AGGREGATE HERD BEHAVIOR: ALTERNATIVE METHODOLOGIES AND INTERPRETATIONS

BY

MR. PHASIN WANIDWARANAN

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
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ABSTRACT

This dissertation mainly focuses on “Herd Behavior” which is referred as a situation in which individuals act coherently as part of a group. Besides explaining the behavior of animals, the term is also used to describe some kinds of human phenomena. When applied to human behavior particularly financial decision-making processes, herding is likely to be one of the main causes of major events occurred in financial markets such as investment bubbles or stock market crashes. Moreover, according to the 2015 CFA Institute’s survey, herding is the most influential behavioral bias that affects investment decisions. While it is important and also interesting to comprehend more about herd behavior and its impact on the investors’ decision-making, yet, there are a limited number of studies that focused on such matter. In order to foster better understanding of herd behavior and its implications for financial markets, three scopes of the issue have been chosen. Those three scopes involve information environment viewing from different perspectives. Such information is recognized as a potential factor behind herd behavior. In an effort to portray an overall picture of the phenomenon, this dissertation merely focuses on an aggregate market herd behavior regardless of investor type.

While the number of studies of return discontinuities in financial markets, so-called jumps, is countless, yet, most of them solely focus on developing measures to detect the occurrence of jumps. There have been studies suggesting that arrivals of jumps represent a utilization of private information implying that it eventually increases investors’ motivation to imitate such trade. However, in order to explore and identify the impact of return jumps on herd behavior, this dissertation develops and applies a new herding detection model by incorporating jump effect. Not only developing the new model, it also demonstrates the impact of private information arrival on herd behavior. The result mostly indicates that herding increases upon the existence of jumps during negative market return circumstances.

Literatures suggest that one of the causes of herd behavior is uncertainty. Different forms of uncertainty can be identified and one of them is "information uncertainty" as a result of information asymmetry. Thus, corporate transparency, particularly in relation to financial information disclosure, is the main focus of this dissertation. Even there has been a research on an association between corporate transparency and herd behavior on aggregate level, however, a limitation caused by a proxy of corporate transparency still keeps us from making the most of research findings. In order to tackle such limitation, this dissertation applies a corporate transparency indicator, a market model R-squared, instead to demonstrate the impact of a firm characteristic, such as corporate transparency, on herd behavior. Especially for decile portfolio technique, the result mostly suggests that herding decreases when holding portfolio of firms with high corporate transparency, and vice versa.

Without a doubt, every one of us has a very limited attention span and that affects our ability to receive information, quantitatively and qualitatively, and to decide accordingly. However, as herding is a convergence of behavior, a number of psychological studies suggest that the size of a crowd affects the possibility of herd behavior. On the other hand, it is also likely that herding attracts the crowd's attention. Accordingly, this dissertation applies a VAR model together with a Google search volume index to explore, unlike previous studies, the association between investor attention and herd behavior. The result shows that there is a tendency that herding in the past can attract investors' attention. However, the influence of investor attention on herd behavior is inconclusive.

Keywords: Herd behavior, Information asymmetry, Uncertainty, Decision-making, Return jump, Private information, Corporate transparency, Market model R-squared, Investor attention, Google search volume index.

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Mr. Phasin Wanidwaranan

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CHAPTER 1
INTRODUCTION

1.1 Motivation

As investors are assumed to be rational, the efficient market hypothesis (Fama, 1970) states that security prices instantaneously and fully reflect all arriving information. Consequently, it is impossible to consistently beat a market without taking additional risks. However, investors are actually irrational and have limited capabilities. As a result, they possess and process information differently. The violations of efficient market hypothesis bring behavioral aspects into consideration. As behavioral finance implicitly allows imperfect decision-making, it attempts to explain an irrational financial decision by combining various fields of knowledge especially psychological theory. Without idealistic assumptions, behavioral finance sheds light on many financial market anomalies that cannot be clarified by neoclassical finance.

One of the most prominent behavioral phenomena, regarding a group action, is herd behavior. It is generally found in human activities including economic decision-making. In financial market, the herd behavior is defined as imitating actions that participants neglect their own information to follow an observed financial decision, for example; analysts' forecast, corporate strategy, and trading decision. Not only occurs in financial market repeatedly, the declining of independent decision also establishes in all groups of investors including sophisticated institutional investors who are anticipated to retain an efficient judgment.

Literature suggests that the herd behavior is stronger in developing markets due to the lack of information transparency (Gelos & Wei, 2005) and the greater number of unsophisticated investors (Venezia et al., 2011). As a weakening of heterogeneous choice is severe during extreme market movement which is also known as a period of uncertainty (Christie & Huang, 1995 and Chang et al., 2000), the reaction is also asymmetry (Chang et al., 2000; Chiang & Zheng; 2010; and Zhou & Lai, 2009). Besides, the imitating action is influenced by firm characteristic especially the firm size. However, evidences are still mixed (Wylie, 2005; Walter & Weber; 2006; Galariotis et al., 2016; Lakonishok et al., 1992; Wermers, 1999; and Dang & Lin, 2016) and a bunch of researchers also indicates that herd behavior is severe in some industries (Zhou & Lai, 2009 and Choi & Sias, 2009). Moreover, there can be herding spillover effect from one market to another, especially between the United States and its neighboring countries (Chiang & Zheng, 2010). Finally, the imitating judgment is not constant. Recent studies denote that it changes over time (Bohl et al., 2013; Sharma et al., 2015; and Ngene et al., 2017).

Even the herd behavior is extensively studied, the phenomenon is mainly proposed to be an irrational choice. The irrational herding is driven by other motives rather than financial causes, such as psychological stimuli and restraints, resulting in a biased decision which destabilizes a security price (Spyrou, 2013). Therefore, it was frequently blamed as a cause of market volatility, financial bubbles, and crashes. On the other hand, a rational herd behavior is an outcome of a decision that market participants try to maximize their returns or minimize their losses. There are three stimuli of herding that are categorized as rational judgments which are job security concern (Scharfstein & Stein, 1990; Froot et al., 1992; and Brown et al., 2014), compensation concern (Trueman, 1994 and Maug & Naik, 2011), and information cascade (Banerjee, 1992 and Bikhchandani et al., 1992). Unlike the irrational peer, the rational herding can carry either inefficiency or efficiency results depending on an intentionality[1] of its contributors.

