(1.35)	(11.17)***	(124.51)***
	12-12	Low	6.88	7.37	0.47
			(1.46)	(10.22)***	(114.31)***

Note: This table reports the average returns (%) for CSM and TSM strategies. At the end of each month, momentum portfolios are formed using J-month lagged returns and held for *K* months. There is no gap between the formation and holding periods. Newey and West (1987) standard errors (%) with 3 lags are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.8 Real Estate Investment Trusts - Time-series and Cross-sectional Momentum Strategies

This study could not generate CS and TSM returns upon examining the REIT returns in Asian emerging markets. The limited number of REIT companies in those markets for each year possible explains the unavailability of momentum returns in Asian REITs. The Malaysian and South Korean markets contained 11 REITs each, the Taiwanese market encompassed five REITs, while the Thai market entailed 52 REITs. The SAS programme proved suitable for markets or sectors with hundreds of companies. Following the paucity of companies, momentum returns could not be examined in the research sample.

6.9 Chapter Summary

The current work performed an extensive range of data analyses to generate empirical outcomes. A step-by-step approach and a systematic and structured presentation of data analyses were provided.

The earlier parts of this chapter discussed both raw and screened daily and monthly returns, followed by CSM and TSM calculations for all the sample markets. Both the momentum returns were conditioned with market states and thoroughly examined. Herding behaviour was analysed in these markets and conditioned with momentum returns. The study discussed REITs before concluding the chapter.

Chapter 7

Conclusion and Recommendations for Future Work

Chapter 7 encapsulates the current study findings and practicality. Section 7.1 details the research contribution, while Sections 7.2 and 7.3 present the theoretical and practical implications, respectively. Section 7.4 denotes the research limitations, Section 7.5 outlines the recommendations for future research, and Section 7.6 concludes the chapter.

This section concludes the study with the findings yielded by implementing momentum strategies conditioned with market states and market herding. In line with Chapter 1, the following research questions were addressed:

1. Do emerging Asian markets experience CSM and TSM returns in stock markets and REITs?
2. Do TSM returns exceed CSM returns in emerging Asian markets?
3. Do momentum returns depend on a market's state in emerging Asian markets?

4. Do REITs and common stocks in emerging Asian markets exhibit herding behaviour?

5. Does herding behaviour induce momentum returns in both emerging Asian common stocks and REIT markets?

6. To ascertain whether REITs in emerging Asian markets generate CSM and TSM returns.

Empirical data from 1990 to 2020 were collected from four Asian emerging markets of Malaysia, South Korea, Taiwan, and Thailand. Codes were developed using the SAS programme to screen the data, calculate returns, and set specific parameters for computing momentum returns and herding.

7.1 Research Contribution

The study first calculated the CSM in emerging Asian markets to address the first research question. Statistically significant CSM returns were found in all the sample markets. Three of them (Malaysia, South Korea, and Thailand) maintained a statistical significance of 1% throughout the formation period (see Tables 5, 6, and 8).

Based on the analysis, the Malaysian market recorded the highest monthly average returns from 25.89% to 18.62% between the 3-3 and 12-12 formation periods, respectively. That of South Korea only recorded slightly modest positive returns spanning 7.05% to 3.07% between the 3-3 and 6-6 formation periods,

respectively. The Thai market recorded a gradual increase from 2.51% to 7.37% between the 3-3 and 12-12 formation periods.

The Malaysian and South Korean market returns dissipated and became statistically insignificant for the extended formation periods (more than 12-12 formations for Malaysia and 6-6 formations for South Korea). The Taiwanese market did not record any statistically significant CSM returns.

The CSM findings denoted Malaysia as the most stable market, followed by those of Thailand and South Korea. As described by Zaremba et al. (2019), these markets demonstrate the short-run momentum. The huge returns of the Malaysian markets can be construed as an opportunity for fund managers to formulate their portfolios and enjoy the returns of short-term momentum as the empirical evidence suggests that this strategy can beat the market in the short to medium term. The returns of around 7% are slightly lower than the industry momentum returns (9.86% for high herding winner and 8.74% for low herding winners) of the 3-month formation period recorded by Demirer and Huang (2019). Albeit lower, the returns are still statistically significant. While market participants can consider CSM in their strategy for these three markets, adherence to the strict parameters highlighted in the methodology is deemed crucial.

The TSM proved to be slightly different, with mixed returns. Based on the analysis, all the markets recorded statistically significant momentum returns. Notably, the TSM returns were significant at the 1% level in all four observed formation periods in the Malaysian, Taiwanese, and Thai markets. The South

Korean market recorded the highest average TS returns at the 1% level for 3-3, 6-6, and 9-9 formations. Returns gradually increased from 2.89% to 14.90% during these periods. In contrast, the 12-12 formation recorded monthly average returns of 17.03% (5% significance level).

The TSM returns existed in these markets, albeit with lower profitability than the South Korean market. Other markets only recorded less than 1% of average returns. Although the TSM returns in the South Korean market gradually increased, the statistically significant value declined during a more extended formation period.

The comparison between TSM and CSM in these markets led to inconclusive outcomes. The South Korean market recorded superior TSM returns. The 6-6 to 12-12 formation periods were higher than those of the CSM. Notably, the returns proved higher during the sixth- and ninth-month formation. Overall, CSM proved to be the best momentum portfolio strategy for Malaysia and Thailand. The TS method was preferred in the South Korean market for the 6-6 to 9-9 holding periods. Taiwan did not record any significant momentum returns with CSM and almost zero returns for TSM. Hence, market participants should avoid applying the momentum strategy in this market.

Different market states also influenced the level of momentum returns. All the markets recorded positive returns when the market was UP (12 months average > 0 returns). During the UP market, momentum returns were higher with the CS rather than TS strategy. The results elicited from the UP/UP market state contradicts prior literature. Taiwan recorded the highest returns at 19.87% for the CS strategy when the market was UP and remained so in

the preceding month. This result necessitates further examination of the relationship pertaining to this profitable strategy. Comparatively, the South Korean market recorded higher returns with the TS strategy in the same market state. Although the market was DOWN for the CSM strategy, both the Malaysian and Taiwanese markets recorded positive returns. The South Korean market recorded a positive 3.04% in the same market state.

