Retail investors and industry-based style investing:
Evidence from the Stock Exchange of Thailand

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A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science Program in Finance
Department of Banking and Finance
Faculty of Commerce and Accountancy
Chulalongkorn University
Academic Year 2016

นักลงทุนรายย่อยและการลงทุนตามรูปแบบที่อิงกับกลุ่มอุตสาหกรรม:
หลักฐานจากตลาดหลักทรัพย์แห่งประเทศไทย

นายธัญพัฒน์ นิรุตติศาสน์

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
สาขาวิชาการเงิน ภาควิชาการธนาคารและการเงิน
คณะพาณิชยศาสตร์และการบัญชี จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2559

Thesis Title	Retail investors and industry-based style investing: Evidence from the Stock Exchange of Thailand
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Field of Study	Finance
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ธัญพัฒน์ นิรุตติศาสน์ : นักลงทุนรายย่อยและการลงทุนตามรูปแบบที่อิงกับกลุ่มอุตสาหกรรม: หลักฐานจากตลาดหลักทรัพย์แห่งประเทศไทย (Retail investors and industry-based style investing: Evidence from the Stock Exchange of Thailand) อ.ที่ปรึกษาวิทยานิพนธ์หลัก: ดร.ธนากร ลิขิตาภิวัฒน์, หน้า.

วิทยานิพนธ์ฉบับนี้ทำการศึกษาว่านักลงทุนรายย่อยในตลาดหลักทรัพย์แห่งประเทศไทยมีการลงทุนตามรูปแบบที่อิงกับอุตสาหกรรมหรือไม่ โดยใช้ข้อมูลรายธุรกรรมในช่วงระยะเวลาปี พ.ศ. 2547-2556 ซึ่งจากการศึกษาพบว่าอุปสงค์ของนักลงทุนรายย่อยมีความสัมพันธ์กันในระดับอุตสาหกรรม อุปสงค์ของนักลงทุนรายย่อยในระดับอุตสาหกรรมมีความสัมพันธ์เชิงลบกับผลตอบแทนของอุตสาหกรรมในอดีตซึ่งต่างกับที่ทฤษฎีระบุไว้ และยังพบว่าไม่สามารถหาความสัมพันธ์ระหว่างอุปสงค์ของนักลงทุนรายย่อยในระดับอุตสาหกรรมกับผลตอบแทนของอุตสาหกรรมในอนาคต นอกจากนี้การศึกษายังพบว่าหลังจากที่นักลงทุนรายย่อยเลือกที่จะลงทุนในอุตสาหกรรมที่น่าสนใจแล้ว ยังตัดสินใจลงทุนในกลุ่มหุ้นขนาดเล็กมากกว่ากลุ่มหุ้นขนาดใหญ่อีกด้วย ผลจากการศึกษาชี้ว่าการตัดสินใจลงทุนของนักลงทุนรายย่อยได้รับอิทธิพลจากการจัดกลุ่มเป็นอุตสาหกรรม และนักลงทุนรายย่อยตัดสินใจเลือกซื้อหุ้นโดยแบ่งการตัดสินใจเป็นสองขั้นตอน

ภาควิชา	การธนาคารและการเงิน	ลายมือชื่อนิสิต	....
สาขาวิชา	การเงิน	ลายมือชื่อ อ.ที่ปรึกษาหลัก	....
ปีการศึกษา	2559		

5882935426 : MAJOR FINANCE
KEYWORDS: RETAIL INVESTORS / STYLE INVESTING / INDUSTRY

THANYAPHAT NIRUTHISARD: Retail investors and industry-based style investing: Evidence from the Stock Exchange of Thailand. ADVISOR: TANAKORN LIKITAPIWAT, Ph.D., pp.

This study investigates if retail investors in the Stock Exchange of Thailand pursue industry-based style investing using transaction data during 2004-2013. It finds the coordination in retail investor demand at the industry-level. In contrast to the prediction of the style investing model, retail investor industry demand is negatively related to past industry returns. No relationship between retail investor industry demand and subsequent industry returns is found across all time horizons. In addition, there is evidence that after choosing to invest in an attractive industry, retail investors prefer to invest in small-cap stocks more than large-cap stocks. These findings suggest that retail investors' investment decisions are influenced by industry-wide categorization, and they make their buying decisions follow a two-step decision-making process.

Department:	Banking and Finance	Student's Signature	....
Field of Study:	Finance	Advisor's Signature	....
Academic Year:	2016		

ACKNOWLEDGEMENTS

The completion of this thesis could not have been possible without the participation and assistance of many people whose name may not all be clarified. Without them, my thesis would not have been possible to come this far. Their contributions are sincerely appreciated and gratefully acknowledged. However, I would like to utter my appreciation and extend my gratitude to the following person.

First, I would like to express the inmost appreciation to my advisor, Tanakorn Likitapiwat, Ph.D., for his dedicated support, patience, and continuous guidance. He is always available whenever I need his assistance. Furthermore, I would like to convey my gratitude to Assoc. Prof. Vimut Vanitcharearnthum, Ph.D., Suparatana Tanthanongsakkun, Ph.D., and my external examiner, Asst. Prof. Nattawut Jenwittayaroje, Ph.D., for their valuable questions and suggestions.

Second, thanks also go to my beloved classmates and staff at the Master of Science in Finance program. I do highly appreciate for their sincerely support and assistance through this master program period.

Eventually, I would like to thank my family for their unconditional and endless support, encouragement, and true understanding during my thesis development period.

CONTENTS

Page

CHAPTER 1

INTRODUCTION

1.1. Background of the study

In financial markets, assets are commonly classified into broad categories, such as but not limited to fixed income securities, equities, and derivatives. Similarly, stocks can be classified into various categories based on their similar characteristics (e.g. small/large, or value/growth). Stocks that are characterized based on similar characteristic can also be referred to as particular 'styles', and the process of allocating funds across styles is referred to as 'style investing' (Barberis & Shleifer, 2003)

According to Barberis and Shleifer (2003), investors pursue style investing because it helps simplify their complex investment decisions by reducing the number of choices (Mullainathan, 2000). Investors who pursue style investing are known as 'style investors'. Specifically, style investors do not allocate funds across individual assets but choose to allocate funds across styles in order to simplify their complex investment decisions. The term 'style investors' also refers to investors who limit themselves to choosing individual assets from a particular style.

The theoretical literature on style investing was pioneered by Barberis and Shleifer (2003). In their model, two types of investors are assumed to participate in the market: 'switchers' and 'fundamental traders'. Switchers are investors who allocate funds at the style-level, and their investment in a particular style depends on that relative past performance of that style. In other words, switchers invest more into those styles with good relative past performance and withdraw funds from styles with bad relative past performance. In contrast, fundamental traders perform as arbitrageurs who attempt to prevent the price of each asset deviating from its fundamental value.

There are three main important implications from the style investing model of Barberis and Shleifer (2003). Firstly, because style investors allocate their funds at the style-level, common factors in terms of asset returns are generated as a result of the coordination in trades (i.e. herding). In other words, their coordinated demand leads assets' prices that are in the same style to co-move beyond the co-movement in stocks selected using a fundamental approach. Secondly, style-level momentum and value strategies can be as profitable as or even more profitable than asset-level momentum and value strategies. Eventually, investment styles have a specific life cycle. A style rises from good fundamental news about the assets in the style, and collapses from arbitrage or bad fundamental news.

The style investing model of Barberis and Shleifer (2003) has generated a number of empirical studies to test their model of style investing. Teo and Woo (2004) find evidence for reversals at the style-level. They also show that the style-level value strategy can earn excess and risk-adjusted return at the annual horizon but not for a style-level momentum strategy. Barberis et al. (2005) report that stocks added to the S&P 500 Index start to correlate more with other stocks in the index as a result of investors' consideration of the S&P 500 Index as one style. Greenwood (2008) also provides similar results for the Nikkei 225. Green and Hwang (2009) show that stocks undergone stock splits start to comove more with low-priced stocks and comove less with high-priced stocks.

Several empirical studies explore the style investing behavior of a specific type of investor in the US. Froot and Teo (2008) find strong evidence that institutional investors reallocate funds across styles (i.e. size, value/growth, and sector) with greater intensity than across random stocks. Choi and Sias (2009) suggest that industry is an another style, and report that institutional investors demand is correlated at the industry-level indicates for industry herding phenomenon. Focusing on retail investors, Kumar (2009) shows evidence of retail investors' preference shifts across style portfolios (i.e. size, and value/growth), and their preference shifts are influenced by past style returns. He also concludes that investment decisions of retail investors are influenced by stock categorization. Jame and Tong (2014) find that retail investor demand is correlated at the industry-level and positively related to past industry returns. They conclude that retail investors pursue industry-based style investing.

In Thailand, empirical research on this subject began with Roongwatanayothin's (2011) investigation of the profitability of style-level momentum and value strategies. His results are consistent with those of Teo and

Woo (2004). That is, the style-level value strategy gives abnormal return at the annual horizon but not for the style-level momentum strategy. Kokasemsook (2012) examines the impact of style investing to stock returns by measuring the predictability power of past style returns to individual stock returns. He reports evidence that past style returns predicted future stock returns during 2007 to 2012 period. Recently, using the unique dataset from the Stock Exchange of Thailand coving the period from 1999 to 2013, Lohitanon (2015) examines the style preferences of four investor types (i.e. retail investors, institutional investors, proprietary traders, and foreign investors) in three style dimensions: size, value/growth, and contrarian/momentum. He shows that all type of investors pursues style investing, and each type of investor has their own preferred style. For example, retail investors prefer to trade in small size, growth, and worst past return stocks.

Since there is a growing interest in empirical research about style investing in Thailand, further investigation of the extent of the style investing offers additional opportunities to uncover interesting evidence about their functioning. According to Choi and Sias (2009), and Jame and Tong (2014), apart from statistical classifications such as size and value/growth, fundamental classifications such as industry is an another potential style. In the US, the market consists of thousands of listed stocks; therefore, it is not surprise that investors pursue style investing to reduce their number of investment choices. For example, industry-based style investing is one way to achieve this reduction in investment choices. However, in Thailand, the market contains fewer listed stocks compared to the US market and it is still considered to be an emerging market, which is known to be less efficient. Many studies usually report different findings between these two market stages. Consequently, industry-based style investing phenomenon may be different in Thailand.

In addition, unlike the US where institutional investors are the main players, retail investors are the dominant investors in Thailand. They possess more than 50% of trading value in the stock market[1]. Apart from being the main investors, it is interesting to examine the style investing behavior of retail investors for several reasons. First, retail investors have more limited resources (e.g. knowledge, time, and information) than other type of investors (Jame and Tong, 2014), which makes them more susceptible to pursue style investing to simplify their complex investment decisions. Second, because retail investors are the dominant players in Thailand, their demand shock tends to have substantial impact on asset prices in the market. In fact, many existing studies report that retail investor trades move the market (e.g. Hvidkjaer, 2008; Kaniel, Saar, & Titman, 2008; Barber, Odean, & Zhu, 2009b); and in markets where retail investors are the main players, the impact of their trades to the asset prices may even be stronger.