The job security and compensation concern are commonly anticipated as motives of analysts' forecast herding. The last stimuli of herding, information cascade, is a circumstance that individuals neglect their own private information to follow an observed action, despite the fact that such individuals cannot tell if there are any contradictions between the observed action's private information and motivation and their own (Banerjee, 1992 and Bikhchandani et al., 1992). Since the information cascade is more pronounced during high uncertainty stage, it is worsened when information asymmetries are severe causing greater information gap between traders. Yet, Bikhchandani et al. (1992) indicate that the cascade can easily be altered by a small

[1] Bikhchandani & Sharma (2000), spurious herding is a consequence of unintentional herd-like judgment. As investors have comparable information, their decisions are likely to be correlated. While, intentional herding is a deliberately imitating behavior regardless of information. Hence, only spurious herding is expected to improve market efficiency.

shock. While the information cascade is often referred as an important cause of the rational herding (Venezia et al., 2011), a study regarding the information-based herding is scarce due to an unavailability of data representing investors' trading information. Moreover, existing works are indirect and mostly experimental ones, for example; Avery & Zemsky (1998), Cipriani & Guarino (2005), Drehmann et al. (2005), and Fernández et al. (2011).

The analysis of herd behavior can also be separated into two groups based on a category of herding detection model which are investor type herding and aggregate market herding. Due to an availability of proprietary data, the investor type herding generally focuses on institutional investors, while aggregate market herding is considered as a combination of market participants' decisions.

As suggested by CFA survey 2015[2], not only being the most dominant behavioral bias that impacts practitioners, herding is also the key phenomenon of a group behavior. In order to discover overall consequences of the declining of independent decision, this dissertation examines the aggregate market herding. With the help of modern databases, missing links between prior studies are explored to a deeper extent. Accompanied by a connection between information asymmetry, information cascade, and herd behavior, this dissertation utilizes three alternatives which are jump component as a representative of informed trade, stock return synchronicity as a measure of corporate transparency, and internet search volume index as a proxy of investor attention.

A rational justification of the three selections is that an occurrence of distinctive trades, which intensifies volatility resulting in more uncertainty, will catch investors' attention and, at the same time, represent an arriving of significant information. Consequently, the crowd tends to follow such distinctive trades in order to minimize the information gap. Since quality and quantity of information disclosure reduce information asymmetry and information uncertainty, corporate transparency enhances investors' access to relevant information and their assessment of such information. As investors are generally flooded by information, they must allocate their

[2] The survey emphasizes an importance of herd behavior in the view of 724 global practitioners. The information is suggested by the CFA's website.
https://blogs.cfainstitute.org/investor/2015/08/06/the-herding-mentality-behavioral-finance-and-investor-biases/

limited attention selectively. This lessens investors' information and, therefore, increases information asymmetry and uncertainty of their decision-making. Three chapters of this dissertation demonstrate the influence of information on investors trading behavior. Also, an impact of diverse information between market participants that stimulates information cascade is also explained. The three chapters all corroborate each other, empowering the study of information cascade which causes an information-based herding.

The first chapter investigates whether the occurrence of jump influences the information-based herding. An impact of discrete jump on herd behavior is supported by the emergent-norm theory (Turner & Killian, 1957). The theory states that ambiguous crowd is likely to follow a key member's decision which leads to a collective behavior. To put it another way, uncertain observers track the key member's signal. As the key member is defined as the one who demonstrates a strong and unique action, it is correlated with a characteristic of discontinuous jump which is a large, rare, and unanticipated movement. Since jump process instantly escalates return volatility (Merton, 1976), it eventually exacerbates an uncertainty of financial market causing a preferable situation for the imitating reaction. The impact of jump on investor decision is also supported by Park (2011)[3] and Lee (2012). As the paper proposes that discontinuous jump is associated with an arriving of significant information-flow, the extreme movement is referred as a representative of informed trade which signals uninformed investors. Besides, Peng et al. (2007), Seasholes & Wu (2007), Barber & Odean (2008), and Li et al. (2017) suggest that retail investors tend to be driven by market-wide factors, public information, and attention-grabbing incidents, for instances; surprising news, return shock, and abnormal trading volume. Investor behavior is expected to change after the occurrence of those events. Furthermore, their results indicate an increasing of herd-like behavior following a noticeable event,

[3] Park (2011) uses jump with percolation model in order to detect the herd behavior. Based on his methodology, discontinuous jump represents an arriving of significant information which increases both trading volume and return volatility. Unlike jump, Park (2011) proposes that the herd behavior only escalates the latter. However, recent evidences contradict his hypothesis. Trading volume is also positively associated with the herd behavior (Tan et al., 2008; Lan & Lai, 2011; Lao & Singh, 2011; and Jlassi & Bensaida, 2014). Moreover, the paper employs a biased estimator of jump date which is interfered by microstructure noise. Finally, Park (2011) did not directly study an impact of discontinuous jump on the herd behavior. However, the results show higher herd behavior during days without discontinuous jump.

especially in developing markets during high uncertainty situations where ambiguous unsophisticated investors are expected to drive the information-based herding when discontinuous jump in market return is taking place. The evidences support the hypothesis that herd behavior is sensitive. It is dramatically influenced by return jump. Also, the declining of heterogeneous decision is mostly stronger during the occurrence of jump especially in negative return period.

The second chapter explores whether corporate transparency influences aggregate market herding. Wang & Huang (2018) is the only paper investigating such issue. Unfortunately, the methodology raises many concerns. By using a stock return synchronicity which is measured by a coefficient of determination (R-squared) from market model, it specifies a level of firm-specific information that is captured by stock return and market return (Morck et al., 2000). As transparent companies have lower asymmetric information, their firm-specific information should be highly and continuously revealed (Jin & Myers, 2006). Consequently, investors can effectively predict the future events and trade accordingly. Hence, a stock price movement is well explained by firm-specific information. Moreover, when a security price reflects the information that lowers the unexpected movement and volatility, stock return of transparent companies should be highly correlated with market return resulting in a high R-squared. As information uncertainty and cascade are predicted to be small in a transparent information environment, the findings mostly confirm the notion that herd behavior is anticipated to be negatively associated with stock return synchronicity especially for the decile portfolio analysis. Hence, corporate transparency improves the independent decision.

The last chapter tests whether a limited investor attention affects investors behavior. As attention is a scarce cognitive resource (Kahneman, 1973), investors must access and assess information selectively. The dynamic relation between investor attention and herd behavior is analyzed by using an internet search volume index from Google Trends (Google SVI) which is the best proxy of investor attention to date. As the internet search volume index represents investor information (Mondria et al., 2010), Google SVI is negatively associated with information asymmetry and information uncertainty. Besides, investor attention also improves investors' capability to analyze and respond to arriving information (Libby et al., 2002; Daniel et al., 2002; and

Hirshleifer et al., 2011). This suggests an essential role of investor attention in making a trading decision. Therefore, the information-based herding is expected to be reduced especially during the time of high investor attention. Peltomäki & Vahamaa (2015) briefly study the interaction. By employing an indirect herding measure under specific scopes, they support the negative relationship between investor attention and herd behavior. However, the results are inconclusive. Herd behavior also increases after the rising of investor attention which signifies the evidence of unintentional herding. Interestingly, this chapter suggests that the declining of independent decision influence investor attention.