Specific codes were run to elicit empirical evidence that supports herding in emerging Asian markets. Excluding the Malaysian market, those of South Korea, Taiwan, and Thailand revealed significant negative coefficients that indicate herding. The Taiwanese market recorded the highest level of herding, followed by South Korea and Thailand. Meanwhile, the QR revealed the level of herding in the data to further explain the herding behaviour. With the highest herding level, Taiwan recorded all negative coefficients (except for the 90% quantile). The results disclosed a weak herding-momentum relationship. Although significant momentum profits were linked to market herding, strong market herding failed to enhance the momentum returns.

Excluding the fourth research question, 'Do REITs and common stocks in emerging Asian markets exhibit herding behaviour?', this study effectively addressed the key research questions.

7.2 Theoretical Implications

This study made significant contributions to behavioural finance theories, including overreaction, underreaction, slow information diffusion, anchoring, and sentiment (Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999). The short-term momentum results contest EMH, where available information is promptly reflected in the prices. Under the behavioural theory, investors' tendency to overreact and buy stocks cause overpricing. Biased self-attribution would exacerbate overpricing with the advent of public information. Nevertheless, investors who perceive the fallibility of their initial overconfidence would undergo a correction phase following the perpetuation of public information. This behavioural trait is evident in Malaysian and South Korean markets. Underreacting to news is palpable in the Thai market, where investors gradually digest information pre-stocks accumulation. Hence, the CSM in Thailand gradually increased over an extended period. This finding corroborates that of Luo et al. (2021), where overconfident investors overestimated their own signal quality while doubting others. This action generated excess liquidity, underreaction, short- run momentum, and reversals.

The TSM in the markets proved to be different. Minimal changes in returns were noticed in Malaysian, Taiwanese, and Thai markets. One key finding is that the t- values are relatively large for the Malaysian and Thai markets. Conversely, the South Korean market reacted similarly to the CSM

in Thailand. Although CSAD could be used to detect herding in markets, the QR proved to be more specific in this identification.

7.3 Practical Implications

The current outcomes revealed several practical implications for investment professionals involving portfolio managers, investment officers, analysts, and other market participants. The empirical results also provided academic insights for researchers examining market efficiency and investor behaviours.

Based on the findings in Chapter 6 (see Table 15), market participants could use different trading strategies to generate riskless momentum returns. These portfolio trading strategies are subject to various conditions. The Malaysian market produced the highest CSM returns, followed by those of South Korea and Thailand. Industry professionals can manipulate this finding by using the CSM strategy to capitalise on short-term trends and enhance returns.

Market participants in Malaysia, South Korea, and Thailand should focus on CSM rather than TSM portfolio strategies. Based on the study, buying (selling) stocks with returns above (below) the CS average can generate positive and significant returns.

Market states potentially impede or enhance the performance of CSM strategies in some markets. In Malaysia, the strategy could not generate

any returns when the market is down one year and continues to be so the following year. While the Malaysian market still generates significant returns in the transition market from UP to DOWN, this scenario is not applicable in South Korea. Market conditions exerted little influence on CSM returns. Regarding the Taiwan market, CSM returns were more prevalent with the CSM strategies conditioned to market states.

In applying individual stocks to calculate herding behaviour, the studies depicted a clearer picture of the herding behaviour in these markets. The Malaysian market reflected the highest level of herding during the shorter 3-3 formation period, with an average of 25.89% per month (the most significant recorded earnings). Fund managers can employ these findings to enhance their portfolio returns.

Conclusively, TSM was not as profitable as those reflected in the US, China, and most developed countries due to limited or regulated short selling in these markets. As suggested by the empirical findings, the TSM strategy is not favourable by the fund managers as it cannot offer positive regular returns in all markets. While TSM strategy has been proven and effective in more developed markets like European region and the United States, the Asian market are less profitable (Chakrabarti, 2015). However, CSM strategy can lead to short-term profit. Policymakers need to be caution when coming up with policy pertaining to this type of strategy. A more stringent approach with regards to stock selection in the portfolio is one strategy that can be implemented. One such approach can be to emulate Jegadeesh and Titman (2023) that exclude stocks below one US dollar.

7.4 Research Limitations

Contrary to past research, this study did not include other risk-adjusted analyses of CAPM and Fama and French. While the risk-adjusted analysis is common in the momentum literature, the authors are more focus on the potential returns of investing in CSM or TSM strategies. In addition, the study is focus on addressing the momentum and herding asymmetric relationship that has been recently discussed in the literature similar to Lin et al. (2021).

The study is limited to four emerging Asian markets (Malaysia, South Korea, Taiwan and Thailand) and may not be generalisable to other markets. While this can be arguably leaning to market-specific biases, these markets are distinct and offers opportunity for research (Lai, 2021).

The sample selection criteria are also specific and may affect the results. The study incorporates the methods of Fama and French (2012), which excludes small capital stocks, which constitutes 10% of the total market capitalisation. Recently Jegadeesh and Titman (2023) demonstrated that excluding stocks priced below USD1 can lead to momentum profit for the Taiwan market post-2000 period.

The limited number of REIT stocks is also an issue. Over the years the study of Asian real estate has been in the limelight and considering the growth in this sector, research opportunities in this area has been increasing. As described by Newell (2021), the Asian real estate markets have distinct characteristics that

need to be more fully understood.

Most empirical works on momentum trading strategy have encountered data mining issues. Following Jegadeesh and Titman (2001), data mining is a natural rather than an intentional outcome in momentum trading literature: "...data mining is typically the hardest to address because empirical research in non-experimental settings is limited by data availability". The thesis dataset proves to be similar. Emerging Asian markets have only been established in the late 50s. Specifically, the Taiwanese stock market was established in the early 60s (Huang, 1997), the South Korean market in the late 50s (Thompson, 1987), the Thai market in the early 60s (SET) and the Malaysian market in the mid-60s (BNM, n.d.). The unavailability of REITs analysis is attributed to the REITs in Asian emerging markets only beginning in 1990. Future researchers can re-examine this variable with the availability of more data to test the outcome robustness.

The current work provided key insights into emerging Asian markets and recommendations for further research. Data mining also proved to be a significant issue in secondary data. The study does not claim to having addressed all the empirical irregularities, including data mining.