[1] Trading value data by investor types is provided by the Stock Exchange of Thailand.

This study is motivated by these differences between emerging and fully-developed markets, and extends previous studies conducting in Thailand by examining style investing under the scope of 'industry-based style investing' focusing on retail investors.

1.2. Objectives of the study / Research questions

The study aims to investigate the style investing behavior of retail investors in Thailand under the scope of 'industry-based style investing'. The following research questions will be explored:

1. Do retail investors in Thailand pursue industry-based style investing?
2. Do past industry returns influence retail investor industry demand?
3. How does retail investor industry demand have an effect on subsequent industry returns?
4. In each industry that attracts retail investors' attention, do retail investors choose stocks by considering the size of the stocks (i.e. market capitalization)?

1.3. Contributions

This study has 4 main contributions as follows:

1. By exploring another potential style (i.e. industry-based style), this study contributes to the growing style investing literature conduct in Thailand.

Specifically, it provides evidence about and to the degree that retail investors in Thailand pursue industry-based style investing.

2. In term of its theoretical contribution, this study shows whether the recent behavior of retail investors in Thailand is consistent with traditional finance or behavioral finance theory. To further elaborate, by examining style investing behavior, it shows whether retail investors are rational, or if they are bounded-rational (i.e. having cognitive, temporal, and attentional limitations). In addition, by examining the relations of retail investor industry demand with past industry returns and subsequent industry returns, it shows whether retail investors make investment decisions based on rational judgement from fundamental news, or are affected by psychological biases.
3. This study further uncovers evidence about the degree to which investment decisions of retail investors have two steps: a screening stage and a decision-making stage, which would provide more in-depth understanding in decision-making process of retail investors. This would contribute to the existing psychological theory (i.e. Image Theory).
4. This study makes a contribution to practicing professionals because it provides useful information to financial institutions that they can use to improve their financial products that will better satisfy retail investors.

CHAPTER 2

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

There are five sections classified as follows: (1) Terminology and concept, (2) Theoretical background, (3) Style investing literature, (4) Retail investor trading behavior literature, and (5) Hypothesis development.

2.1. Terminology and concept

2.1.1. Bounded-rationality

'Bounded-rational concept' is firstly proposed by Herbert A. Simon (Simon, 1947). In contrast to the classical economic theory that views human in a rational sense, he suggests that rationality of human is partial or bounded because of many limitations (e.g. information, cognitive capacity, time, attention). Sentiment or emotion would drive the remaining part of their decisions and actions.

Therefore, human would only make the decision that is good enough or just satisfactory for them, not something that is optimal. This decision-making process of human is also known as a 'heuristics'. Furthermore, bounded-rationality can lead human to have psychological bias causing their decisions to deviate from rational judgement, which may be defined as 'irrationality' (Kahneman and Tversky, 1972).

2.1.2. Style investing

Style investing, in essence, is built up on the view that investors are bounded-rational. According to Barberis and Shleifer (2003), investors simplify their investment decisions by grouping assets into categories based on some similar characteristics to reduce the number of choices. Then, they choose to invest in individual assets from their preferred styles. Therefore, in the presence of categorizing behavior, investors would decide how to allocate their money across styles. This process is called as ‘style investing’. And, ‘industry-based style investing’ refers to the phenomenon that investors move or allocate their money across industries.

2.1.3. Herding, correlation in trades, and style investing

Herding can be defined as many investors buy or sell the same industry or individual assets at the same time (Sias, 2004). It can be interpreted as many investors trade in the same direction (buy or sell). In addition, herding is often used in the same meaning of the correlation in trades (Chiang and Zheng, 2009).

Several studies use herding definition to measure the presence of industry-based style investing (e.g. Choi and Sias, 2009; Jame and Tong, 2014). The logic behind its usage is that if investors pursue industry-based style investing, they will trade in the same direction (buy or sell) at the industry-level. Therefore, herding concept is applied to measure the existence of industry-based style investing phenomenon.

2.2. Theoretical background

2.2.1. Traditional finance

Traditional finance is developed on the efficient market hypothesis (EMH). According to efficient market view, investors are fully rational and stock prices fully reflect all available information (Fama, 1991). Under EMH, investor trading patterns are random, and correlation in trades that cause movements in stock prices are influenced by either review in their fundamental values encouraged by the new information release or the discount rate change. Any mispricing (i.e. deviation of stock prices from a rational judgement of their fundamental values) is quickly eliminated by rational arbitrageurs (Barberis and Thaler, 2003). Therefore, demand shocks do not have an impact on stock prices under efficient market hypothesis.

2.2.2. Behavioral finance

Behavioral finance is an alternative theory arising from the anomalies in the financial markets that cannot be explained by traditional finance. Efficient market hypothesis (EMH) lost ground rapidly since Shiller's (1981) volatility test has been published, it is found that stock market volatility is much greater than could be justified by changes in cash flows.

According to Shleifer and Summer (1990), the behavioral finance lies with two assumptions: investor sentiment and limits to arbitrage. To illustrate, they assume that two types of investors participate in the market: uninformed investors (e.g. retail investors) and informed investors (e.g. institutional investors or arbitrageurs). The former group of investors is assumed to be bounded-rational and their demand for risky assets is partially influenced by their sentiment and psychological biases, while the latter group of investors is assumed to make more rational investment decision. The theory also states that arbitrage is limited and risky because of the fundamental risk and unpredictable future resale price (De Long et al., 1990). Therefore, mispricing in stock prices caused by correlation in trades occurred from the shifts in investor sentiment cannot fully absorbed by rational arbitrageurs. Consequently, demand shifts of uninformed investors (e.g. retail investors) may impact stock returns (Barberis and Thaler, 2003).

2.2.3. Image Theory

Image Theory is the descriptive theory about how human make decisions. The theory states that there are two types of decisions, adoption decisions and progress decisions. Human may make their decisions using either or both of these decisions (Beach and Mitchell, 1987).

Adoption decisions can be divided into two steps, screening step and decision step. Screening step is the step of eliminating unsatisfied candidates. Decision step is the step of selecting the most satisfied choice among the remaining from screening step.

Progress decision is the process of analyzing the suitability between the forecasted future resulting from making the decision and the ideal future in their aspect. Unsuitability causes rejection of the decisions, and adoption of a new substitute.

2.3. Style investing literature

The theoretical study of style investing is pioneered by Barberis and Shleifer (2003), in which, in the essence, is built up from the behavioral finance ground. They state that grouping objects into categories based on their similarities is one of the most common mechanisms of human thought. When making investment decisions, many investors often group assets into broad categories such as value stocks, and government bonds and then decide how to allocate their funds across the categories rather than across the individual assets. This is because grouping would help simplify complicated investment decision and allow investors to process huge amount of information more efficiently (Mullainathan, 2000). Stocks that are characterized based on similar characteristic can also be referred to as having a particular 'styles', and the process of allocating funds across styles is referred to as 'style investing' (Barberis & Shleifer, 2003).

In their model, two types of investors are assumed to participate in the market: 'switchers' and 'fundamental traders'. Switchers are investors who allocate funds at the style-level, and their investment in a particular style depends on that relative past performance of that style. In other words, switchers invest more into those styles with good relative past performance and withdraw funds from styles with bad relative past performance. In contrast, fundamental traders perform as arbitrageurs who attempt to prevent the price of each asset deviating from its fundamental value.

There are three main important implications from the style investing model of Barberis and Shleifer (2003). Firstly, because style investors allocate their funds at the style-level, common factors in terms of asset returns are generated as a result of the coordination in trades (i.e. herding). In other words, their coordinated demand leads assets' prices that are in the same style to comove beyond the comovement in stocks selected using a fundamental approach. Secondly, style-level momentum and value strategies can be as profitable as or even more profitable than asset-level momentum and value strategies. Eventually, investment styles have a specific life cycle. A style rises from good fundamental news about the assets in the style, and collapses from arbitrage or bad fundamental news.

Barberis and Shleifer's (2003) publication of their style investing models rapidly generates a number of empirical studies on category-based investment. Teo and Woo (2004) find evidence for reversals at the style-level. They also show that a style-level value strategy can earn excess risk-adjusted return at annual horizon but not for style-level momentum strategy. Barberis et al. (2005) report that stocks added to the S&P 500 Index start to correlate more with other stocks in the index as a result of investors' consideration of the S&P 500 Index as a one style. Greenwood (2008) also provides similar results for the Nikkei 225. Green and Hwang (2009) show that stocks undergone stock splits start to comove more with low-priced stocks and comove less with high-priced stocks. Focusing on institutional investors, Froot and Teo (2008) find strong evidence that institutional investors reallocate funds across styles (i.e. size, value/growth, and sector) with greater intensity than across random stocks. Choi and Sias (2009) suggest that industry is an another style, and report that institutional investors demand is correlated at the industry-level indicates for industry herding phenomenon.

There are relatively few empirical studies that examine retail investor trades at the style-level. Using the US dataset, Kumar (2009) reports that retail investors systematically shift their preferences across style portfolios (i.e. small/large, and value/growth), and their preference shifts are influenced by past style returns. He also concludes that investors' investment decisions are influenced by stock categorization. Motivated by the style investing model, Jame and Tong (2014) examine industry-based style investing of retail investors in the US, and find that retail investor trading is highly correlated at the industry-level and strongly related to past returns. Their results lead them to conclude that investment decisions of retail investors are influenced by industry-wide categorization.

In Thailand, research in this area began with Roongwatanayothin (2011) who investigates the profitability of style-level momentum and value strategies. His results are consistent with the results of Teo and Woo (2004). That is, the style-level value strategy gives abnormal profit at annual horizon but not for style-level momentum strategy. Kokasemsook (2012) examines the impact of style investing to stock returns by measuring predictability power of past style returns to individual stock returns. He reports evidence that past style returns did predict future stock returns during 2007 to 2012 period. Recently, Lohitanon (2015) examines the style preferences of four investor types (i.e. retail investors, institutional investors, foreign investors, and proprietary investors) in three style dimensions: size, value/growth, and contrarian/momentum. He shows that all type of investors pursues style investing, and each type of investor has their own preferred style. For retail investors, they prefer to trade in growth stocks, lowest past return stocks, and small-cap stocks.

2.4. Retail investor trading behavior literature

Retail investors or individual investors are considered to be uninformed traders because of their sentiment and psychological biases (Lee, Shleifer, and Thaler, 1991). Their trades are likely to be systematically correlated. In other words, they exhibit herding behavior.