1.2 Background

Herd behavior is a common phenomenon that can be found in animals and human beings. In terms of finance, it is defined as an event that individuals imitate observed financial decision without knowing reasons behind it and neglecting their own information. The empirical evidences of herd behavior are investigated by using two groups of models which are an investor type herding and an aggregate market herding. Lakonishok et al. (1992) and Sias (2004) are the important contributors of the investor type herding model. Institutional investors are the main focus of this model due to an obtainability of proprietary data. The institutional herding is denoted by a correlation between adjacent periods of institutional investor demand. The second model used to investigate herd behavior is the aggregate market herding which is originated by Christie & Huang (1995) and Chang et al. (2000). Their models are developed based on a rational asset pricing that takes into account a relationship between equity return dispersion and overall market return.

This dissertation examines the aggregate market herding by modifying the study of Christie & Huang (1995) and Chang et al. (2000). The main difference between these two models is an interpretation of rational asset pricing model. While both models propose that heterogeneous decisions are reduced because of an uncertainty during a period of extreme market movement, Christie & Huang (1995) strongly put that a negative linear correlation between stock return dispersion and market return is a sign of herd behavior. On the other hand, Chang et al. (2000) indicate that herd behavior carries a non-linearity to the relationship. In addition, Chang et al. (2000) fix an outlier effect in Christie & Huang (1995)'s cross-sectional standard deviation (CSSD) by introducing a cross-sectional absolute deviation of returns (CSAD).

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{1.1}$$

where $CSAD_t$ is a cross-sectional absolute deviation of returns at time t. N is the number of firms in a portfolio. $R_{i,t}$ is a stock return of firm i at time t which is equal to $100 \times (\ln P_{i,t} - \ln P_{i,t-1})$. $R_{m,t}$ is an equally weighted portfolio return at time t.

Chang et al. (2000) support their interpretation by introducing a non-linear term to the detection model.

$$CSAD_t = \propto + \gamma_1\left|R_{m,t}\right| + \gamma_2\left(R_{m,t}\right)^2 + \varepsilon_t \tag{1.2}$$

Later, Chiang & Zheng (2010) simplify a test of asymmetric herding between up-market and down-market by reducing Chang et al. (2000)'s models into one equation.

$$CSAD_t = \propto + \gamma_1 R_{m.t} + \gamma_2\left|R_{m.t}\right| + \gamma_3 R_{m,t}^2 + \varepsilon_i \tag{1.3}$$

Besides, Yao et al. (2014) improve the detection power of Chang et al. (2000) by introducing one-day lagged CSAD to the model. They also reduce the multicollinearity between explanatory variables by modifying the non-linear term.

$$CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2\left|R_{m,t}\right| + \gamma_3\left(R_{m,t} - \overline{R_m}\right)^2 + \varepsilon_t \tag{1.4}$$

On the other hand, Bui et al. (2017) enhance the strength of Yao et al. (2014) by adjusting the mean centering non-linear term which they suggest that a larger portion of multicollinearity problem will be diminished.

$$CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2\left|R_{m,t}\right| + \gamma_3\left(\left|R_{m,t}\right| - \overline{R_m}\right)^2 + \varepsilon_t \tag{1.5}$$

Alternatively, Blasco et al. (2017) expand Chiang & Zheng (2010) by following Yao et al. (2014) who include one-day lagged CSAD to the model.

$$CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m.t} + \gamma_3\left|R_{m.t}\right| + \gamma_4 R_{m,t}^2 + \varepsilon_i \tag{1.6}$$

A herding indicator is the same as Chang et al. (2000) which is a coefficient of non-linear term. As herd behavior is promoted by a deterioration of independent judgment, a drop of return dispersion is expected during the time of extreme market return resulting in negative and significant coefficient of non-linearity. Additionally, recent papers are proposing a time-varying property of herd behavior (Bohl et al., 2013; Sharma et al., 2015; and Ngene et al., 2017). This dissertation captures the dynamic herding by computing daily coefficient of non-linear term from five-minute data in the chapter of investor attention.

1.3 Objective and contribution

This dissertation attempts to develop a better understanding of herd behavior by exploring mechanisms of an imitating action. As information cascade is a major cause of rational herd behavior, this study also examines the information-based herding at an aggregate market level by using equity market data. Apart from the investor type herding, the aggregate market herding is an outcome from overall investors' decisions which demonstrates an impact of investors' behavior on the whole market. This dissertation explores an influence of information on investor behavior regarding the information-based herding. In order to identify the most appropriate aggregate market herding detection models as well as to enhance prior studies' methodologies, six widely-cited models are compared. Furthermore, as research data covers up to 21 largest equity markets in 19 countries, a comparative analysis between international financial markets having different stages of development and economic structures is improved.

Discontinuous jump is considered as an attention-grabbing event. Not only increases volatility and affects investor decision, the occurrence of jump also represents an incident of informed trading which subsequently leads to an increase in information-based herding especially during a period of uncertainty. The new herding detection model is introduced to capture the jump and asymmetric market condition influences. As the effect of equity index jump on aggregate market herding is tested, this study clarifies an impact of abnormal market-wide adjustment and private information on investor behavior. Unlike Park (2011), this chapter employs unbiased estimator of bipower variation which is a vital element of jump detection model. As recent literature violates percolation model's assumption used by Park (2011), the rational asset pricing model has been applied in this study. To the best of my knowledge, this is the first paper that directly examines the association between jump and herd behavior.

If a firm has a high corporate transparency, managers and investors should have comparable information. Therefore, corporate transparency diminishes information uncertainty and decrease the tendency of information cascade and rational herd behavior. Despite a clear foundation, the study of the connection between corporate transparency and aggregate market herding is limited. Wang & Huang (2018) is the only paper that explores such connection by using a country-specific transparency index. Yet, this dissertation attempts to examine the relationship between stock return synchronicity and information-based herding which indicates the effect of firm characteristic on investor judgment. It also aims at promoting corporate transparency so that investors are given fair access to information necessary for informed decision-making.

Google search volume index (Google SVI) represents the investor attention which implies investors' information and judgment proficiency. Therefore, Google SVI lessens the data limitation encountered by prior studies. As the dynamic relation between investor attention and information-based herding is examined, this study, even previous evidence regarding the association is scarce, also sheds light on an influence of investors' attribute over their decisions. Peltomäki & Vahamaa (2015) employed an indirect measure of aggregate market herding with a very specific scope. Without setting additional criteria, they strictly focus on Eurozone sovereign debt crisis's attention, which affects national European banking index, by using "euro crisis" as an enquiry keyword although it is questionable for its validity. This chapter improves the shortcomings of Peltomäki & Vahamaa (2015). Moreover, the time-varying feature of herd behavior is captured by the analysis of daily coefficient of non-linear term from high frequency data.