Similar to Kim (2022) and Goyal and Jegadeesh (2017), the study applied the equal-weighted portfolio strategy for the TSM portfolios based on the prior raw returns of stocks in excess of the risk-free rate. Future works can perform in-depth analysis to determine the robustness of the data and variables of interest.

7.5 Recommendations for Future Research

Potential scholars could include multiple bourses or stock exchanges with larger samples of companies in both categories. The comparison can be between the emerging markets of South America, Africa and Asia. More robustness tests can be conducted to identify the critical difference between distinctive models. Further research with a more robust test is key to understanding how the level of herding impacts the momentum returns in both strategies. Example could be to include dynamic herding, or herding in up and down markets.

Future works should also incorporate other variables and introduce different models. For example, researchers can include Gao et al. (2021) recently introduced systematic risk of stocks (β), apply the different stock selection methods in a portfolio as shown in the previous section, and condition herding to generate potential momentum trading strategies.

7.6 Chapter Summary

This study drew inspiration from past works on momentum strategy profitability to examine the behavioural and rational explanations of applying this strategy in emerging Asian markets. Evidently, CS differences in expected returns primarily catalysed the profitability of CSM strategy. The

short-term reversal generally associated with investors' overreaction appeared to be isolated. Underreaction was also prevalent in the other portfolio strategy. The elicited outcomes enrich the current body of knowledge on CSM portfolio strategies and the implications for market efficiency.

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Appendices

Appendix 1. Sample of SAS codes

```
/* Assigning a library for Msia/Korea/Taiwan/Thailand */
Libname msia '/home/angadan0/msia';
Libname cs '/home/angadan0/msia/cs';
Libname result '/home/angadan0/msia/result';
Libname ts '/home/angadan0/msia/ts';
Libname ff '/home/angadan0/msia/ff';
Libname state '/home/angadan0/state';
Run;

/** Import CSV file **/
PROC IMPORT DATAFILE="/home/angadan0/msia/mprice21.csv/"
            OUT=msia.mprice
            DBMS=csv
            REPLACE;
run;

PROC IMPORT DATAFILE="/home/angadan0/msia/mvol21.csv/"
            OUT=msia.mvol
            DBMS=csv
            REPLACE;
run;

PROC IMPORT DATAFILE="/home/angadan0/msia/mmv.csv/"
            OUT=msia.mcap
            DBMS=csv
            REPLACE;
run;

PROC IMPORT DATAFILE="/home/angadan0/msia/mvapr.csv/"
            OUT=msia.totalmcap
            DBMS=csv
            REPLACE;
run;


 Data msia.totalmcap;
 Infile '~/msia/mvapr.csv'
 OLM=',
 FIRSTOBS=2 OB5=15000000;
 Input Date MMV Total;
 SET msia.totalmcap;
 Datevar= input(datevar,anydtdte32.);
   Format datevar mmddyy10.;
 Run;

/*Proc transpose data*/
Proc transpose data=msia.mprice out=result.mprice(rename=(_name_=company coll=price));
 by Date;
 Var MALY--YTLC;
RUN;

proc sort data=msia.dprice;
 by date; run;

data dpricel;
 set msia.dprice;
 if date ='.' then delete;
 run;

Proc transpose data=dpricel out=result.dprice(rename=(_name_=company coll=price));
```

```
/* Assigning a library for TimeSeries */
Libname msiats '/home/angadan0/msia/msiats';
Libname result20 '/home/angadan0/msia/result20';
Libname cs '/home/angadan0/msia/cs';
Libname state '/home/angadan0/state';
Libname ts '/home/angadan0/msia/ts';
/*libname herding '/home/angadan0/msia/herding';*/
Run;

/** Import CSV file. **/
PROC IMPORT DATAFILE="~/ts/tbill.CSV/"
    OUT=msiats.tbill
    DBMS=csv
    REPLACE;
run;

/* To define and set variables and observations*/

Data msiats.tbill;

 Infile '~/ts/tbill.CSV/'
 DLM=','
 FIRSTOBS=2 OB5=1500000;
 Input Date rf;
 Set msiats.tbill;
 Datevar= input(datevar,anydtdte32.);
 Format datevar mmddyy10.;
 Run;

;/* Prepare macro for printing and contents*/

%macro print_this(DSN);
proc print data=&DSN;
run;
%mend print_this;

 %macro contents_of(DSN);
  proc contents data=&DSN;
 run;
%mend contents_of;

 %macro proc_means(DSN);
  proc means data=&DSN;
 run;
%mend means_of;

/*proc sort data=msiats.tbill;
 by date rf;
run;

/* Merge Msia returns with Risk Free rate*/

data msiats.ts;
 merge cs.mret msiats.tbill;
 by date;
run;

/* Keep date, company, returns, rf and months*/

data msiats.tsmsia;
 set msiats.ts;
 keep Date company return rf;
run;

data msiats.tsmsial;
 set msiats.tsmsia;
 if return=. then delete;
 format date ddmmyy10.;
 run;

/* To calculate number of stocks on a particular date*/
proc sql;
 create table msiats.count as
 select date, count(distinct company) as count_company
 from msiats.excess
```

```
/* Assigning a library for Msia Market States*/
Libname state '/home/angadan0/state';
Libname msia '/home/angadan0/state/msia';
Libname twn '/home/angadan0/state/twn';
Libname th '/home/angadan0/state/th';
Run;


/** Import CSV file.  **/
PROC IMPORT DATAFILE="/home/angadan0/klci/KLCidays.csv/"
            OUT=state.klci
            DBMS=csv
            REPLACE;
    run;

PROC IMPORT DATAFILE="/home/angadan0/klci/klcimonths.csv/"
            OUT=state.klcim
            DBMS=CSV
            REPLACE;
    run;

;PROC IMPORT DATAFILE="/home/angadan0/klci/klcivolmonths.csv/"
            OUT=state.klcivol21
            DBMS=CSV
            REPLACE;
    run;

proc import datafile="/home/angadan0/klci/KLCI_vol.csv/"
            out=state.klcivol
            dbms=csv
            replace;
    run;

PROC IMPORT DATAFILE="/home/angadan0/cs/twn/twnindex.csv/"
            OUT=state.twn
            DBMS=csv
            REPLACE;
    run;

PROC IMPORT DATAFILE="/home/angadan0/cs/kor/korindex.csv/"
            OUT=state.kospi
            DBMS=csv
            REPLACE;
    run;


PROC IMPORT DATAFILE="/home/angadan0/cs/thai/thaiindex.csv/"
            OUT=state.thindex
            DBMS=CSV
            REPLACE;
    run;

/* To define and set variables and observations*/
data state.klci;
 Infile '/folders/myfolders/msia/klci/KLCidays.csv/'
 DLM=','
```

```
1
2  libname klci'/home/angadan0/klci';
3  libname daily '/home/angadan0/msia/daily';
4  libname herd '/home/angadan0/msia/herd';
5  Libname msia '/home/angadan0/msia';
6  Libname state '/home/angadan0/state';
7  Libname cs '/home/angadan0/msia/cs';
8  run;
9
10 %put My Version of SAS is &sysvlong;
11 /*Import files into SAS*/
12 /*proc import datafile='/home/angadan0/klci/KLCidays.csv'
13     out=klci.msia
14     DBMS=csv
15     Replace;
16     Getnames=yes;
17     run;
18 proc import datafile='/home/angadan0/klci/KLCI_vol.csv'
19     out=klci.vol
20     DBMS=csv
21     Replace;
22     Getnames=yes;
23     run;
24
;  proc import datafile='/home/angadan0/msia/dprice.csv'
27     out=daily.dprice
28     DBMS=CSV
29     Replace;
30     Getnames=yes;
31     run;
32
33 proc import datafile='/home/angadan0/msia/dvol.csv'
34     out=daily.dvol
35     DBMS=csv
36     Replace;
37     Getnames=yes;
38     run;
39
40 proc import datafile='/home/angadan0/msia/dmv21.csv'
41     out=daily.dmv
42     DBMS=CSV
43     Replace;
44     Getnames=yes;
45     run;
46
47 PROC IMPORT DATAFILE='/home/angadan0/msia/dmvapr.csv/'
48             OUT=daily.totaldmv
49             DBMS=CSV
50             REPLACE;
51 run;
52
53 /* to remove NA and change it to 0 numeric*/
54 proc sort data=daily.dprice;
55  by date;
56 proc sort data=daily.dvol;
57  by date;
58 proc sort data=daily.dmv;
59  by date; run;
60
61 Proc transpose data=daily.dprice out=herd.dprice(rename=(_name_=company col1=price ))
62  by Date;
63  Var MALY--YTLC;
64 RUN;
65
66 Proc transpose data=daily.dvol out=herd.dvol(rename=(_name_=company col1=volume ))
67  by Date;
68  Var MALY--TACP;
69 RUN;
70
71 Proc transpose data=daily.dmv out=herd.dmv (rename=(_name_=company col1=dmv));
72  by Date;
73  Var MALY--YTLA;
74 RUN;
75
76 proc means data=msia.totaldmv;
77  run;
```