Several studies further suggest that retail investors have more cognitive and temporal limitations as to how much information they can process compared to other types of investors (e.g. Kumar and Lee, 2006; Barber and Odean, 2008; Barber, Odean, and Zhu, 2009a). To be specific, retail investors tend to consider and trade only groups of stocks that attract their attention leading to correlated trading in that group of stocks. Using more than 1.85 million retail investor transactions, Kumar and Lee (2006) show that retail investor trades are highly correlated. They also argue that retail investors spend little time on investment analysis, and commit to more attention-based trading. In other words, retail investors prefer stocks that are sensitive to their sentiment shifts (i.e. small-cap, value, lower institutional ownership, and lower-priced stocks). Consistent with Barber and Odean (2008), they test and confirm that attention greatly contributes to retail investors' buying decisions. Retail investors limit their choice set and may consider only group of stocks that first catch their attention (e.g. stocks that are in the news or stocks with high returns) because humans have limited abilities to process information. Within the group of stocks that catches their attention, retail investors tend to choose stocks based on their personal preferences. In fact, this statement is consistent with Beach and Mitchell's (1987) 'Image Theory' model, which states that humans' decision-making process has two steps: a screening step and a decision step.

Many studies further investigate the impact of retail investor correlated trading on asset prices. Using signed small-trade turnover (SSTT) as a measurement of retail investor trading behavior, Hvidkjaer (2008) shows that stocks with intense sell volume outperform stocks with intense buy volume. This return difference continues from one month to two years in the future. He suggests that stocks favored by retail investors are likely to face with large and prolonged under performance in the future, relative to stocks out of favor with retail investors. At weekly horizon, Kaniel, Saar, and Titman (2008) argue that stocks heavily bought (sold) by retail investors in the prior week outperform (underperform) in the subsequent week. Later, findings of Hvidkjaer (2008) and Kaniel, Saar, and Titman (2008) are confirmed by Barber, Odean, and Zhu (2009b). Over annual horizon, stocks heavily bought by retail investors underperform stocks heavily sold by 4.4 percent the subsequent year. Over weekly horizon, retail investor trading forecast returns in the opposite direction. Stocks heavily bought one week earn strong returns the following week, while stocks heavily sold earn poor returns.

2.5. Hypothesis development

If retail investors pursue industry-based style investing, their investment decisions shall have an industry-wide component. They would reallocate their funds at the industry-level with greater intensity than reallocate across stocks grouped randomly (Jame and Tong, 2014). That is, retail investors' attention to particular category leads them to have coordination in demand at the category-level (Barber, Odean, and Zhu, 2009a). In other words, industry-based style investing would make retail investors to exhibit herding behavior at the industry-level. Therefore:

Hypothesis 1: *Retail investor demand is correlated at the industry-level.*

Several empirical studies report that style demand of retail investors is influenced by past style returns. In the US, Kumar (2009) shows that retail investors shift their demand across styles (small/large, and value/growth), and these demand shifts are influenced by past style returns. Jame and Tong, 2014 examine industry-based style investing, and report that retail investor industry demand is positively related to past industry returns. Conversely, in Thailand, Lohitanon (2015) finds that retail investors' preference is negatively related to past style returns. Therefore:

Hypothesis 2: *Retail investor industry demand is influenced by past industry returns.*

Retail investors are often thought to be noise traders (Shleifer and Summers, 1990). Many studies find evidence that their demand shifts have predictability power on asset prices in the market (e.g. Hvidkjaer, 2008; Kaniel, Saar, and Titman, 2008; Barber, Odean, and Zhu, 2009b). To be specific, existing literature suggests that retail investor demand drive asset prices in the short run (i.e. weekly horizon), leading to long-term reversal (i.e. monthly and annual/ horizon). This price pattern is still hold at the style-level (Barberis and Shleifer, 2003; and Jame and Tong, 2014). Therefore:

Hypothesis 3: *Retail investor industry demand drives industry values.*

Hypothesis 3-1: *Retail investor industry demand positively relates to subsequent industry returns in the short run (i.e. weekly horizon).*

Hypothesis 3-2: *Retail investor industry demand negatively relates to subsequent industry returns in the long run (i.e. monthly and annual horizon).*

Within the group of stocks (i.e. industry) that catches retail investors' attention, retail investors are likely to purchase stocks that match their preferences (Barber and Odean, 2008). This statement is consistent with Beach and Mitchell's (1987) 'Image Theory' model, which states that humans' decision-making process has two steps: a screening step and a decision step. Based on the findings of Kumar and Lee (2006), and Lohitanon (2015), retail investors are found to prefer to invest in small-cap stocks. That is, after screening stocks by industry, if retail investors prefer to invest in small-cap stocks more than large-cap stocks, the degree of buying demand in small-cap stocks should be greater than the buying demand in large-cap stocks. Therefore:

Hypothesis 4: *The degree of coordination of retail investor buying demand is greater in small-cap stocks than large-cap stocks in the industry that attracts their attention.*

CHAPTER 3

DATA

3.1. Trading transaction data of retail investors

The dataset includes all retail investors' transaction data that have been executed on actively traded stocks listed in the Stock Exchange of Thailand (SET) from January 2004 to December 2013. The data was provided by the Stock Exchange of Thailand. 'Deal data file' is used in this study.

In the deal data file, there are 4 types of investors: retail investors, institutions, proprietary traders, and foreign investors. Retail investors can be identified by investor type identification flags. In addition, trade directions (i.e. buy or sell) that are executed by retail investors can be also identified by order time.

3.2. Industry classification

Sector classification system classified by the Stock Exchange of Thailand (SET) is applied for industry categorization. There are 28 sectors in total; however, 5 sectors are excluded from this study according to its characteristics and lack of company in the sector as shown in Table 1. Each stock is assigned to one of these 23 sectors.

Table 1 : *Industry categorization*

This table presents sector classification system classified by the Stock Exchange of Thailand (SET). 5 sectors: PERSON, PAPER, MINE, and PROF are excluded from the analysis because of their lack of company in the sector. PF&REIT is excluded due to its unique characteristics.

Symbol	Name of Sector
AGRI	Agribusiness
FOOD	Food & Beverage
FASHION	Fashion
HOME	Home & Office Products
BANK	Banking
FIN	Finance & Securities
INSUR	Insurance
AUTO	Automotive
IMM	Industrial Materials & Machinery
PETRO	Petrochemicals & Chemicals
PKG	Packaging
STEEL	Steel
CONMAT	Construction Materials
PROP	Property Development
CONS	Construction Services
ENERG	Energy & Utilities
COMM	Commerce
HELTH	Health Care Services
MEDIA	Media and Publishing
TOURISM	Tourism & Leisure
TRANS	Transportation & Logistics
ETRON	Electronic Components
ICT	Information & Communication Technology

3.3. Industry returns

First, weekly and monthly adjusted prices of all stock are obtained from *Thomson Reuter Datastream*. Then, weekly and monthly return of each stock is calculated as follow:

$$R_{k,t} = \ln\left(\frac{P_{k,t}}{P_{k,t-1}}\right) \times 100 \tag{1}$$

where $R_{k,t}$ = return of stock k for week t (month t)

$P_{k,t}$ = adjusted price of stock k at the end of week t (month t)

$P_{k,t-1}$ = adjusted price of stock k at the end of week t-1 (month t-1)

Second, weighted-average industry returns are calculated using the formula:

$$R_{i,t} = \sum_{k=1}^{n} R_{k,t} \times w_{k,t} \tag{2}$$

where $R_{i,t}$ = return of industry i for week t (month t)

$R_{k,t}$ = return of stock k in industry i for week t (month t)

$w_{k,t}$ = % market-cap of stock k to industry market-cap at the beginning of week t (month t)

n = number of stocks in industry i

3.4. Market capitalization

Market capitalization is the total market value of the outstanding shares calculated by multiplying the amount of company's outstanding shares by the current market price of one share. Monthly market capitalization of all stock is obtained from *Thomson Reuter Datastream*.

3.5. Price-to-book ratio

Price-to-book ratio is a ratio compared market stock price to book value per share of the company. Monthly price-to-book ratio of all stock is obtained from *Thomson Reuter Datastream*.

CHAPTER 4

METHODOLOGY

4.1. Retail investor industry demand

As this study focuses on industry-based style investing of retail investors, therefore, first, retail investor industry demand (i.e. buying demand or selling demand) need to be measured. To measure retail investor industry demand, proportion bought is calculated from January 2004 to December 2013 as a proxy using the formula as follow:

$$p_{i,t} = \frac{b_{i,t}}{b_{i,t}+s_{i,t}} = \frac{b_{i,t}}{n_{i,t}} \quad (3)$$

where $b_{i,t}$ = number of retail investor buy transaction in industry *i* in time *t*

$s_{i,t}$ = number of retail investor sell transaction in industry *i* in time *t*

$n_{i,t}$ = number of total retail investor transaction in industry *i* in time *t*

Time t mentioned above refer to the different time horizons: 1 week, 1 month, 3 months, 6 months, and 12 months. To further elaborate, 1 week proportion bought is calculated weekly. For 1 month, 3 months, 6 months, and 12 months proportion bought, they are calculated monthly.

4.2. Coordination in demand at the industry-level

If retail investors pursue industry-based style investing, coordination in demand at the industry-level should be observed. To examine *Hypothesis 1* whether retail investor demand is correlated at the industry-level, following Choi and Sias (2009), and Jame and Tong (2014), the Lakonishok, Shleifer, and Vishny (1992) herding measure is applied. It should be noted again that herding is often used to describe the correlation in trades as a result of interactions between investors (Chiang and Zheng, 2010). In other words, the LSV herding measure tests whether retail investors trade in the same direction across industry. The LSV herding measure of industry *i* in month *t* is calculated as follow:

$$HM_{i,t} = \left|p_{i,t} - \bar{p}_{i,t}\right| - AF_{i,t} \qquad (4)$$

where $p_{i,t}$ = proportion bought of industry *i* in month *t*

$\bar{p}_{i,t}$ = average proportion bought across all industry in month *t*

$AF_{i,t}$ = adjustment factor of industry *i* in month *t*

The former term measures the absolute difference between the proportion bought of industry *i* in month *t* and the average proportion bought across all industry. Because the difference is an absolute value, the first term will always be positive. The latter term, $AF_{i,t}$ is an adjustment factor that accounts for the fact that in the case of no herding, $\left|p_{i,t} - \bar{p}_{i,t}\right|$ can be greater than zero by chance. In other words, the adjustment factor ($AF_{i,t}$) allows the capture of the random variation of $p_{i,t}$ around $\bar{p}_{i,t}$, under independent trading situation, and is computed by assuming the number of total retail investor transaction of industry *i* in month *t* ($n_{i,t}$) follows a binomial distribution with the probability of buying set equal to $\bar{p}_{i,t}$. According to Bellando (2010), the adjustment factor of industry *i* in month *t* ($AF_{i,t}$) is given by:

$$\begin{aligned} AF_{i,t} &= \sum_{k=0}^{n_{i,t}} prob\left(b_{i,t}=k\right)\left|\frac{k}{n_{i,t}}-\bar{p}_{i,t}\right| \\ &= \sum_{k=0}^{n_{i,t}} \binom{n_{i,t}}{k} \bar{p}_{i,t}^{k}(1-\bar{p}_{i,t})^{n_{i,t}-k}\left|\frac{k}{n_{i,t}}-\bar{p}_{i,t}\right| \end{aligned} \quad (5)$$

The core idea of the LSV herding measure is that it examines whether the observed distribution of industry proportion bought is fat tailed relative to the expected distribution under the null hypothesis of no herding.