1.4 Structure of dissertation

This dissertation explores the information-based herding at the aggregate market level by using data from up to 19 countries. It can be separated into four chapters. The first chapter is an introduction which summarizes the whole dissertation.

The second chapter examines an influence of discontinuous jump on investor decision. By adjusting Chang et al. (2000), the reduction of independent decision is compared between jump day and other periods. The third chapter investigates an impact of corporate transparency on information-based herding by evaluating stock return synchronicity. Lastly, the fourth chapter shows the interaction between investor attention on aggregate market herding by using the daily internet search volume index from Google Trends as a proxy of investor attention.

CHAPTER 2
AN INFLUENCE OF DISCONTINUOUS JUMP ON INFORMATION-BASED HERDING

2.1 Introduction

Collective behavior refers to any distinctive action that large number of people engages. It has long been described by one of the most prominent psychological principles called the emergent-norm theory proposed by Turner & Killian (1957). The theory states that a crowd behavior can be guided by the key member, a minority individual who has strong and unique action, especially during periods of uncertainty. Also, Couzin et al. (2011) indicate that the theory causes a rational collective behavior. Consequently, the strong and unique decision is likely to drive the imitating reaction by an uncertain crowd.

Since herd behavior is a subcategory of the collective behavior, it can be explained by the emergent-norm theory. Interestingly, the definition of the key member is correlated with characteristics of return jump which is large and rare unanticipated price change. Because, jump signals an arriving of major information (Niederhoffer, 1971; Lee, 2012; and Boudoukh et al, 2015). However, Cutler et al. (1989) indicate that large movements also arise during the days without significant public announcement aligning with the study of market model R-squared from Roll (1988). As returns of non-announcement date should be described by systematic factor, Roll (1988) directs the event as the effect of private information. Furthermore, Daniel et al. (1998) confirm that investors overreact to private information and underreact to public information. The role of discontinuous market index jump in clarifying herd behavior is also reinforced by following literature. Kahneman (1973) suggests that attention is a scarce cognitive resource. Investors generally allocate their consideration selectively. Barber & Odean (2008) and Li et al. (2017) state that retail investors' trading is driven by public information and noticeable events, such as return shock, abnormal trading volume, and unexpected announcement. Also, Peng et al. (2007) denote that investors allocate their attention more on market-wide information after a macroeconomic surprise which intensifies overall market uncertainty. The situation increases security price comovement that is a herd-like behavior. Seasholes & Wu (2007) indicate that retail investors trade more after the occurrence of eye-catching incidences. The paper signifies that those trades account for informed investors' profit who are doubted as the key contributor of attention-grabbing event.

As suggested by information cascade theory, information-based herding is initiated by investors who observe and imitate other's trade without aware of its motive and disregards their own private information. Venezia et al. (2011) state that rational herd behavior is generally driven by information cascade. Also, Bikhchandani et al. (1992) emphasize a fragility of information cascade that can be altered by a small information shock. As the discontinuous jump worsens return volatility (Merton, 1976), the surging of uncertainty is a desirable condition for herd behavior (Christie & Huang, 1995). Additionally, jump is a sign of asymmetric information stressing information uncertainty. Brav & Heaton (2002) infer that the number of uninformed traders is associated with high stock price drift and uncertainty. I propose that retail investors, who play an important role in creating aggregate market herding (Venezia et al., 2011), are expected to pay more attention on the jump events generating the declining of independent decision.

As far as I am concerned, Park (2011) is the only paper that links herd behavior by incorporating a jump component. He introduces a daily herding detection technique by using percolation model which examines a relationship between return volatility and trading volume. As discontinuous jump represents a significant information-flow, the model proposes that return volatility and trading volume is increasing with jump. In contrast, herd behavior only escalates the volatility. However, the assumption is violated by recent works that suggest a positive association between herd behavior and trading volume (Tan et al., 2008; Lan & Lai, 2011; Lao & Singh, 2011; and Jlassi & Bensaida, 2014). Moreover, a jump detection model that has been employed in the paper is affected by microstructure noise causing a biased estimation. Most importantly, Park (2011) does not directly explore the impact of jump on the aggregate market herding. As market return jump is a market-wide eye-catching incident, therefore, it is predicted to be associated with the change of information-based herding.

This chapter is the first to directly examine the influence of return jump on information-based herding in aggregate level. By analyzing discontinuous jump, this study reduces methodology limitations from literature. As Dumitru & Urga (2012) suggest that a jump detection process from Barndorff-Nielsen & Shephard (2004) is applicable for high volatility period, this chapter also improves Park (2011) by using an unbiased estimator of bipower variation proposed by Huang & Tauchen (2005). Moreover, this study mitigates the drawback of Park (2011)'s percolation model by working with the rational asset pricing model. The six competitive aggregate market herding detection models are compared suggesting the most appropriate herding equation. By introducing the new herding detection model incorporating jump, different market conditions are also considered. As the association between market return jump and information-based herding is examined, it sheds light on an impact of private information investor behavior.

2.2 Literature review

The development of psychology theories that describe collective behavior has begun with the contagion theory by Le Bon (1895). Le Bon proposes that emotional and irrational action of an individual is driven by the crowd. In contrast, convergence theory states crowd's decision is motivated by individuals who join the group of like-minded people (Allport, 1924 and Goode, 1992). Even convergence theory supports a rationality of crowd's action, it does not deny a case that some actions will not occur outside a group as a responsibility is lower within the crowd. Turner & Killian (1957) introduce the emergent-norm theory which lies between the contagion theory and convergence theory. The reason is that the crowd is rational than as assumed by the contagion theory. However, it is less predictable than the convergence theory. During a period of uncertainty, individuals are uncertain about their appropriate actions. As individuals observe the crowd' action which normally led by the key member. If that action is acceptable which maximizes a benefit or minimizes a cost, individuals will follow. Le Bon (1895) also signifies the deindividuation theory. It indicates that individuals are avoid to perform a distinctive action, which deviates from a social convention, during high attention periods. While, Leonard et al. (2012) show that number of uninformed individuals is positively correlated with their attention and a cooperation decision. As return jump is an eye-catching event, a return dispersion, which implies an independent behavior, is anticipated to be reduced with the occurrence of jump.