Appendix 2. Sample of Cross-sectional Momentum Returns

Goyal and Jegadeesh (2017) Table 1: Returns of Cross-Sectional Momentum Portfolios
Portfolios based on 3 month lagged return and held for 3 months

The MEANS Procedure

Analysis Variable : mewret				
Momentum Portfolio	N Obs	Mean	t Value	Pr > |t|
1	322	0.0490438	5.99	<.0001
2	322	0.3079642	37.05	<.0001

Goyal and Jegadeesh (2017) Table 1: Returns of Cross-Sectional Momentum Portfolios
Portfolios based on 3 month lagged return and held for 3 months

The MEANS Procedure

Variable	N	Mean	t Value	Pr > |t|
Buy	322	0.3079642	37.05	<.0001
Sell	322	0.0490438	5.99	<.0001
Buy_Sell	322	0.2589203	30.58	<.0001

Newey and West (1987) T statistics for Cross-Sectional Momentum Portfolios

The MODEL Procedure

Model Summary	
Model Variables	1
Endogenous	1
Parameters	1
Equations	1
Number of Statements	1

Model Variables	Buy_Sell
Parameters	b0
Equations	Buy_Sell

The Equation to Estimate is	
Buy_Sell =	F(b0(1))
Instruments	1

NOTE: At GMM Iteration 0 convergence assumed because OBJECTIVE=1.084568E-30 is almost zero (<1E-12).

Newey and West (1987) T statistics for Cross-Sectional Momentum Portfolios

The MODEL Procedure
GMM Estimation Summary

Data Set Options	
DATA=	CS.MEWRETDAT2

Minimization Summary	
Parameters Estimated	1
Kernel Used	BARTLETT

Minimization Summary	
I(n)	3
Method	Gauss
Iterations	0

Final Convergence Criteria	
R	1
PPC	0
RPC	.
Object	.
Trace(S)	0.023006
Objective Value	1.08E-30

Observations Processed	
Read	322
Solved	322

Newey and West (1987) T statistics for Cross-Sectional Momentum Portfolios

The MODEL Procedure

Nonlinear GMM Summary of Residual Errors							
Equation	DF Model	DF Error	SSE	MSE	Root MSE	R-Square	Adj R-Sq
Buy_Sell	1	321	7.4079	0.0230	0.1517	-0.0000	-0.0000

Nonlinear GMM Parameter Estimates				
Parameter	Estimate	Approx Std Err	t Value	Approx Pr > |t|
b0	0.25892	0.0126	20.52	<.0001

Number of Observations		Statistics for System	
Used	322	Objective	1.085E-30
Missing	0	Objective*N	3.492E-28

GMM Test Statistics			
Test	DF	Statistic	Prob
Overidentifying Restrictions	0	0.00	.