After completing the calculation of herding measure of industry *i* in month *t* ($HM_{i,t}$), $HM_{i,t}$ are tested by t-statistics, and are expected to be significantly greater than zero, which would indicate for industry herding. In other words, retail investors trade in the same direction at the industry-level

4.3. Past industry returns and retail investor industry demand

To examine the relation between past industry returns and retail investor industry demand, a regression model is adopted. Following Jame and Tong (2014), industry proportion bought is regressed on the past industry returns. The regression model is useful to explore the response of retail investor industry demand to past industry returns over different horizons. The model is estimated as follow:

$$\begin{aligned} Ind_{PB_{i,t}} = \alpha + {} & \beta_1 IndSize_{i,t} + \beta_2 IndPTB_{i,t} + \beta_3 Ind_{Ret_{i,t-1}} \\ & + \beta_4 Ind\_Ret_{i,t-3,t-2} + \beta_5 Ind\_Ret_{i,t-6,t-4} + \beta_6 Ind\_Ret_{i,t-12,t-7} \\ & + \beta_7 Ind\_Ret_{i,t-24,t-13} + \beta_8 Ind\_PB_{i,t-1} + \beta_9 Ind\_PB_{i,t-3,t-2} \end{aligned}$$

$$+\beta_{10}Ind\_PB_{i,t-6,t-4} + \beta_{11}Ind\_PB_{i,t-12,t-7}$$
$$+\beta_{12}Ind\_PB_{i,t-24,t-13} + \varepsilon_{i,t} \quad (6)$$

where $Ind\_PB_{i,t}$ = industry proportion bought of industry *i* in month *t*

$IndSize_{i,t}$ = average size (market capitalization) of firms in industry *i* in month *t* (natural log)

$IndPTB_{i,t}$ = average price-to-book ratio of firms in industry *i* in month *t*

$Ind\_Ret_{i,t-1}$ = return of industry *i* in month *t – 1*

$Ind\_Ret_{i,t-3,t-2}$ = return of industry *i* over month *t – 3* to *t – 2*

$Ind\_Ret_{i,t-6,t-4}$ = return of industry *i* over month *t – 6* to *t – 4*

$Ind\_Ret_{i,t-12,t-7}$ = return of industry *i* over month *t – 12* to *t – 7*

$Ind\_Ret_{i,t-24,t-13}$ = return of industry *i* over month *t – 24* to *t – 13*

$Ind\_PB_{i,t-1}$ = proportion bought of industry *i* in month *t – 1*

$Ind\_PB_{i,t-3,t-2}$ = proportion bought of industry *i* over month *t – 3* to *t – 2*

$Ind\_PB_{i,t-6,t-4}$ = proportion bought of industry *i* over month *t – 6* to *t – 4*

$Ind\_PB_{i,t-12,t-7}$ = proportion bought of industry *i* over month *t – 12* to *t – 7*

$Ind\_PB_{i,t-24,t-13}$= proportion bought of industry *i* over month *t – 24* to *t – 13*

Several studies present evidence that retail investors are likely to have style preferences based on size and price-to-book ratio (e.g. Kumar, 2009; Lohitanon, 2015). Due to the fact that stocks in the same industries are likely to have similar characteristics such as size and price-to-book ratios, retail investor industry demand that is tested in *Hypothesis 1* may arise because of these style preferences. Therefore, in this regression model, $IndSize_{i,t}$ and $IndPTB_{i,t}$ are included to control for the possible causal relations of industry average size and industry average price-to-book ratio to industry proportion bought. In addition, Choi and Sias (2009), and Jame and Tong (2014) show that investors' demand are persistent over time. Therefore, past industry proportion bought (i.e. $Ind\_PB_{i,t-1}$, $Ind\_PB_{i,t-3,t-2}$, $Ind\_PB_{i,t-6,t-4}$, $Ind\_PB_{i,t-12,t-7}$, $Ind\_PB_{i,t-24,t-13}$) are also included to control for possible causal relations between past industry proportion bought and present industry proportion bought. It should be noted that the time interval of lagged industry returns is increased as the time go further into the past. This is because investors may look at a bigger picture at the time that is far from present.

Consequently, if there is any relationship between industry proportion bought and past industry returns, retail investors' investment decision shall have industry-wide component. In the statistical perspective, after controlling with the variables mentioned above, β_3, β_4, β_5, β_6, and β_7 are tested by t-statistics, and are expected to be significantly different from zero.

4.4. Retail investor industry demand and subsequent industry returns

To capture the dynamic relations between retail investor industry demand (i.e. industry proportion bought) and subsequent industry returns, trading strategies with different formation periods and holding periods are applied. This approach was first used by Jegadeesh and Titman (1993), and has been applied by many studies to examine the relations between retail investor trading and subsequent asset returns (e.g. Hvidkjaer, 2008; Barber, Odean, and Zhu, 2009b; Jame and Tong, 2014).

Four strategies with different formation periods and holding periods are considered as follows:

1. 1 week formation period and 1 week holding period (1 week – 1 week strategy)
2. 3 months formation period and 3 months holding period (3 month – 3 month strategy)
3. 6 months formation period and 6 months holding period (6 month – 6 month strategy)
4. 12 months formation period and 12 months holding period (12 month – 12 month strategy)

To further illustrate, for 1 week – 1 week strategy, the following steps are conducted:

1. At the beginning of each week, industries are ranked in ascending order according to their prior 1 week proportion bought (i.e. formation period).
2. Industries that are already ranked are sorted into five quintile portfolios; industries that are heavily sold are assigned to the first quintile portfolios, and industries that are heavily bought are assigned to the fifth quintile portfolio as shown in Figure 1.

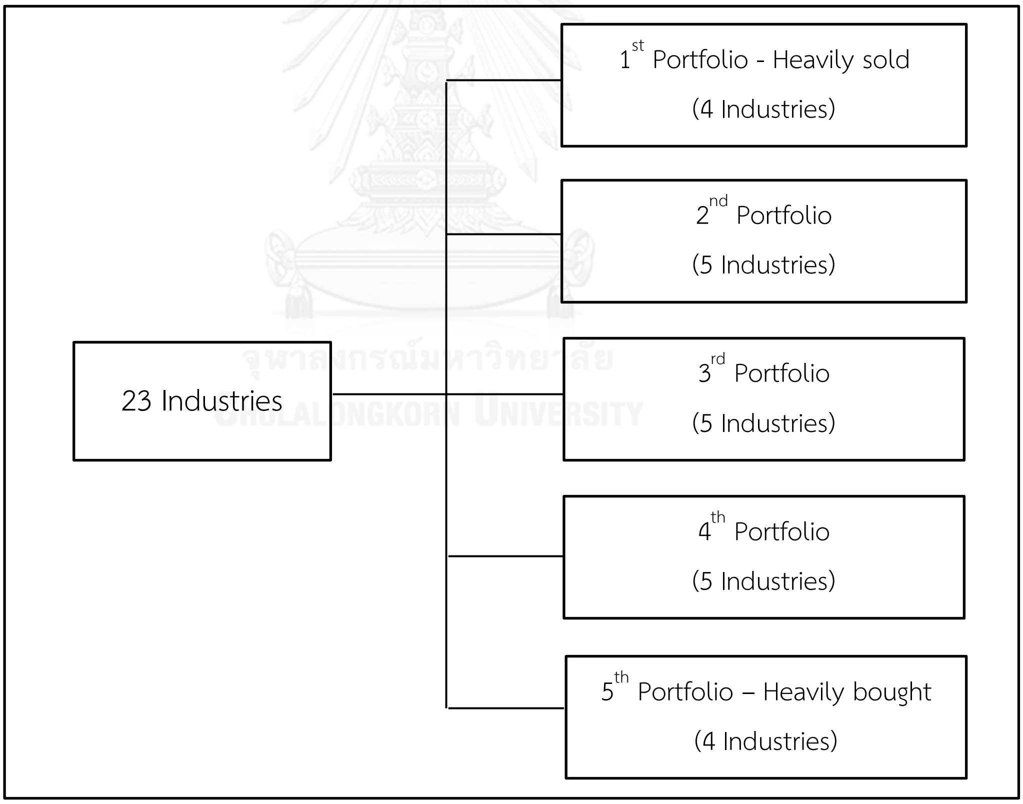

Figure 1 : The method of forming five quintile portfolios sorted by past proportion bought

3. In each quintile portfolio, subsequent portfolio returns over the 1 week holding period are computed by taking the equally-weighted average of each industry return in its portfolio.
4. Time series of weekly returns in each quintile portfolio are compounded into time series of monthly returns.
5. Lastly, the difference of return between the fifth quintile portfolio and the first quintile portfolio is tested by *t*-statistics, and it is expected to be significantly different from zero, which would indicate that retail investor industry demand has predictability power on subsequent industry returns.

For 3 month – 3 month strategy, the following steps are conducted:

1. At the beginning of each month, industries are ranked in ascending order according to their prior 3 months proportion bought (i.e. formation period).
2. Industries that are already ranked are sorted into five quintile portfolios; industries that are heavily sold are assigned to the first quintile portfolio, and industries that are heavily bought are assigned to the fifth quintile portfolio as shown in Figure 1.
3. In each quintile portfolio, subsequent monthly portfolio returns over the 3 months holding period are computed by taking the equally-weighted average of each industry return in its portfolio. It should be noted that in any given

month, the strategies hold a set of portfolios that are constructed in the current month as well as in the previous 2 months as shown in Figure 2.

4. As the portfolios are constructed with overlapping holding periods, particular month's returns of each quintile portfolio are calculated as the average of the current month's return of the current month's and previous 2 months' portfolios. This would give a time series of monthly returns.

5. Lastly, the difference of return between the fifth quintile portfolio and the first quintile portfolio is tested using *t*-statistics, and it is expected to be significantly different from zero, which would indicate that retail investor industry demand has predictability power on subsequent industry returns..