In terms of financial study, Peng & Xiong (2006) examine the investor learning process based on a limited investor attention. Depend on an inattention level, they assert that investors focus on market-wide information and neglect firm-specific information which is called the category-learning behavior. Peng et al. (2007) support Peng & Xiong (2006) which emphasize that investors rely on market-wide information. With an occurrence of macroeconomic shock, they indicate that a rise of uncertainty and investor inattention lead to stock price comovement. As investors put more weight on market factors, return dispersion is expected to be low which implies herd behavior. While, Seasholes & Wu (2007) denote attention-based buying from retail investors. As investors have limited attention, they propose that attention-grabbing events affect investor trading behavior. However, they only concentrate on upper-price limit as a proxy of eye-catching event. Barber & Odean (2008) support Seasholes & Wu (2007) by using various kinds of attention-grabbing event, for examples; abnormal return, abnormal trading volume, and news release. Based on an inattention hypothesis, they indicate that individual investors buy stock that catch their limited attention. So, an impact of discontinuous jump on buy-herding may be stronger than sell-herding. By using trading volume-based herding measure, Li et al. (2017) show that individual investor herd behavior links with public information, market sentiment, and eye-catching events. While, Yuan (2015) denotes that positive market-wide attention-grabbing event resulting a price reversal.

The effect of discontinuous jump in financial market has been widely studied. Due to a significant of discontinuous path in explaining asset return volatility, Merton (1976) introduces the option pricing model that integrates both continuous terms and jump process. Lee (2012) denotes a relationship between real-time news announcement and the occurrence of jump for both macro- and micro-level. The association signifies that jump instantaneously transfers important unexpected information to a market which supports Lee & Mykland (2008) and Lahaye et al. (2011). While, Joulin et al. (2008) indicate that jump is followed by a high volatility which is different from a result of a news. So, they propose that an illiquidity is a cause of discontinuous jump. Taylor (2002) mentions that herd behavior is anticipated to be strong in less liquid stocks which are a small firm that has high asymmetric information, whereas, Galariotis et al. (2016) show a positive relationship between herding and liquidity. In order to capture discontinuous jump, financial scholars continuously introduce the detection models. However, nonparametric jump tests are established as the appropriate technique. Dumitru & Urga (2012) compare nine eminent nonparametric jump detection models. They denote that Andersen et al. (2007) and Lee & Mykland (2008) are the top all-round techniques. However, they tend to overestimate jump when test with high uncertainty period. With a time of extreme volatility, Dumitru & Urga (2012) suggest a model from Barndorff-Nielsen & Shephard (2004).

Since fat-tail stock prices are normally found in equity market, it violates stochastic behavior that is defined by the Gaussian distribution. Furthermore, excessive price fluctuation cannot be explained by fundamental factors. As prior studies assert that herd behavior is positively correlated with return volatility, Cont & Bouchaud (2000) propose that herd behavior might be the main contributor of fat-tail stock prices. They introduce the Cont–Bouchaud percolation model which examines an impact of herd behavior on stock return and trading volume. By using an interaction within a group of agents as a herd behavior's proxy, the model shows that herd behavior leads to price fluctuation. However, trading volume is not driven by herd behavior. The reason is that herd behavior is resulted from a decrease of investor heterogeneity which diminishes the independent trade. As a result, it restricts the growth of trading volume.

The prior study regarding an association between jumps and herd behavior is limited. Park (2011) examines aggregate market herding by using trading volume in Korea Stock Exchange with the percolation model. The study signifies jump as a proxy of significant information-flow. Based on a relationship between return volatility and trading volume, the paper signifies that information-flow increases return volatility and trading volume. Unlike information-flow, herd behavior only increases return volatility (Cont & Bouchaud, 2000). Park (2011) finds herd behavior in 22 percent of trading days including jump day and 26 percent of trading days without jump. Unfortunately, this study did not directly investigate the relationship between jumps and herd behavior. Moreover, recent studies discover the positive correlation between herd behavior and trading volume which contradicts to the percolation model (Tan et al., 2008; Lan & Lai, 2011; Lao & Singh, 2011; and Jlassi & Bensaida, 2014). In addition, an estimator of bipower variation that has been used by Park (2011) is affected by microstructure noise producing a biased jumps detection.

2.3 Data

In order to maintain an accuracy of the jump detection model and minimize the effect of microstructure noise (Andersen & Bollerslev, 1997; Andersen et al., 2001; Bandi & Russell, 2008; and Liu et al., 2015), this chapter utilizes five-minute market indices from Thomson Reuters DataScope Select. The aggregate market herding is identified by using daily stock prices from Thomson Reuters Datastream. The data has been modified according to Ince & Porter (2006). As Thomson Reuters DataScope Select has collected five-minute data since 1996, the study period is starting from January 1, 1996 to June 30, 2018.

21 leading stock exchanges from 19 countries are incorporated in this chapter which are Australia (Australian Securities Exchange), Brazil (Bovespa), Canada (Toronto Stock Exchange), China (Shanghai Stock Exchange), France (Euronext Paris), Germany (Deutsche Börse AG), Greece (Athens Exchange), India (Bombay Stock Exchange), Ireland (Euronext Dublin), Italy (Borsa Italiana), Japan (Tokyo Stock Exchange), Portugal (Euronext Lisbon), Russia (Moscow Exchange), South Africa (Johannesburg Stock Exchange), Spain (Bolsa de Madrid and Mercado Continuo Espanol), Thailand (Stock Exchange of Thailand and Market for Alternative Investment), the United Arab Emirates (Abu Dhabi Securities Exchange), the United Kingdom (London Stock Exchange), and the United States (New York Stock Exchange).

From the above list, only Spain and Thailand that the study explores two stock exchanges. For Spain, IBEX35 is the most renowned Spanish equity index and being used for the jump detection. It is a benchmark of Bolsa de Madrid. However, Bolsa de Madrid has only 30 active stocks at the end of June 2018. Thus, this paper includes Mercado Continuo Espanol, which has the highest number of active Spanish stocks. Also for Thailand, this chapter aims to examine herd behavior of all listed companies in country. Hence, both Stock Exchange of Thailand and Market for Alternative Investment are incorporated. As the Stock Exchange of Thailand is the leading market in Thailand, the SET index is used to detect jump. Based on MSCI's Market Classification 2018[4], eleven countries on the list above are considered as the developed markets, while eight countries are emerging ones.

Table 2.1 presents the data description of equity markets in 19 countries. Due to the availability of five-minute market indices from Thomson Reuters DataScope Select, the longest possible study period ranges from January 1, 1996 to June 30, 2018. Comparing with other countries, Canada, Italy, Russia, South Africa, and UAE have shorter research interval, while Italy has the shortest sample period starting from June 1, 2009 to June 30, 2018. Moreover, France and Italy have the highest and the lowest number of trading days which equal to 5,732 days and 2,413 days respectively. In view of both active and delisted companies, the number of stocks ranges from 49 stocks in Irish Stock Exchange to 3,671 stocks in Bombay Stock Exchange. Such quantities represent the overall number of companies including both listed and delisted companies.