Appendix 3. Sample of Time-series Momentum Returns

Goyal and Jegadeesh (2017): Returns of Time-Series Momentum Portfolios - Malaysian Market Portfolios based on 3 month lagged return and held for 3 months

The **MEANS** Procedure

Analysis Variable : mewret				
Momentum Portfolio	**N** Obs	Mean	t Value	**Pr>** |t|
	322	-0.4133290	-104.86	<.0001
2	322	0.4563817	79.37	<.0001

Goyal and Jegadeesh (2017): Returns of Time-Series Momentum Portfolios - Malaysian Market Portfolios based on 3 month lagged return and held for 3 months

The MEANS Procedure

Variable	N	Mean	!Value	Pr> ltl
Sell	322	-0.4133290	-104.86	<.0001
Buy	322	0.4563817	79.37	<.0001
TSMOM	322	0.0024644	69.10	<.0001

Goyal and Jegadeesh (2017): Returns of Time-Series Momentum Portfolios - Malaysian Market Portfolios based on 3 month lagged return and held for 3 months

The **MODEL Procedure**

Model Summary
Model Variables
Endogenous
Parameters
Equations
Number of Statements

Model Variables	Buy
Parameters	
Equations	

The Equation to Estimate is	
Buy=	F(b0(1))
Instruments	

NOTE: At GMM Iteration O convergence assumed because OBJECTIVE=7.037893E-30 is almost zero (<1E-12).

Goyal and Jegadeesh (2017): Returns of Time-Series Momentum Portfolios - Malaysian Market Portfolios based on 3 month lagged return and held for 3 months

The MODEL Procedure
GMM Estimation Summary

Data Set Options	
DATA=	MSIATS.MEWRETDAT2

Minimization Summary	
Parameters Estimated	1

Minimization Summary	
Kernel Used	BARTLETT
l(n)	3
Method	Gauss
Iterations	0

Final Convergence Criteria	
R	1
PPC	0
RPC	.
Object	.
Trace(S)	0.010613
Objective Value	7.04E-30

Observations Processed	
Read	323
Solved	323
Used	322
Missing	1

Goyal and Jegadeesh (2017): Returns of Time-Series Momentum Portfolios - Malaysian Market Portfolios based on 3 month lagged return and held for 3 months

The MODEL Procedure

Nonlinear GMM Summary of Residual Errors							
Equation	DF Model	DF Error	SSE	MSE	Root MSE	R-Square	Adj R-Sq
Buy	1	321	3.4173	0.0106	0.1030	0.0000	0.0000

Nonlinear GMM Parameter Estimates				
Parameter	Estimate	Approx Std Err	t Value	Approx Pr> Jtl
b0	0.456382	0.00884	51.63	<.0001

Number of Observations		Statistics for System	
Used	322	Objective	7.038E-30
Missing	1	Objective*N	2.266E-27

GMM Test Statistics			
Test	DF	Statistic	Prob
Overidentifying Restrictions	0	0.00	.

Goyal and Jegadeesh (2017): Returns of Time-Series Momentum Portfolios - Malaysian Market Portfolios based on 3 month lagged return and held for 3 months

The MODEL Procedure

Model Summary	
Model Variables	
Endogenous	
Parameters	
Equations	
Number of Statements	

Model Variables	Sell
Parameters	
Equations	

The Equation to Estimate is	
Sell=	F(b0(1))
Instruments	

NOTE: At GMM Iteration O convergence assumed because OBJECTIVE=1.004179E-30 is almost zero (<1E-12).

Goyal and Jegadeesh (2017): Returns of Time-Series Momentum Portfolios - Malaysian Market Portfolios based on 3 month lagged return and held for 3 months

The MODEL Procedure
GMM Estimation Summary

Data Set Options	
DATA=	MSIATS.MEWRETDAT2

Minimization Summary	
Parameters Estimated	
Kernel Used	BARTLETT
l(n)	3
Method	Gauss
Iterations	0

Final Convergence Criteria	
R	
PPC	0
RPC	
Object	
Trace(S)	0.004988
Objective Value	1E-30

Observations Processed	
Read	323
Solved	323
Used	322

Observations Processed	
Missing	1

Goyal and Jegadeesh (2017): Returns of Time-Series Momentum Portfolios - Malaysian Market Portfolios based on 3 month lagged return and held for 3 months

The MODEL Procedure

Nonlinear GMM Summary of Residual Errors							
Equation	DF Model	DF Error	SSE	MSE	Root MSE	R-Square	Adj R-Sq
Sell	1	321	1.6060	0.00499	0.0706	0.0000	0.0000

Nonlinear GMM Parameter Estimates				
Parameter	Estimate	Approx Std Err	t Value	Approx Pr> |t|
b0	-0.41333	0.00600	-68.87	<.0001

Number of Observations		Statistics for System	
Used	322	Objective	1.004E-30
Missing	1	Objective*N	3.233E-28

GMM Test Statistics			
Test	DF	Statistic	Prob
Overidentifying Restrictions	0	0.00	.

Goyal and Jegadeesh (2017): Returns of Time-Series Momentum Portfolios • Malaysian Market Portfolios based on 3 month lagged return and held for 3 months

The MODEL Procedure

Model Summary	
Model Variables	1
Endogenous	1
Parameters	1
Equations	1
Number of Statements	1

Model Variables	TSMOM
Parameters	bO
Equations	TSMOM

The Equation to Estimate is	
TSMOM =	F(b0(1))
Instruments	1

NOTE: At GMM Iteration O convergence assumed because OBJECTIVE=5.970094E-31 is almost zero (<1E-12).

Goyal and Jegadeesh (2017): Returns of Time-Series Momentum Portfolios - Malaysian Market Portfolios based on 3 month lagged return and held for 3 months

The MODEL Procedure
GMM Estimation Summary

Data Set Options	
DATA=	MSIATS.MEWRETDAT2

Minimization Summary	
Parameters Estimated	1
Kernel Used	BARTLETT
l(n)	3
Method	Gauss
Iterations	0

Final Convergence Criteria	
R	1
PPC	0
RPC	.
Object	.
Trace(S)	4.083E-7
Objective Value	5.97E-31

Observations Processed	
Read	323
Solved	323
Used	322

Observations Processed	
Missing	1

Goyal and Jegadeesh (2017): Returns of Time-Series Momentum Portfolios - Malaysian Market Portfolios based on 3 month lagged return and held for 3 months

The MODEL Procedure

Nonlinear GMM Summary of Residual Errors							
Equation	DF Model	DF Error	SSE	MSE	Root MSE	R-Square	Adj R-Sq
TSMOM	1	321	0.000131	4.083E-7	0.000639	0.0000	0.0000

Nonlinear GMM Parameter Estimates				
Parameter	Estimate	Approx Std Err	t Value	Approx Pr> |t|
b0	0.002464	0.000059	42.11	<.0001

Number of Observations		Statistics for System	
Used	322	Objective	5.97E-31
Missing	1	Objective*N	1.922E-28

GMM Test Statistics			
Test	DF	Statistic	Prob
Overidentifying Restrictions	0	0.00	.