The same approach of 3 month – 3 month strategy is applied to 6 month – 6 month strategy by changing the formation periods and holding periods to 6 months. It is also applied to 12 month – 12 month strategy by changing the formation periods and holding periods to 12 months.

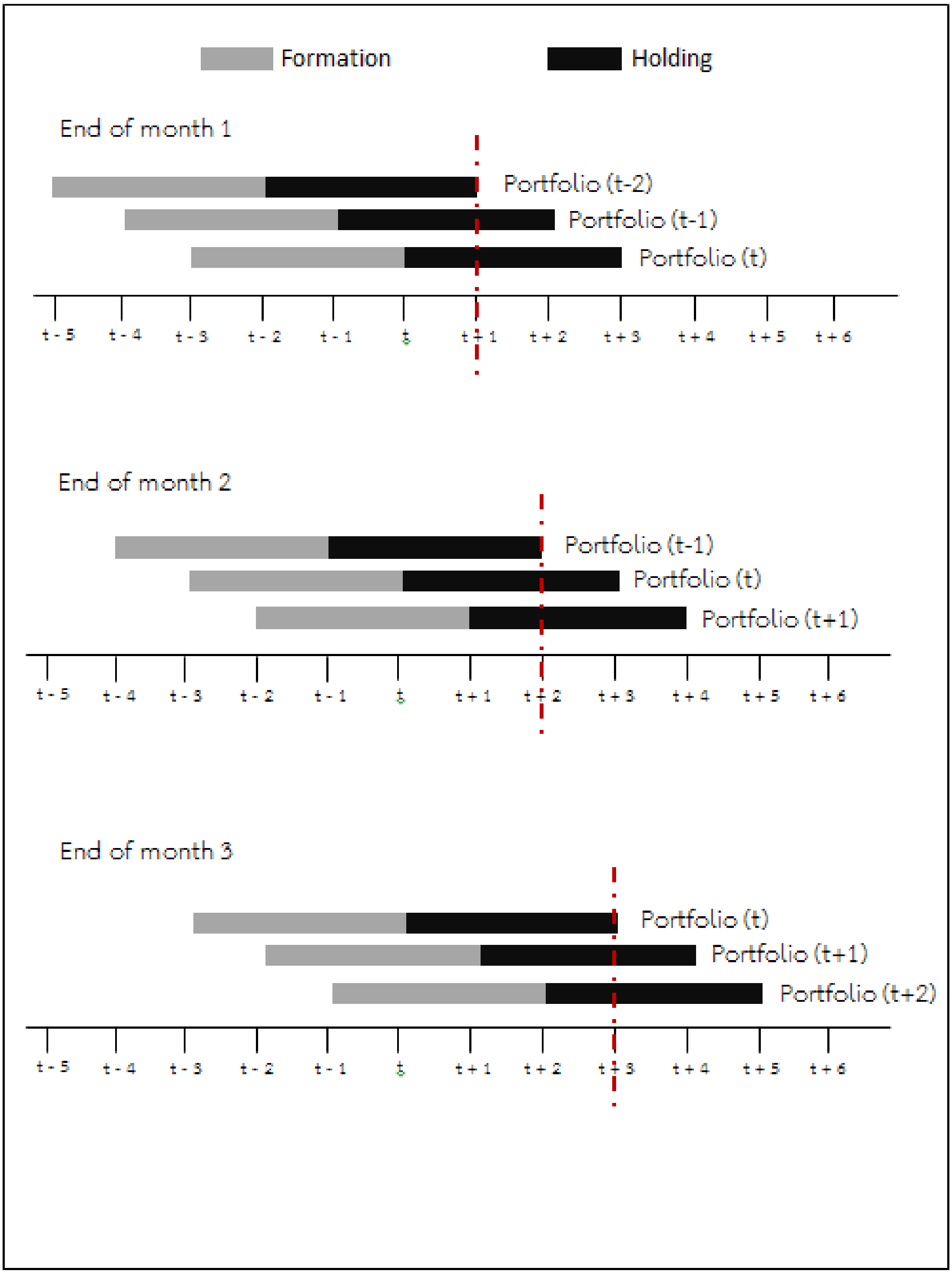

Figure 2 : Illustration of portfolios constructed with overlapping holding periods in the case of 3 month – 3 month strategy

4.5. Small-cap stocks and large-cap stocks in attractive industry

The LSV herding measure is modified to test whether retail investors prefer to invest in small-cap stocks more than large-cap stocks within each industry that catch their attention. First, to represent the industries that catch retail investors' attention, only industries having buy herding are used in the analysis. The logic behind this filter is that if the industry is attractive and catches retail investors' attention, they should have higher average buying demand in that industry. Following Wermers (1999), the industry having buy herding ($BHM_{i,t}$) are defined as the industry that has proportion bought higher than average proportion bought $\left(BHM_{i,t} = HM_{i,t} \middle| p_{i,t} > \bar{p}_{i,t}\right)$.

Second, in each month, within each industry having buy herding, stocks are assigned into two groups namely small-cap stocks and large-cap stocks based on their monthly market capitalization. The median value of the market capitalization is used as the cutoff point. In the industries having buy herding, retail investor industry-size demand is computed using the formula as follow:

$$p_{i,j,t} = \frac{b_{i,j,t}}{b_{i,j,t}+s_{i,j,t}} = \frac{b_{i,j,t}}{n_{i,j,t}} \qquad (7)$$

where $b_{i,j,t}$ = number of retail investor buy transaction in group of stock *j* (small-cap/large-cap) in industry having buy herding *i* in month *t*

$s_{i,j,t}$ = number of retail investor sell transaction in group of stock *j* (small-cap/large-cap) in industry having buy herding *i* in month *t*

$n_{i,j,t}$ = number of total retail investor transaction in group of stock *j* (small-cap/large-cap) in industry having buy herding *i* in month *t*

Then, the LSV herding measure is separately applied to small-cap stocks and large-cap stocks in the industries having buy herding in month *t*, which is calculated as follows:

$$BHM_{i,j,t} = \left|p_{i,j,t} - \bar{p}_{i,t}\right| - AF_{i,j,t} \qquad (8)$$

where $BHM_{i,j,t}$= buy herding measure of group of stock *j* (small-cap/large-cap) in industry having buy herding *i* in month *t*

$p_{i,j,t}$ = proportion bought of group of stock *j* (small-cap/large-cap) in industry having buy herding *i* in month *t*

$\bar{p}_{i,t}$ = average proportion bought across all industry in month *t* as in Eq. 3

$AF_{i,j,t}$ = adjustment factor of group of stock *j* (small-cap/large-cap) in industry having buy herding *i* in month *t*

The former term measures the absolute difference between the proportion bought of group of stock *j* (small-cap/large-cap) in industry having buy herding *i* in month t and the average proportion bought across all industry. The latter term, $AF_{i,j,t}$ is an adjustment factor that accounts for the fact that in the case of no herding, $\left|p_{i,t} - \bar{p}_{i,t}\right|$ can be greater than zero by chance. In other words, the adjustment factor ($AF_{i,j,t}$) allows the capture of the random variation of $p_{i,j,t}$ around $\bar{p}_{i,t}$, under independent trading situation, and is computed by assuming the number of total retail investor transaction in group of stock *j* (small-cap/large-cap) in industry having buy herding *i* in month t ($n_{i,j,t}$) follows a binomial distribution with the probability of buying set equal to $\bar{p}_{i,t}$. According to Bellando (2010), the adjustment factor of group of stock *j* (small-cap/large-cap) in industry having buy herding *i* in month *t* ($AF_{i,j,t}$) is given by:

$$AF_{i,j,t} = \sum_{k=0}^{n_{i,j,t}} prob\left(b_{i,j,t} = k\right)\left|\frac{k}{n_{i,j,t}} - \bar{p}_{i,t}\right|$$

$$= \sum_{k=0}^{n_{i,j,t}} \binom{n_{i,j,t}}{k} \bar{p}_{i,t}^{k}(1 - \bar{p}_{i,t})^{n_{i,j,t}-k}\left|\frac{k}{n_{i,j,t}} - \bar{p}_{i,t}\right| \qquad (9)$$

After completing the calculation of the buy herding measure of small-cap stocks and large-cap stocks in the industries having buy herding in month *t* ($BHM_{i,j,t}$), $BHM_{i,j,t}$ of small-cap stocks are tested using *t*-statistics, and are expected to be significantly greater than $BHM_{i,j,t}$ of large-cap stocks, which would indicate that after deciding to invest in the attractive industry, retail investors prefer to invest in small-cap stocks more than large-cap stocks.

CHAPTER 5

EMPIRICAL RESULTS

5.1. Descriptive statistics

Panel A in Table 2 reports the time series average of cross-sectional industry trading descriptive statistics. The average number of retail investor trades is 80,686 ranging from a minimum of 3,550 to a maximum of 310,899. Retail investor industry demand using proportion bought as a proxy averages near 50% showing that, on average, retail investors are as likely to buy or sell, but they seem to be a net buyer over the sampling. However, there is significant cross-sectional variation in retail investor industry demand. That is, in the highest retail investor demand industry, retail investors trade with buy order transaction around 58% of total trades and around 43% of total trades in the lowest retail investor demand industry. Panel B reports that, on average, industries contain 19 stocks ranging from a minimum of 8 stocks to a maximum of 46 stocks. The largest industry, on average, accounts for 28.21% of the market. The largest firm accounts for 34.14% of the industry's capitalization presenting that industries seem to have high-level of concentration.

In Table 3, it reports time series descriptive statistics for each of the 23 industries. Property Development contains with the highest number of stocks, while Industrial Materials & Machinery consists of the lowest number of stocks. Furthermore, although Property Development contains with the highest number of

Table 2 : Basic industry statistics

Stocks are classified into one of 23 sectors classified by the Stock Exchange of Thailand (SET). Sectors, namely PERSON, PAPER, MINE, and PROF are excluded from the analysis because of the lack of company in the sector. PF&REIT is excluded due to its unique characteristics. Panel A reports the time series average of the cross-sectional descriptive statistics for the number of retail investor trades made in each sector, the proportion bought in each sector. Panel B reports the time series average of the cross-sectional descriptive statistics for the number of firms in each sector, the fraction of total market capitalization accounted for by each sector, and the fraction of sector market capitalization accounted for by the largest firm in the industry.

	Panel A: Industry trading statistics				
	Mean	Median	Minimum	Maximum	Std. dev.
Number of retail investor trades in an industry	80,686	52,854	3,550	310,899	82,251
Proportion bought (%)	50.87	51.04	43.10	58.15	3.35

	Panel B: Industry statistics				
	Mean	Median	Minimum	Maximum	Std. dev.
Number of firms in industry	19	16	8	46	9
Industry capitalization/market capitalization (%)	4.35	1.7	0.18	28.21	6.58
Largest firm in sector/industry capitalization (%)	34.14	31.46	13.73	71.91	14.058

stocks, Energy & Utilities is the industry that has largest market capitalization in term of the percentage of market capitalization to the market portfolio. Time series averages of each industry's proportion bought are also reported in the Table 3.