Table 2.2 shows the descriptive statistics of daily cross-sectional absolute deviations (CSAD) and daily equally weighted market portfolio returns (R_m). The average daily CSAD ranges from 1.361% to 3.145% in Spain and Australia respectively. The lowest daily equally weighted average market return is identified in Australia which is -0.049%, while Russia has the value of 0.039% which is the highest figure. As China has the highest daily standard deviation of return, the lowest dispersion is found in France. Based on MSCI's 2018 market classification, emerging markets are generally characterized as markets with higher volatility resulting in having higher average daily return as well. The Augmented Dickey–Fuller statistics are significant for both daily CSAD and market return suggesting that time-series samples are stationary. Leaving out Brazil, Portugal, Russia, and Spain, time-series of CSAD are highly autocorrelated for every country. Hence, all standard errors of the estimated regression coefficients are adjusted for heteroscedasticity and autocorrelation by utilizing the method proposed by Newey & West (1987).

[4] The annual classification of MSCI market review is as follow.
https://www.msci.com/market-classification

Table 2.1 Data description for each equity market.

Note: This table reports research interval, number of observations, target stock exchange and market index, and number of stocks for 19 sample countries.

Country	Period	No. of Obs.	Exchange (Market index)	No. of stocks
AUS	1/1/1996 to 30/6/2018	5,414	Australian Securities Exchange (AORD)	2,524
BRA	1/1/1996 to 30/6/2018	5,568	Sao Paulo Stock Exchange (BVSP)	337
CAN	1/5/2002 to 30/6/2018	4,043	Toronto Stock Exchange (TSX300)	1,339
CHN	1/1/1996 to 30/6/2018	5,453	Shanghai Stock Exchange (SSEC)	1,433
FRA	1/1/1996 to 30/6/2018	5,732	Euronext Paris (CAC40)	1,221
GER	1/1/1996 to 30/6/2018	5,007	Frankfurt Stock Exchange (DAX)	1,203
GRE	1/1/1996 to 30/6/2018	5,583	Athens Exchange (ATG)	294
IND	1/1/1996 to 30/6/2018	5,584	Bombay Stock Exchange (SENSEX)	3,671
IRE	1/1/1996 to 30/6/2018	5,646	Euronext Dublin (ISEQ)	49
ITA	1/6/2009 to 30/6/2018	2,413	Borsa Italiana (FTSEMIB)	455
JAP	1/1/1996 to 30/6/2018	5,543	Tokyo Stock Exchange (N225)	3,312
POR	1/1/1996 to 30/6/2018	5,699	Euronext Lisbon (PSI20)	75
RUS	1/7/1998 to 30/6/2018	5,032	Moscow Exchange (RTS)	337
SAF	1/7/2002 to 30/6/2018	3,975	Johannesburg Stock Exchange (FTSEJSE)	408
SPA	1/1/1996 to 30/6/2018	5,724	Bolsa de Madrid and Mercado Continuo Espanol (IBEX35)	245
THA	1/1/1996 to 30/6/2018	5,416	Stock Exchange of Thailand and Market for Alternative Investment (SET)	752
UAE	1/1/2004 to 30/6/2018	3,625	Abu Dhabi Securities Exchange (ADI)	71
UK	1/1/1996 to 30/6/2018	5,707	London Stock Exchange (FTSE100)	2,226
USA	1/1/1996 to 30/6/2018	5,674	New York Stock Exchange (NYSE)	2,083

Table 2.2 Descriptive statistics of the daily cross-sectional absolute deviations (CSAD) and daily market returns (R_m).

Note: This table reports descriptive statistics of daily cross-sectional absolute deviations (CSAD) and daily equally weighted market portfolio returns (R_m) for 19 sample countries. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

Country	Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag				
							1	2	3	5	20
AUS	$CSAD$	3.145	0.009	15.438	0.664	-7.64***	0.698	0.630	0.562	0.507	0.382
	R_m	-0.049	-17.359	9.673	0.866	-13.67***	0.221	0.179	0.103	0.112	0.062
BRA	$CSAD$	1.747	0.118	31.347	0.965	-10.10***	0.209	0.164	0.171	0.144	0.120
	R_m	0.011	-15.925	7.220	0.942	-14.50***	0.073	0.078	0.036	0.049	0.047
CAN	$CSAD$	2.578	0.005	8.959	0.772	-4.23***	0.892	0.883	0.868	0.856	0.811
	R_m	0.003	-11.301	8.373	0.913	-13.04***	0.210	0.121	0.087	0.040	0.032
CHN	$CSAD$	1.565	0.322	5.714	0.574	-6.60***	0.753	0.692	0.663	0.634	0.508
	R_m	0.032	-10.359	9.714	1.889	-16.14***	0.066	-0.005	0.056	0.004	0.001
FRA	$CSAD$	1.850	0.009	5.456	0.535	-5.84***	0.784	0.768	0.746	0.716	0.615
	R_m	-0.003	-5.216	3.456	0.619	-13.77***	0.297	0.187	0.115	0.084	0.059
GER	$CSAD$	2.706	0.002	7.230	0.855	-4.39***	0.859	0.831	0.817	0.798	0.724
	R_m	-0.039	-5.340	4.258	0.824	-13.06***	0.212	0.131	0.118	0.056	0.039
GRE	$CSAD$	2.344	0.027	9.360	0.715	-6.07***	0.689	0.662	0.642	0.615	0.531
	R_m	-0.026	-11.650	8.337	1.619	-14.88***	0.210	0.035	0.051	0.039	0.027
IND	$CSAD$	2.772	0.001	11.773	1.210	-7.75***	0.893	0.871	0.858	0.843	0.737
	R_m	-0.016	-5.387	8.296	0.849	-15.24***	0.502	0.288	0.238	0.167	-0.014
IRE	$CSAD$	2.506	0.143	18.477	1.469	-6.08***	0.532	0.443	0.440	0.442	0.395
	R_m	-0.004	-12.427	9.018	1.350	-13.92***	0.030	0.020	0.051	0.031	0.026
ITA	$CSAD$	1.631	0.941	8.957	0.432	-5.82***	0.738	0.689	0.662	0.628	0.469
	R_m	-0.017	-6.686	4.620	0.980	-11.64***	0.170	0.103	0.061	0.023	0.027

Table 2.2 (continued)