Appendix 4. Sample of Cross-sectional Momentum Conditioned with Market States

The MEANS Procedure

Variable	N	Mean	t Value	Pr > |t|
Sell	58	0.0615532	3.90	0.0003
Buy	58	0.2939459	16.69	<.0001
Buy_Sell	58	0.2323926	14.38	<.0001

New Wey West Statistics - CS Mom and Market States 3 months

The MODEL Procedure

Model Summary	
Model Variables	1
Endogenous	1
Parameters	1
Equations	1
Number of Statements	1

Model Variables	Buy
Parameters	b0
Equations	Buy

The Equation to Estimate is	
Buy =	F(b0(1))
Instruments	1

NOTE: At GMM Iteration 0 convergence assumed because OBJECTIVE=1.094049E-33 is almost zero (<1E-12).

New Wey West Statistics - CS Mom and Market States 3 months

The MODEL Procedure
GMM Estimation Summary

Data Set Options	
DATA=	MEWRETDAT2

Minimization Summary	
Parameters Estimated	1
Kernel Used	BARTLETT
I(n)	3
Method	Gauss
Iterations	0

Final Convergence Criteria	
R	1
PPC	0
RPC	.
Object	.
Trace(S)	0.017678
Objective Value	1.09E-33

Observations Processed

Observations Processed	
Read	58
Solved	58

New Wey West Statistics - CS Mom and Market States 3 months

The MODEL Procedure

Nonlinear GMM Summary of Residual Errors							
Equation	DF Model	DF Error	SSE	MSE	Root MSE	R-Square	Adj R-Sq
Buy	1	57	1.0253	0.0177	0.1330	-0.0000	-0.0000

Nonlinear GMM Parameter Estimates				
Parameter	Estimate	Approx Std Err	t Value	Approx Pr > |t|
b0	0.293946	0.0266	11.05	<.0001

Number of Observations		Statistics for System	
Used	58	Objective	1.094E-33
Missing	0	Objective*N	6.345E-32

GMM Test Statistics			
Test	DF	Statistic	Prob
Overidentifying Restrictions	0	0.00	.

New Wey West Statistics - CS Mom and Market States 3 months

The MODEL Procedure

Model Summary	
Model Variables	1
Endogenous	1
Parameters	1
Equations	1
Number of Statements	1

Model Variables	Sell
Parameters	b0
Equations	Sell

The Equation to Estimate is	
Sell =	F(b0(1))
Instruments	1

NOTE: At GMM Iteration 0 convergence assumed because OBJECTIVE=4.057418E-33 is almost zero (<1E-12).

New Wey West Statistics - CS Mom and Market States 3 months

The MODEL Procedure
GMM Estimation Summary

Data Set Options	
DATA=	MEWRETDAT2

Minimization Summary	
Parameters Estimated	1
Kernel Used	BARTLETT
I(n)	3
Method	Gauss
Iterations	0

Final Convergence Criteria	
R	1
PPC	0
RPC	.
Object	.
Trace(S)	0.014185
Objective Value	4.06E-33

Observations Processed	
Read	58
Solved	58

New Wey West Statistics - CS Mom and Market States 3 months

The MODEL Procedure

Nonlinear GMM Summary of Residual Errors							
Equation	DF Model	DF Error	SSE	MSE	Root MSE	R-Square	Adj R-Sq
Sell	1	57	0.8227	0.0142	0.1191	0.0000	0.0000

Nonlinear GMM Parameter Estimates				
Parameter	Estimate	Approx Std Err	t Value	Approx Pr > |t|
b0	0.061553	0.0212	2.90	0.0053

Number of Observations		Statistics for System	
Used	58	Objective	4.057E-33
Missing	0	Objective*N	2.353E-31

GMM Test Statistics			
Test	DF	Statistic	Prob
Overidentifying Restrictions	0	0.00	.

New Wey West Statistics - CS Mom and Market States 3 months

The MODEL Procedure

Model Summary	
Model Variables	1
Endogenous	1
Parameters	1
Equations	1
Number of Statements	1

Model Variables	Buy_Sell
Parameters	b0
Equations	Buy_Sell

The Equation to Estimate is	
Buy_Sell =	F(b0(1))
Instruments	1

NOTE: At GMM Iteration 0 convergence assumed because OBJECTIVE=1.892709E-31 is almost zero (<1E-12).

New Wey West Statistics - CS Mom and Market States 3 months

The MODEL Procedure

GMM Estimation Summary

Data Set Options	
DATA=	MEWRETDAT2

Minimization Summary	
Parameters Estimated	1
Kernel Used	BARTLETT
l(n)	3
Method	Gauss
Iterations	0

Final Convergence Criteria	
R	1
PPC	0
RPC	.
Object	.
Trace(S)	0.01488
Objective Value	1.89E-31

Observations Processed	
Read	58
Solved	58

New Wey West Statistics - CS Mom and Market States 3 months

The MODEL Procedure

Nonlinear GMM Summary of Residual Errors							
Equation	**DF Model**	**DF Error**	**SSE**	**MSE**	**Root MSE**	**R-Square**	**Adj R-Sq**
Buy_Sell	1	57	0.8630	0.0149	0.1220	-0.0000	-0.0000

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.232393	0.0207	11.25	<.0001

Number of Observations		Statistics for System	
Used	58	**Objective**	1.893E-31
Missing	0	**Objective*N**	1.098E-29

GMM Test Statistics			
Test	**DF**	**Statistic**	**Prob**
Overidentifying Restrictions	0	0.00	.

Appendix 5. Sample of Time-series Momentum Returns Conditioned with Market States

Goyal and Jegadeesh (2017) Table 1: Returns of TS Momentum and Market States
Portfolios based on 3 month lagged return and held for 3 months

The MEANS Procedure

Variable	N	Mean	t Value	Pr > |t|
Sell	85	-0.6723425	-35.44	<.0001
Buy	85	-0.0289053	-1.25	0.2155
TSMOM	85	0.0338110	8.24	<.0001

Korea Newey West Test for Buy, Sell and Buy_Sell 3 holding period

The MODEL Procedure

Model Summary	
Model Variables	1
Endogenous	1
Parameters	1
Equations	1
Number of Statements	1

Model Variables	Buy
Parameters	b0
Equations	Buy

The Equation to Estimate is	
Buy =	F(b0(1))
Instruments	1

NOTE: At GMM Iteration 0 convergence assumed because OBJECTIVE=3.098465E-34 is almost zero (<1E-12).