Table 4 reports time series descriptive statistics of weighted-average industry return for each of the 23 industries. It shows that Health Care Services gives highest average monthly return by 1.65%, while Steel gives lowest average monthly return by -1.71%. Eventually, Table 5 reports time series descriptive statistics of each quintile portfolio's return with different forming and holding periods.

Table 3 : Basic industry statistics by industry

The table reports time series descriptive statistics for each of the 23 sectors including the average number of firms in the sector, the sector's market capitalization weight, and the mean, median, minimum, maximum, and standard deviation of retail investor demand for the sector.

Industry	# of Firms	Market cap. (%)	Proportion bought (%)				
			Mean	Median	Minimum	Maximum	Std. dev.
Agribusiness	13	0.55	49.25	49.47	39.73	55.02	3.29
Food & Beverage	32	4.07	50.49	50.61	42.37	58.78	2.89
Fashion	24	0.89	48.53	49.04	35.05	68.13	5.64
Home & Office Products	9	0.19	49.83	49.97	39.40	56.51	3.25
Banking	13	18.00	51.72	51.91	40.78	62.75	4.15
Finance & Securities	30	1.50	50.61	50.60	45.37	57.57	2.19
Insurance	18	1.28	48.75	48.37	31.87	73.10	6.25
Automotive	17	0.69	50.92	50.75	39.57	63.61	3.41
Industrial Materials & Machinery	8	0.20	49.37	49.72	37.45	62.43	4.47
Petrochemicals & Chemicals	12	4.22	50.29	50.59	41.29	59.72	3.43
Packaging	15	0.38	50.82	51.02	40.21	58.65	3.28
Steel	24	1.37	51.80	51.94	46.19	60.01	2.84
Construction Materials	18	7.05	52.03	51.61	45.70	63.17	2.72
Property Development	46	5.48	52.11	52.34	45.83	57.56	2.11
Construction Services	16	1.25	51.39	51.39	45.98	55.19	1.84
Energy & Utilities	26	28.20	51.67	51.96	45.74	57.75	2.06
Commerce	16	4.56	51.88	52.11	41.92	62.80	3.35
Health Care Services	13	1.78	50.64	51.33	34.03	64.00	4.97
Media and Publishing	26	2.12	51.92	51.73	44.34	60.27	2.68
Tourism & Leisure	13	0.79	52.49	51.47	38.01	77.30	6.88
Transportation & Logistics	14	3.90	51.14	51.47	41.72	56.21	2.97
Electronic Components	11	1.27	50.12	49.98	41.23	58.56	3.03
Information & Communication Technology	26	10.28	52.27	52.25	46.00	57.38	2.11

Table 4 : Weighted-average industry returns by industry

The table reports time series descriptive statistics of weighted-average industry return for each of the 23 sectors. Weighted-average industry return is calculated as in Equation (3). Descriptive statistics include the mean, median, minimum, maximum, and standard deviation.

Industry	Mean	Median	Minimum	Maximum	Std. dev.
Agribusiness	0.55	0.58	-25.47	20.27	6.35
Food & Beverage	0.87	0.68	-28.06	13.28	6.26
Fashion	-0.12	0.18	-10.64	7.94	3.22
Home & Office Products	-0.41	0.12	-29.50	15.08	6.32
Banking	0.29	0.80	-26.38	14.78	7.45
Finance & Securities	-0.38	-0.19	-20.15	18.34	7.50
Insurance	1.06	0.92	-24.84	14.91	5.42
Automotive	-0.61	-0.23	-27.77	12.99	6.97
Industrial Materials & Machinery	-0.61	-0.18	-34.43	23.28	8.38
Petrochemicals & Chemicals	0.77	1.57	-29.19	27.83	9.75
Packaging	-0.33	-0.41	-25.60	23.62	7.87
Steel	-1.71	-0.12	-26.99	19.13	8.29
Construction Materials	0.14	0.09	-25.52	21.72	7.67
Property Development	0.11	1.34	-27.15	23.17	8.72
Construction Services	-1.08	0.50	-32.03	27.44	11.72
Energy & Utilities	0.28	0.92	-29.66	23.10	8.02
Commerce	1.48	1.79	-20.56	17.17	6.17
Health Care Services	1.65	2.19	-32.45	14.89	6.65
Media and Publishing	0.30	0.58	-18.51	17.24	6.18
Tourism & Leisure	0.15	0.40	-25.15	15.10	5.87
Transportation & Logistics	0.34	1.82	-24.28	19.20	7.71
Electronic Components	0.01	0.11	-37.26	25.22	8.20
Information & Communication Technology	0.36	0.46	-19.33	15.29	6.67

Table 5 : *Holding period return of quintile portfolio*

The table reports time series descriptive statistics of holding period return of each quintile portfolio with different forming and holding periods constructed by using the method mentioned in Section 4.4. Panel A reports descriptive statistics of holding period returns for 1 week – 1 week strategy. Panel B reports descriptive statistics of holding period returns for 3 months – 3 months strategy. Panel C reports descriptive statistics of holding period returns for 6 months – 6 months strategy. Panel D reports descriptive statistics of holding period returns for 12 months – 12 months strategy. Numbers in the table are shown in the unit of percent.

Portfolio	Mean	Median	Minimum	Maximum	Std. Dev.
			Panel A: 1 week - 1 week		
1 (Sold)	0.27	0.70	-12.12	15.47	4.80
2	0.60	0.68	-16.09	13.87	5.82
3	0.46	1.17	-17.40	14.79	5.71
4	-0.07	0.54	-16.67	12.44	5.97
5 (Bought)	0.42	0.22	-15.43	14.17	5.52
			Panel B: 3 months - 3 months		
1 (Sold)	0.61	0.79	-22.78	12.69	4.99
2	0.23	1.01	-18.27	13.02	5.39
3	0.53	1.33	-25.07	13.92	5.84
4	0.24	0.69	-20.89	14.00	6.13
5 (Bought)	0.27	1.27	-21.92	11.29	5.77
			Panel C: 6 months - 6 months		
1 (Sold)	0.63	0.65	-23.38	12.79	4.70
2	0.42	0.83	-20.45	13.65	5.51
3	0.19	0.77	-23.12	15.22	5.79
4	0.16	1.26	-21.17	12.55	6.05
5 (Bought)	0.53	1.12	-20.68	13.62	5.90
			Panel D: 12 months - 12 months		
1 (Sold)	0.71	1.03	-23.27	10.01	4.49
2	0.41	0.80	-19.41	14.07	5.41
3	0.24	0.85	-23.25	14.72	5.91
4	0.20	1.33	-23.47	13.08	6.00
5 (Bought)	0.36	0.85	-19.06	16.05	6.23

5.2. Is retail investor demand correlated at the industry-level?

Table 6 : *Evidence of LSV herding measure*

This table presents mean values of the LSV herding measure of retail investors at the industry-level during January 2004 to December 2013. The LSV herding measure ($HM_{i,t}$) of each industry in each month is defined as $HM_{i,t} = |p_{i,t} - \bar{p}_{i,t}| - AF_{i,t}$, where $p_{i,t}$ is the proportion bought of industry *i*, $\bar{p}_{i,t}$ is the average proportion bought across all industry, and $AF_{i,t}$ is an adjustment factor that accounts for the fact that in the case of no herding, $|p_{i,t} - \bar{p}_{i,t}|$ can be greater than zero by chance. *T*-statistics are reported in parenthesis. *, **, and *** indicate statistically significance at the 10%, 5%, and 1% level, respectively.

	All stock	Exclude stock with highest level of herding
Mean	0.0221***	0.0192***
t-Statistics	(50.14)	(51.99)
Obs.	2760	2760

As shown in Table 6, the mean of the LSV herding measure ($HM_{i,t}$) across the 2,760 observations (23 industries * 120 months) during January 2004 to December 2013 is 2.21%, and it is significantly greater than zero at the 1% probability level. To get the sense of economic interpretation, the average industry herding measure of 2.21% can be interpreted as meaning that if the average proportion bought was 50%, it is expected that, on average, 52.21% of retail investor trades would be on one side of the industry (buying or selling) and 47.79% of retail investor trades would be on the other side.

Furthermore, according to Barber, Odean, and Zhu (2009b), retail investor demand is also correlated at the individual-stock-level. As a result, the LSV herding measure that suggests the existence of the coordination of retail investor industry demand can be a manifestation of the coordination in demand of the individual stock. To provide additional evidence that the coordination of retail investor industry demand is not a manifestation of the coordination in demand at the individual-stock-level under the LSV herding measure framework, methodology from Celiker et al. (2015) is used. The stock with the highest level of herding is excluded from each industry in each month, then LSV herding measure is repeatedly calculated. According to Caliker et al. (2015), the logic of this filter is that, if the evidence of industry herding is still found after excluding the stock with the highest level of herding, then the observed industry herding cannot be driven by individual stock herding. The result shows that after the exclusion, the mean of industry herding measure is 1.92% and it is still significantly greater than zero at the 1% probability level.

Consistent with *Hypothesis 1*, there is evidence of the coordination in retail investor demand at the industry-level, and this phenomenon is not a manifestation of the coordination in demand of the individual stock. This suggests that retail investors in Thailand pursue industry-based style investing similar to retail investors in the US as reported by Jame and Tong (2014).

5.3. Do past industry returns influence retail investor industry demand?

In table 7, column 1 reports the results before controlling for lagged industry proportion bought, and column 3 reports the results after controlling it. In column 1, only the industry returns over past 2 to 6 months have negative effects on industry

Table 7 : *Retail investor industry demand and past industry returns*

This table presents the results from panel regressions estimated for each month from January 2006 to December 2013. Retail investor industry proportion bought is regressed on industry average value of ln(size), industry average price-to-book ratio, lagged industry returns, and lagged retail investor industry proportion bought. The monthly regression coefficients are reported. *T*-statistics are based on Newey and West (1987) standard errors, and are reported in parenthesis. *, **, and *** indicate statistically significance at the 10%, 5%, and 1% level, respectively.