Country	Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag				
							1	2	3	5	20
JAP	$CSAD$	1.677	0.001	6.910	0.517	-7.17***	0.822	0.770	0.723	0.688	0.550
	R_m	-0.004	-13.889	11.662	1.080	-16.29***	0.172	0.054	0.021	0.007	-0.006
POR	$CSAD$	1.764	0.248	17.345	1.096	-11.54***	0.234	0.171	0.140	0.097	0.102
	R_m	-0.016	-7.400	9.612	0.986	-15.01***	0.032	0.026	0.020	0.013	-0.010
RUS	$CSAD$	2.255	0.002	43.305	1.937	-8.94***	0.195	0.161	0.148	0.133	0.107
	R_m	0.039	-24.153	21.492	1.463	-15.00***	0.091	0.061	0.047	0.043	0.033
SAF	$CSAD$	2.411	0.027	6.624	0.658	-7.33***	0.561	0.512	0.498	0.479	0.442
	R_m	0.017	-5.149	2.873	0.706	-12.12***	0.110	0.083	0.089	0.057	0.007
SPA	$CSAD$	1.361	0.001	30.506	0.613	-8.76***	0.346	0.309	0.304	0.275	0.219
	R_m	0.006	-12.500	7.053	0.834	-14.80***	0.128	0.042	0.026	0.023	0.003
THA	$CSAD$	1.923	0.827	9.662	0.910	-6.29***	0.832	0.789	0.750	0.712	0.657
	R_m	-0.012	-11.404	9.056	1.047	-13.64***	0.196	0.122	0.065	0.042	0.023
UAE	$CSAD$	1.479	0.143	7.220	0.679	-7.14***	0.572	0.534	0.492	0.493	0.418
	R_m	0.007	-7.107	6.167	0.795	-11.84***	0.192	0.049	0.040	0.069	0.033
UK	$CSAD$	1.693	0.001	5.197	0.587	-5.78***	0.817	0.770	0.751	0.723	0.625
	R_m	-0.023	-5.414	4.057	0.640	-14.11***	0.348	0.198	0.168	0.132	0.044
USA	$CSAD$	1.561	0.018	6.246	0.572	-5.50***	0.869	0.830	0.812	0.795	0.690
	R_m	0.024	-12.024	10.908	1.243	-17.46***	0.006	-0.008	0.033	-0.044	0.045

2.4 Methodology

The research methodology is separated into two parts. First, jump date is identified by adapting a well-known technique from Barndorff-Nielsen & Shephard (2004). Second, aggregate market herding between jump and non-jump periods are compared by modifying Chang et al. (2000).

As securities prices are overloaded by unanticipated large number of extreme movements, their return distributions are frequently a fat-tail. The non-normal property interferes the statistical inference. Consequently, the discontinuous jump process is considered to be an important factor in explaining asset return. Considering log of the asset price in continuous-time which is assumed to be described by the stochastic jump-diffusion model.

$$dp_t = \mu_t dt + \sigma_t dW_t + \kappa_t dq_t;\ t \geq 0 \tag{2.1}$$

where p_t is a log-price during period t, μ_t is a drift term. σ_t is an instantaneous volatility. W_t is a standard Brownian motion. q_t is a Poisson process with $dq_t = 1$ when there is a jump during period t and 0 otherwise. κ_t is a size of discrete jump during period t with $dq_t = 1$.

By using a high frequency data, Andersen et al. (2007) assert that an integral of drift term is small and negligible. As a result, a quadratic variation of cumulative return (QV) is a sum of integrated volatility (IV) and a sum of squared jump size during period t. The key different between various jump detection models is an approximation procedure of quadratic variation and integrated volatility.

$$IV(t) = \int_{t-1}^{t} \sigma^2(s) ds \tag{2.2}$$

$$QV(t) = IV(t) + \sum_{j=1}^{M} {\kappa_{t,j}}^2 \tag{2.3}$$

As quadratic variation is unobservable, Barndorff-Nielsen & Shephard (2002), Andersen et al. (2003), Koopman et al. (2005), and Andersen et al. (2007) highlight that realized variance (RV) converges to a quadratic variation as a high sampling frequency data ($M \rightarrow \infty$) is employed.

$$RV(t) = \sum_{j=1}^{M} {r_{t,j}}^2 \tag{2.4}$$

$$RV(t) \rightarrow QV(t) \equiv IV(t) + \sum_{j=1}^{M} {\kappa_{t,j}}^2 \tag{2.5}$$

where $r_{t,j}$ is a return of discretely sampled period j during day t. M is a number of sample period during day t.

$$r_{t,j} = p_{t,j} - p_{t,j-1}; j = 1, \dots, M; t = 1, \dots T \tag{2.6}$$

For ($M \rightarrow \infty$), Barndorff-Nielsen & Shephard (2004) propose that the integrated volatility is estimated by a bipower variation (*BV*). As a result, jump component is a product of realized variance and bipower variation.

$$BV(t) \rightarrow IV(t) \equiv \int_{t-1}^{t} \sigma^2(s)ds \tag{2.7}$$

However, Huang & Tauchen (2005) show that a high frequency data also intensifies a market microstructure noise to the original bipower variation from Barndorff-Nielsen & Shephard (2004) which is utilized by Park (2011). As ($M \rightarrow \infty$), the noise stimulates a serial correlation between two adjacent returns, $r_{t,j-1}$ and $r_{t,j}$, which leads to a biased prediction. Hence, this chapter mitigates the problem by utilizing a staggered returns process from Andersen et al. (2004).

$$BV(t) = \mu_1^2 \left(\frac{M}{M-2}\right) \sum_{j=3}^{M} |r_{t,j-2}| \, |r_{t,j}| \, ; \mu_1 = \sqrt{\frac{2}{\pi}} \tag{2.8}$$

$$J(t) \equiv RV(t) - BV(t) \rightarrow \sum_{j=1}^{M} {\kappa_{t,j}}^2 \tag{2.9}$$

In addition, Huang & Tauchen (2005) recommend a statistic testing (Z) for detecting a date of significant extreme change, or jumps day, under a null hypothesis of no discontinuous jump. The model compares a difference between realized variance and bipower variation. Jump date is identified by using five-minute market index return. If ($Z(t) > \phi_\alpha$) then that day is a significant jump date, where $TP(t)$ is a tri-power quarticity statistic (Huang & Tauchen, 2005). ϕ_α is a critical value of standard normal distribution at a level of significant α. As suggested by Andersen et al. (2010, 2011), α is equal to 0.99 to 0.999.

$$Z(t) = \frac{\frac{RV(t) - BV(t)}{RV(t)}}{\sqrt{\left[\left(\frac{\pi}{2}\right)^2 + \pi - 5\right]\frac{1}{M} max\left[1, \frac{TP(t)}{BV(t)^2}\right]}} \tag{2.10}$$

$$TP(t) = M\mu_{4/3}^{-3}\left(\frac{M}{M-4}\right)\sum_{j=5}^{M}\left|r_{t,j-4}\right|^{4/3}\left|r_{t,j-2}\right|^{4/3}\left|r_{t,j}\right|^{4/3}, \tag{2.11}$$

$$where\ \mu_{4/3} = \frac{2^{2/3}\Gamma\left(\frac{7}{6}\right)}{\Gamma\left(\frac{1}{2}\right)}$$

On the other hand, aggregate market herding detection model is generally based on the modification of Chang et al. (2000). Disregarding the influence of jump, the pure herding analysis compare six competitive models which are Chang et al. (2000), Chiang & Zheng (2010), lagged CSAD and non-lagged CSAD model from Yao et al. (2014), Bui et al. (2017), and Blasco et al. (2017).