Korea Newey West Test for Buy, Sell and Buy_Sell 3 holding period

The MODEL Procedure
GMM Estimation Summary

Data Set Options	
DATA=	TS.MEWRETDAT2

Minimization Summary	
Parameters Estimated	1
Kernel Used	BARTLETT
l(n)	3
Method	Gauss
Iterations	0

Final Convergence Criteria	
R	1
PPC	0
RPC	.
Object	.
Trace(S)	0.045054

Final Convergence Criteria	
Objective Value	3.1E-34

Observations Processed	
Read	98
Solved	98
Used	85
Missing	13

Korea Newey West Test for Buy, Sell and Buy_Sell 3 holding period

The MODEL Procedure

Nonlinear GMM Summary of Residual Errors							
Equation	DF Model	DF Error	SSE	MSE	Root MSE	R-Square	Adj R-Sq
Buy	1	84	3.8296	0.0451	0.2123	-0.0000	-0.0000

Nonlinear GMM Parameter Estimates				
Parameter	Estimate	Approx Std Err	t Value	Approx Pr > |t|
b0	-0.02891	0.0322	-0.90	0.3718

Number of Observations		Statistics for System	
Used	85	Objective	3.098E-34
Missing	13	Objective*N	2.634E-32

GMM Test Statistics			
Test	DF	Statistic	Prob
Overidentifying Restrictions	0	0.00	.

Korea Newey West Test for Buy, Sell and Buy_Sell 3 holding period

The MODEL Procedure

Model Summary	
Model Variables	1
Endogenous	1
Parameters	1
Equations	1
Number of Statements	1

Model Variables	Sell
Parameters	b0
Equations	Sell

The Equation to Estimate is	
Sell =	F(b0(1))
Instruments	1

NOTE: At GMM Iteration 0 convergence assumed because OBJECTIVE=1.584703E-32 is almost zero (<1E-12).

Korea Newey West Test for Buy, Sell and Buy_Sell 3 holding period

The MODEL Procedure
GMM Estimation Summary

Data Set Options	
DATA=	TS.MEWRETDAT2

Minimization Summary	
Parameters Estimated	1
Kernel Used	BARTLETT
l(n)	3
Method	Gauss
Iterations	0

Final Convergence Criteria	
R	1
PPC	0
RPC	.
Object	.
Trace(S)	0.03024
Objective Value	1.58E-32

Observations Processed	
Read	98
Solved	98
Used	85
Missing	13

Korea Newey West Test for Buy, Sell and Buy_Sell 3 holding period

The MODEL Procedure

Nonlinear GMM Summary of Residual Errors							
Equation	DF Model	DF Error	SSE	MSE	Root MSE	R-Square	Adj R-Sq
Sell	1	84	2.5704	0.0302	0.1739	0.0000	0.0000

Nonlinear GMM Parameter Estimates				
Parameter	Estimate	Approx Std Err	t Value	Approx Pr > |t|
b0	-0.67234	0.0248	-27.16	<.0001

Number of Observations		Statistics for System	
Used	85	Objective	1.585E-32
Missing	13	Objective*N	1.347E-30

GMM Test Statistics			
Test	DF	Statistic	Prob
Overidentifying Restrictions	0	0.00	.

Korea Newey West Test for Buy, Sell and Buy_Sell 3 holding period

The MODEL Procedure

Model Summary	
Model Variables	1
Endogenous	1
Parameters	1
Equations	1
Number of Statements	1

Model Variables	TSMOM
Parameters	b0
Equations	TSMOM

The Equation to Estimate is	
TSMOM =	F(b0(1))
Instruments	1

NOTE: At GMM Iteration 0 convergence assumed because OBJECTIVE=2.422399E-33 is almost zero (<1E-12).

GMM Estimation Summary

Data Set Options	
DATA=	TS.MEWRETDAT2

Minimization Summary	
Parameters Estimated	1
Kernel Used	BARTLETT
I(n)	3
Method	Gauss
Iterations	0

Final Convergence Criteria	
R	1
PPC	0
RPC	.
Object	.
Trace(S)	0.001414
Objective Value	2.42E-33

Observations Processed	
Read	98
Solved	98
Used	85
Missing	13

Korea Newey West Test for Buy, Sell and Buy_Sell 3 holding period

The MODEL Procedure

Nonlinear GMM Summary of Residual Errors							
Equation	**DF Model**	**DF Error**	**SSE**	**MSE**	**Root MSE**	**R-Square**	**Adj R-Sq**
TSMOM	1	84	0.1202	0.00141	0.0376	-0.0000	-0.0000

Nonlinear GMM Parameter Estimates				
Parameter	**Estimate**	**Approx Std Err**	**t Value**	**Approx Pr > |t|**
b0	0.033811	0.00648	5.22	<.0001

Number of Observations		**Statistics for System**	
Used	85	**Objective**	2.422E-33
Missing	13	**Objective*N**	2.059E-31

GMM Test Statistics			
Test	**DF**	**Statistic**	**Prob**
Overidentifying Restrictions	0	0.00	.