	[1] Coefficient	[2] *t*-Statistics	[3] Coefficient	[4] *t*-Statistics
constant	46.9237***	(502.99)	7.8280***	(30.54)
ln(size)	0.3916**	(5.27)	0.1593***	(9.21)
price-to-book	-0.0647	(2.20)	-0.0412**	(4.07)
ind_ret_{t-1}	-0.0048	(0.23)	-0.0284***	(7.11)
$ind\_ret_{t-3,t-2}$	-0.0133**	(5.76)	-0.0116**	(5.35)
$ind\_ret_{t-6,t-4}$	-0.0143**	(6.03)	-0.0101**	(6.25)
$ind\_ret_{t-12,t-7}$	-0.0036	(0.71)	-0.0021	(0.75)
$ind\_ret_{t-24,t-13}$	0.0001	(0.00)	-0.0013	(0.68)
ind_pb_{t-1}			0.3887***	(113.02)
$ind\_pb_{t-3,t-2}$			0.0901*	(3.54)
$ind\_pb_{t-6,t-4}$			0.1242***	(9.97)
$ind\_pb_{t-12,t-7}$			0.0910***	(8.32)
$ind\_pb_{t-24,t-13}$			0.1197**	(6.02)
Adjusted R^2	0.03		0.30	
Obs.	2208		2208	

proportion bought. ln(size) that is included for controlling purpose is also significantly different from zero. However, adjusted R^2 of 0.03 indicates that the regressors added in the model are still not good to explain retail investor industry demand.

In column 3, after adding lagged industry proportion to the regression model, the coefficients of past industry returns (i.e. $Ind\_Ret_{i,t-1}$, $Ind\_Ret_{i,t-3,t-2}$, $Ind\_Ret_{i,t-6,t-4}$, $Ind\_Ret_{i,t-12,t-7}$, and $Ind\_Ret_{i,t-24,t-13}$) all have negative value.

However, only the coefficients of $Ind\_Ret_{i,t-1}$, $Ind\_Ret_{i,t-3,t-2}$, and $Ind\_Ret_{i,t-6,t-4}$ are significantly different from zero with the value of -0.0284, -0.0116, and -0.0101, respectively. In other words, industry proportion bought is significantly negatively related to past industry returns over 1 to 6 months.

Lagged industry proportion bought variables added to the model show strong positive relationship to present industry proportion bought showing the supporting evidence of persistence in industry demand over time. The coefficients of ln(size) and price-to-book are 0.1593 and -0.0412, respectively. Both are significantly different from zero. The result indicates that retail investors consider size and price-to-book ratio when they make investment decisions. The value of adjusted R^2 also substantially increases from 0.03 to 0.30 indicating the goodness of fit of the model.

The result provide evidence consistent with *Hypothesis 2* that retail investor demand is influenced by past industry returns. That is, retail investor industry demand is negatively related to past 1 to 6 months industry returns. Retail investors would invest in the industry that performs worse and withdraw funds from the industry that performs well back to the past 6 months. In other word, retail investors in Thailand tend to be contrarians at the style-level. For example, 1% increase in the industry return over the past 1 month would decrease the industry proportion bought by 0.0284%. This suggests that retail investors' investment decision have industry-wide component.

Interestingly, this finding does not support the style investing model of Barberis and Shleifer (2003) and previous empirical studies conducting in the US (i.e. Kumar, 2009; Jame and Tong, 2014), in which they suggest that retail investors conduct style-level momentum trading behavior. However, the empirical results from this study support the finding of Lohitanon (2015) who reports that retail investors in Thailand are contrarians at the style-level. Therefore, the contrasting findings between empirical studies conducting in the US and Thailand suggest that the behavior of retail investors between these two countries are indeed different.

One possible explanation for this phenomenon is that, in contrast to the US, retail investors in Thailand may feel that stocks belonging to the industries that have bad past performance are relatively cheap. As a result, they prefer to buy stock in industries that are underperformed. In addition, retail investors in Thailand mostly rely on technical analysis. Specifically, the majority of retail investors participate in the stock market for speculative purpose, so they use technical analysis to make short-term investment decisions because they believe that technical analysis will help them to buy or sell stocks at the right time. The most common tools for technical analysis are resistance line and support line. Investors who use these tools make buy decision when the stock price drops to the support line and make sell decision when the stock price rises to the resistance line.

5.4. How does retail investor industry demand have an effect on subsequent industry returns?

In this section, it is expected to observe retail investor industry demand has predictability power on subsequent industry values. In other words, retail investor industry demand will have a positive relationship with subsequent industry returns over weekly horizon, and a negative relationship with subsequent industry returns over monthly horizon or yearly horizon. That is, in short run (e.g. weekly horizon), the fifth portfolio (heavily bought) should have significantly higher return than the first portfolio (heavily sold) and vice versa in long run.

Interestingly, the result in Table 8 shows that the differences of return between the fifth portfolio (heavily bought) and the first portfolio (heavily sold) of 1 week – 1 week, 3 months – 3 months, 6 months – 6 months, and 12 months – 12 months strategy are 0.1510, -0.3451, -0.1081, and -0.3467, respectively; however, they are not significantly different for all strategy, which does not support the *Hypothesis 3*. This finding suggests that retail investor industry demand does not have any relationship with subsequent industry returns. In other words, retail investor industry demand does not drive industry value.

Table 8 : Retail investor industry demand and subsequent industry returns

From January 2004 to December 2013, portfolios are formed based on past retail investor industry proportion bought over the past week (Panel A), 3 months (Panel B), 6 months (Panel C), or 12 months (Panel D). The industries most heavily bought (sold) are assigned to portfolio 5 (1). Then, average portfolio return over the subsequent week (Panel A), 3 months (Panel B), 6 months (Panel C), and 12 months (Panel D) are calculated. For overlapping observations in the case of 3 months, 6 months, and 12 months, Jegadeesh and Titman's (1993) calendar time aggregation method is applied to calculate returns. For each industry, monthly value-weighted return is computed. The portfolio return is the equally-weighted return across the industries in the portfolio. The return differential between portfolio 5 and 1 is reported. *T*-statistics are reported in parenthesis. *, **, and *** indicate statistically significance at the 10%, 5%, and 1% level, respectively.

	Raw return (%)	
Portfolio	Monthly return	*t*-Statistics
	Panel A: 1 week - 1 week	
1 (Sold)	0.2679	(0.61)
2	0.6014	(1.13)
3	0.4623	(0.89)
4	-0.0714	(-0.13)
5 (Bought)	0.4190	(0.83)
B-S (5-1)	0.1510	(0.23)
	Panel B: 3 months - 3 months	
1 (Sold)	0.6130	(1.34)
2	0.2230	(0.47)
3	0.5276	(0.99)
4	0.2420	(0.43)
5 (Bought)	0.2679	(0.51)
B-S (5-1)	-0.3451	(-0.49)
	Panel C: 6 months - 6 months	
1 (Sold)	0.6334	(1.47)
2	0.4199	(0.83)
3	0.1931	(0.36)
4	0.1640	(0.30)
5 (Bought)	0.5254	(0.97)
B-S (5-1)	-0.1081	(-0.16)

Table 8 : Retail investor industry demand and subsequent industry returns (cont.)

	Raw return (%)	
Portfolio	Monthly return	*t*-Statistics
	Panel D: 12 months - 12 months	
1 (Sold)	0.7077*	(1.72)
2	0.4085	(0.82)
3	0.2427	(0.45)
4	0.1980	(0.36)
5 (Bought)	0.3610	(0.63)
B-S (5-1)	-0.3467	(-0.49)

This phenomenon raises another interesting question as to why a relationship is not found; how is it possible that retail investors in emerging market like Thailand do not move asset prices while in developed market they do (e.g. Barber, Odean, and Zhu, 2009b; Jame and Tong, 2014). Most existing literature would say it means that investors conduct their trades based on new information disseminated into the market. Therefore, retail investor demand does not move asset prices. However, it is not reasonable to explain the result using this logic because Thailand is still at the developing country stage, which makes it is hard to believe that retail investors in Thailand are informed traders.

The alternative story is that although retail investors are the majority group of investors in Thailand, institutional investors are also a group that is known to play a significant role in the market. According to Lohitanon (2015), institutional investors pursue a momentum style. That is, if the industry performs well in the past, institutional will make buying decision, and vice versa. Conversly, retail investors are contrarians at the style-level. To be specific, according to the opposite style preference, if the demand of both type of investors (i.e. retail investors, and institutional investors) have an impact on asset prices, retail investor demand shock that should have an effect on industry value is offset by institutional investor demand shock. Consequently, no relationship between retail investor demand and subsequent industry return is found.

It may have some concern that the number of industry in each quintile portfolio is not too few to draw the conclusion. Therefore, in Appendix A, industries are sorted into four portfolios and three portfolios to increase the number of industry in the portfolios, but no any different results are found.

5.5 Is the degree of buying demand is greater in small-cap stocks than large-cap stocks in the industry that attracts retail investors' attention?

According to Barber and Odean (2008), the decision-making process between the decisions to buy and to sell is fundamentally different. To be specific, investors are encountered with a search problem when buying a stock causing the decisions to buy to be relatively more complicated than the decisions to sell. Therefore, this section attempts to investigate further about the buying decisions of retail investors whether after firstly simplify their investment decisions by considering industry-wide categorization, retail investors consider size of the stocks before finalizing their buying decisions. The result in this section would contribute to the style investing literature,

Table 9 : Herding levels of small-cap group and large-cap group

This table presents mean values of the LSV herding measure conditional buy and sell at the industry-level (Panel A) during January 2004 to December 2013. The LSV herding measure ($HM_{i,t}$) of each industry in each month is defined as $HM_{i,t} = |p_{i,t} - \bar{p}_{i,t}| - AF_{i,t}$, where $p_{i,t}$ is the proportion bought of industry *i*, $\bar{p}_{i,t}$ is the average proportion bought across all industry, and $AF_{i,t}$ is an adjustment factor that accounts for the case of no herding $|p_{i,t} - \bar{p}_{i,t}|$ can be greater than zero by chance. The buy herding measure is the LSV herding measure conditional on retail investors having above average demand for the industry, and the sell herding measure is the LSV herding measure conditional on retail investors having below average demand for the industry. In Panel B, buy herding measure are shown separately into two groups: both small-cap and large-cap are bought, and only small-cap or large-cap is bought. In Panel C, buy herding of 'both small-cap and large-cap are bought' group is further used for testing buy herding of small-cap and buy herding of large-cap. The differences between these two groups are also reported. *T*-statistics are reported in parenthesis. *, **, and *** indicate statistically significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Buy and sell herding measure	
	Buy herding measure	Sell herding measure
Mean	0.0217***	0.0225***
t-Statistics	(35.98)	(34.92)
Obs.	1434	1326

	Panel B: Buy herding measure	
	Both small and large buy	Small or large buy
Mean	0.0261***	0.0170***
t-Statistics	(31.85)	(19.90)
Obs.	741	693

	Panel C: Buy herding measure for large and small		
	Small-cap	Large-cap	Diff.
Mean	0.0307***	0.0243***	0.0064***
t-Statistics	(26.07)	(21.60)	(3.76)
Obs.	741	741	

and would uncover weak evidence for the two-step decision-making process of Image Theory (Beach and Mitchell, 1987).

To investigate, first, industries that are attractive to retail investors are defined as the industries having buy herding. Following Wermers (1999), the industry having buy herding ($BHM_{i,t}$) are defined as the industry that has proportion bought higher than average proportion bought $\left(BHM_{i,t} = HM_{i,t} \middle| p_{i,t} > \bar{p}_{i,t}\right)$. The industry having sell herding ($SHM_{i,t}$) are defined as the industry that has proportion bought lower than average proportion bought $\left(SHM_{i,t} = HM_{i,t} \middle| p_{i,t} < \bar{p}_{i,t}\right)$. In Panel A, the mean of buy herding is 0.0217, and the mean of sell herding is 0.0225, and both are significantly greater than zero at the 1% probability level.

Then, we conduct further examination by separating stocks in the industry into large-cap and small-cap groups using the median value of market capitalization as the cutoff point. The analysis reveals that the industry having buy herding consists of 2 situations that could occur (i.e. Both small-cap and large-cap are bought, and only small-cap or large-cap is bought)[2]. It should be noted that industries having buy herding do not require all stock to be bought but just the majority; which means that in some months, industries can have the situation that only small-cap or large-cap stocks are purchased.

In Panel B, it shows the mean of herding measure in the situations that both small-cap and large-cap are bought, and only small-cap or large-cap is bought. The former case presents the buy herding measure of 0.0261, while the latter case

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[2] See Appendix B for further details.

presents the buy herding measure of 0.0170, and both are significantly greater than zero at the 1% probability level. As the former case shows higher mean of herding measure, it would be implied that it may better represent the industry that is attractive for retail investors so that they have more coordination in their demand. Therefore, this group of observation is used to test further if the two-step investment decisions really exist.

In Panel C, the result shows that buy herding measures for small-cap group and buy herding measure for large-cap group in the industry that attract retail investors' attention are 0.0307 and 0.0243, respectively. Both are significantly greater than zero at the 1% probability level. In addition, the buy herding measure for small-cap group is significantly higher than large-cap group by 0.64% at the 1% probability level. This suggests that after choosing to invest in an attractive industry, retail investors prefer to invest in small-cap stocks more often than large-cap stocks. In other words, retail investors first screen stocks by industry, and then, consider size of the stocks before making the investment decisions. This finding provides weak evidence that support a two-step decision-making process of the Image Theory. For the economic interpretation, assuming in the attractive industry that both large-cap and small-cap are bought, on average, the retail investors would conduct buying order for small-cap stocks in the industry more than large-cap stocks by 0.64%.

As this section investigates about the investors' behavior, therefore, it is not reasonable to presume that retail investors have homogeneous behavior. It should be noted that the result in this section only suggests that there are large group of retail investors that, first, screen stocks by industry-wide categorization, then consider size of the stocks before finalizing their buying decisions. It does not mean that every retail investors always do so.

CHAPTER 6
CONCLUSION

This study investigates whether retail investors in Thailand pursue industry-based style investing. Using the LSV herding measure, the result shows that retail investor demand is correlated at the industry-level, even after excluding the stock with the highest level of herding. Therefore, the result suggests that there is evidence of the coordination in retail investor demand at the industry-level, and this phenomenon is not a manifestation of the coordination in demand of the individual stock.

This study further examines the relationship between retail investor industry demand and past industry returns. In contrast to the style investing model, retail investor industry demand is negatively related to past 1 to 6 months industry returns. This finding suggests that retail investors' investment decision have industry-wide component.

The relationship between retail investor industry demand and subsequent industry returns is also investigated. By constructing a portfolio over different formation and holding periods, no relationship between retail investor industry demand and subsequent industry returns is found over all time horizons.

In addition, according to the fact that the decisions to buy are more complicated than the decisions to sell, this study shows new evidence that retail investors prefer to invest in small-cap stocks more than large-cap stock after choosing to invest in the industry that attract their attention. This finding contributes to the style investing literature by providing evidence that retail investors do simplify their investment decisions by considering more than one style at the same time when they are to make buying decisions. It also provides weak evidence that supports the two-step decision-making process of the Image Theory.

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APPENDIX

Appendix A

***Table 10 :** Sorting into 4 portfolios*

The industries most heavily bought (sold) are assigned to portfolio 4 (1). Else, methodology is similar to the description in Table 7.

	Raw return (%)	
Portfolio	Monthly return	*t*-Statistics
	Panel A: 1 week - 1 week	
1 (Sold)	0.3595	(0.79)
2	0.3981	(0.77)
3	0.2252	(0.41)
4 (Bought)	0.3655	(0.74)
B-S (4-1)	0.0060	(0.01)
	Panel B: 3 months - 3 months	
1 (Sold)	0.5467	(1.22)
2	0.3851	(0.75)
3	0.2845	(0.52)
4 (Bought)	0.1810	(0.33)
B-S (4-1)	-0.3677	(-0.52)
	Panel C: 6 months - 6 months	
1 (Sold)	0.5870	(1.32)
2	0.2661	(0.51)
3	0.1853	(0.35)
4 (Bought)	0.4580	(0.84)
B-S (4-1)	-0.1290	(-0.18)
	Panel D: 12 months - 12 months	
1 (Sold)	0.5759	(1.35)
2	0.4781	(0.94)
3	0.0999	(0.18)
4 (Bought)	0.3194	(0.56)
B-S (4-1)	-0.2565	(-0.36)

Table 11 : *Sorting into 3 portfolios*

The industries most heavily bought (sold) are assigned to portfolio 3 (1). Else, methodology is similar to the description in Table 7.

Portfolio	Raw return (%)	
	Monthly return	*t*-Statistics
	Panel A: 1 week - 1 week	
1 (Sold)	0.4541	(0.97)
2	0.4361	(0.84)
3 (Bought)	0.1321	(0.26)
B-S (3-1)	-0.3220	(-0.47)
	Panel B: 3 months - 3 months	
1 (Sold)	0.4687	(1.02)
2	0.4029	(0.76)
3 (Bought)	0.2439	(0.46)
B-S (3-1)	-0.2249	(-0.32)
	Panel C: 6 months - 6 months	
1 (Sold)	0.5096	(1.12)
2	0.2289	(0.44)
3 (Bought)	0.3551	(0.65)
B-S (3-1)	-0.1545	(-0.22)
	Panel D: 12 months - 12 months	
1 (Sold)	0.5602	(1.28)
2	0.2526	(0.47)
3 (Bought)	0.2838	(0.51)
B-S (3-1)	-0.2765	(-0.39)

Appendix B

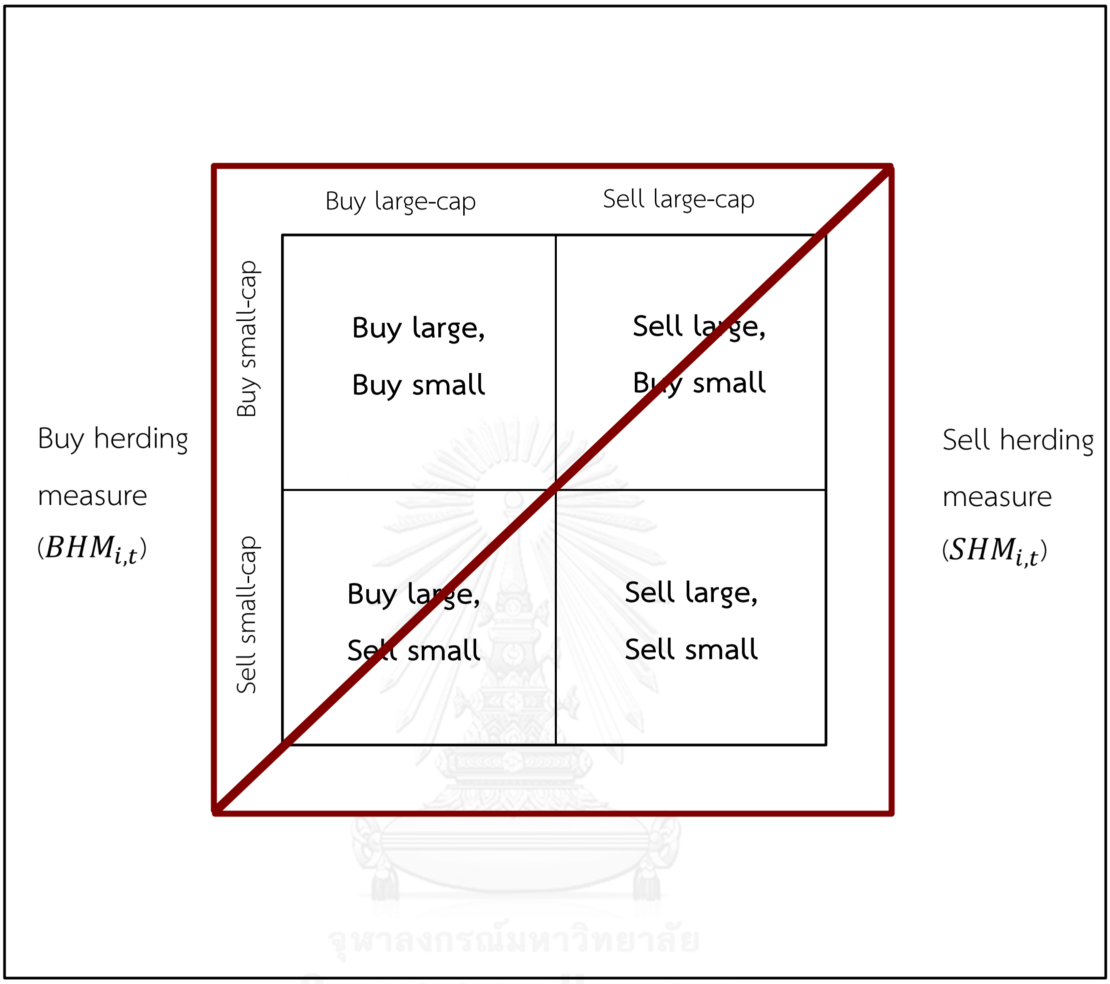

Figure 3 : Illustration of situations that could occur in the industry that shows buy and sell herding.

As shown in Figure 3, herding measure $(HM_{i,t})$ can be divided into buy herding measure $(BHM_{i,t})$ and sell herding measure $(SHM_{i,t})$. Buy herding measure is used to represent the industry having buy herding. Sell herding measure is used to represent the industry having sell herding.

After analyze further by assigning stocks into two groups: small-cap and large-cap, it reveals that the industry having buy or sell herding consists of two situations that could occur. For buy herding measure, the first situation is both small-cap and large-cap stocks in the industry are bought. The second situations are only small-cap stocks and large-cap stocks in the industry is bought. For sell herding measure, the first situation is both small-cap and large-cap stocks in the industry are sold. The second situations are only small-cap stocks and large-cap stocks in the industry is sold.

VITA

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