Appendix 6. Sample of Quantile Regression

The QUANTREG Procedure

Model Information	
Data Set	HERDING.MSIA2
Dependent Variable	CSADt
Number of Independent Variables	4
Number of Observations	1589362
Optimization Algorithm	Interior
Method for Confidence Limits	Resampling

Number of Observations Read	1589373
Number of Observations Used	1589362
Missing Values	11

Summary Statistics						
Variable	**Q1**	**Median**	**Q3**	**Mean**	**Standard Deviation**	**MAD**
indret	-0.00440	0.000332	0.00480	0.000229	0.0135	0.00681
absind	0.00203	0.00459	0.00920	0.00758	0.0112	0.00459
avediff	0.000131	0.000483	0.00176	0.00604	0.0479	0.000633
lagCSAD	-0.0109	-0.00223	0.00511	-0.00255	0.0140	0.0118
CSADt	-0.0109	-0.00223	0.00511	-0.00255	0.0140	0.0118

The QUANTREG Procedure
Quantile Level = 0.1

Quantile Level and Objective Function	
Quantile Level	0.1
Objective Function	36.7863
Predicted Value at Mean	-0.0026

Parameter Estimates							
Parameter	**DF**	**Estimate**	**Standard Error**	**95% Confidence Limits**		**t Value**	**Pr > |t|**
Intercept	1	-0.0000	0.0000	-0.0000	-0.0000	-3.17	0.0015
indret	1	0.0000	0.0000	-0.0000	0.0000	0.04	0.9673
absind	1	-0.0000	0.0000	-0.0000	0.0000	-0.01	0.9883
avediff	1	-0.0000	0.0000	-0.0000	0.0000	-0.00	0.9981
lagCSAD	1	1.0000	0.0000	1.0000	1.0000	3.33E14	<.0001

The QUANTREG Procedure
Quantile Level = 0.25

Quantile Level and Objective Function	
Quantile Level	0.25
Objective Function	36.7925
Predicted Value at Mean	-0.0026

Parameter Estimates							
Parameter	DF	Estimate	Standard Error	95% Confidence Limits		t Value	Pr > |t|
Intercept	1	-0.0000	0.0000	-0.0000	0.0000	.	.
indret	1	0.0000	0.0000	-0.0000	0.0000	0.03	0.9748
absind	1	-0.0000	0.0000	-0.0000	0.0000	-0.11	0.9146
avediff	1	-0.0000	0.0000	-0.0000	0.0000	-0.00	0.9976
lagCSAD	1	1.0000	0.0000	1.0000	1.0000	3.68E14	<.0001

The QUANTREG Procedure
Quantile Level = 0.5

Quantile Level and Objective Function	
Quantile Level	0.5
Objective Function	36.8028
Predicted Value at Mean	-0.0026

Parameter Estimates							
Parameter	DF	Estimate	Standard Error	95% Confidence Limits		t Value	Pr > |t|
Intercept	1	-0.0000	0.0000	-0.0000	0.0000	.	.
indret	1	-0.0000	0.0000	-0.0000	0.0000	-0.00	0.9977
absind	1	0.0000	0.0000	-0.0000	0.0000	0.00	0.9969
avediff	1	0.0000	0.0000	-0.0000	0.0000	0.00	0.9996
lagCSAD	1	1.0000	0.0000	1.0000	1.0000	4.01E14	<.0001

The QUANTREG Procedure
Quantile Level = 0.75

Quantile Level and Objective Function	
Quantile Level	0.75
Objective Function	36.8131
Predicted Value at Mean	-0.0026

Parameter Estimates							
Parameter	**DF**	**Estimate**	**Standard Error**	**95% Confidence Limits**		**t Value**	**Pr > |t|**
Intercept	1	0.0000	0.0000	-0.0000	0.0000	.	.
indret	1	0.0000	0.0000	-0.0000	0.0000	0.01	0.9932
absind	1	0.0000	0.0000	-0.0000	0.0000	0.05	0.9587
avediff	1	0.0000	0.0000	-0.0000	0.0000	0.00	0.9998
lagCSAD	1	1.0000	0.0000	1.0000	1.0000	4.01E14	<.0001

The QUANTREG Procedure
Quantile Level = 0.9

Quantile Level and Objective Function	
Quantile Level	0.9
Objective Function	36.8193
Predicted Value at Mean	-0.0026

Parameter Estimates							
Parameter	**DF**	**Estimate**	**Standard Error**	**95% Confidence Limits**		**t Value**	**Pr > |t|**
Intercept	1	0.0000	0.0000	-0.0000	0.0000	.	.
indret	1	0.0000	0.0000	-0.0000	0.0000	0.01	0.9905
absind	1	0.0000	0.0000	-0.0000	0.0000	0.05	0.9620
avediff	1	-0.0000	0.0000	-0.0000	0.0000	-0.00	1.0000
lagCSAD	1	1.0000	0.0000	1.0000	1.0000	3.97E14	<.0001

Appendix 7. Sample of Newey and West T-statistics for Herding

Newey and West (1987) T statistics for Herding - 3 months

The MODEL Procedure

Model Summary	
Model Variables	3
Endogenous	1
Exogenous	2
Parameters	3
Equations	1
Number of Statements	1

Model Variables	CSAD_t absmeanret absmeansq
Parameters	b0 b1 b2
Equations	CSAD_t

The Equation to Estimate is	
CSAD_t =	F(b0(1), b1(absmeanret), b2(absmeansq))
Instruments	1 absmeanret absmeansq

NOTE: At GMM Iteration 0 convergence assumed because OBJECTIVE=2.703242E-29 is almost zero (<1E-12).

Newey and West (1987) T statistics for Herding - 3 months

The MODEL Procedure
GMM Estimation Summary

Data Set Options	
DATA=	DEZHANGQTR1EDIT

Minimization Summary	
Parameters Estimated	3
Kernel Used	BARTLETT
I(n)	3
Method	Gauss
Iterations	0

Final Convergence Criteria	
R	1
PPC	0
RPC	.
Object	.
Trace(S)	0.000032
Objective Value	2.7E-29

Observations Processed	
Read	320
Solved	320

Newey and West (1987) T statistics for Herding - 3 months

The MODEL Procedure

Nonlinear GMM Summary of Residual Errors							
Equation	DF Model	DF Error	SSE	MSE	Root MSE	R-Square	Adj R-Sq
CSAD_t	3	317	0.0104	0.000032	0.00570	0.2593	0.2547

Nonlinear GMM Parameter Estimates				
Parameter	Estimate	Approx Std Err	t Value	Approx Pr > |t|
b0	0.015201	0.000601	25.31	<.0001
b1	0.542016	0.1032	5.25	<.0001
b2	-4.54339	1.1267	-4.03	<.0001

Number of Observations		Statistics for System	
Used	320	Objective	2.703E-29
Missing	0	Objective*N	8.65E-27

GMM Test Statistics			
Test	DF	Statistic	Prob
Overidentifying Restrictions	0	0.00	.