Considering the jump effect, this chapter chooses the most appropriate model by analyzing the information selection criteria which are Akaike information criterion (AIC), corrected Akaike information criterion (AICc), Bayesian information criterion (BIC), and Hannan–Quinn information criterion (HQIC). The models that produce the lowest information loss are selected based on the smallest value of overall information criteria.

Therefore, the lagged CSAD version of Yao et al. (2014), the model of Bui et al. (2017), and the model of Blasco et al. (2017) are modified by using the interaction terms between jump dummy variable and the coefficient of non-linear term to capture the influence of jump on aggregate market herding. Besides, this chapter also examines the effect during different market conditions by incorporating down-markets dummy variable.

$$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 CSAD_{t-1} + \gamma_3 D_j CSAD_{t-1} + \gamma_4\left|R_{m,t}\right| + \gamma_5 D_j\left|R_{m,t}\right| \tag{2.12}$$

$$+ \gamma_6\left(R_{m,t} - \overline{R_m}\right)^2 + \gamma_7 D_j\left(R_{m,t} - \overline{R_m}\right)^2 + \varepsilon_t$$

$$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 CSAD_{t-1} + \gamma_3 D_j CSAD_{t-1} + \gamma_4 |R_{m,t}| + \gamma_5 D_j |R_{m,t}| \quad (2.13)$$
$$+ \gamma_6 \left(|R_{m,t}| - \overline{R_m}\right)^2 + \gamma_7 D_j \left(|R_{m,t}| - \overline{R_m}\right)^2 + \varepsilon_t$$

$$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 CSAD_{t-1} + \gamma_3 D_j CSAD_{t-1} + \gamma_4 R_{m,t} + \gamma_5 D_j R_{m,t} \quad (2.14)$$
$$+ \gamma_6 |R_{m,t}| + \gamma_7 D_j |R_{m,t}| + \gamma_8 \left(R_{m,t}\right)^2 + \gamma_9 D_j \left(R_{m,t}\right)^2 + \varepsilon_t$$

where $CSAD_{t-1}$ is a cross-sectional absolute deviation of returns during time t-1. D_j is a dummy variable which specifies jump period. It is equal to one on the jump date, and zero otherwise. $\overline{R_m}$ is an average market portfolio return. $R_{m,t} - \overline{R_m}$ is a demean market portfolio return from Yao et al. (2014). $|R_{m,t}| - \overline{R_m}$ is a demean absolute market portfolio return from Bui et al. (2017).

For robustness proposes, this study utilizes non-staggered return process for bipower variation as an alternative jump detection model considering 99% confidence level.

$$BV(t) = \mu_1^2 \left(\frac{M}{M-2}\right) \sum_{j=3}^{M} |r_{t,j-1}| \, |r_{t,j}| \quad (2.15)$$

2.5 Empirical results

2.5.1 Pure herd behavior

Panel A of Table 2.3 shows regression results from pure herding analysis for the whole sample which is the combination of all market conditions. Six models built on Chang et al. (2000) are used to detect aggregate market herding. Based on the rational asset pricing, the coefficient of absolute market return is expected to be positive and significant as the return dispersion should be higher during extreme market movements. All test results confirm this argument. As negative and significant coefficient of non-linear term indicates the ignorance of investors' own private information signals, herding can be found among eleven stock markets which are Brazil, Canada, France, Germany, Greece, India, Japan, South Africa, Thailand, UAE, and UK. In terms of detection power, Chang et al. (2000) and the first model of Yao et al. (2014) detect herding in ten countries. Blasco et al. (2017), the second model of Yao et al. (2014), and Bui et al. (2017) demonstrate herd behavior in eight equity markets, while, Chiang & Zheng (2010) identify herding in seven economies. Brazil, Greece, South Africa, Thailand, and UAE show the strongest evidence of herd behavior. Thus, the negative and significant non-linear relationship can be identified by all equations.

Based on these approaches, herd behavior cannot be detected in Australia, China, Ireland, Italy, Portugal, Russia, Spain, and USA. Eleven markets that show the sign of herding are emerging ones situated in six countries. In contrast, 75% of countries that cannot detect herd behavior are developed markets. As positive and significant coefficient of non-linear term indicate the sign of anti-herding, the increase in independent trading decision during extreme market conditions can be identified in China, Germany, Portugal, Russia, Spain, and USA. Four of them are developed markets, while others are the BRICS's members, a group of five major emerging national economies. These findings confirm prior studies that herd behavior is greater in developing countries rather than advanced markets (Christie & Huang, 1995; Chang et al., 2000; Demirer et al., 2010; and Yao et al., 2014). This is due to the fact that emerging and frontier markets have favorable conditions to build up the decrease in independent trading decision, for examples, more direct investment of retail investors (Venezia et al., 2011), weaker disclosure standards (Gelos & Wei, 2005), higher volatilatility (Christie & Huang, 1995 and Chang et al., 2000), and a greater number of small stocks (Lakonishok et al., 1992; Wermers, 1999; Chang et al., 2000; and Dang & Lin, 2016).

The coefficient of determination from Blasco et al. (2017), the second model of Yao et al. (2014), and Bui et al. (2017) are higher than other models. On average, the adjusted R-squared is larger than 0.500 which implies that data are well analyzed by the proposed models. Interestingly, however, the result of Chiang & Zheng (2010) is close to Chang et al. (2000), yet it only provides small incremental information to Chang et al. (2000) concerning herding detection as its inclusion of non-absolute term does not help explain the samples. Also, Blasco et al. (2017), the second model of Yao et al. (2014), and Bui et al. (2017) suggest almost identical result in that the model's modification of squared return offers small incremental information as well. On the other hand, lagged CSAD offers important information to both Chang et al. (2000) and Chiang & Zheng (2010).

Table 2.3 Regression results of the daily $CSAD_t$ on herding equations regardless of jump effect.

Panel A: Regression results of the daily $CSAD_t$ on six herding equations regardless of jump effect (Whole sample).

Note: This table reports regression statistics of the whole sample by using six models which are

$CSAD_t = \propto + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2 + \varepsilon_t$ (Chang et al., 2000: CCK),

$CSAD_t = \propto + \gamma_1 R_{m,t} + \gamma_2|R_{m,t}| + \gamma_3(R_{m,t})^2 + \varepsilon_t$ (Chiang & Zheng, 2010: CZ),

$CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m,t} + \gamma_3|R_{m,t}| + \gamma_3(R_{m,t})^2 + \varepsilon_t$ (Blasco et al., 2017: BCF),

$CSAD_t = \propto + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (Yao et al., 2014: YMH1),

$CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2|R_{m,t}| + \gamma_3(R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (Yao et al., 2014: YMH2),

and $CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2|R_{m,t}| + \gamma_6(|R_{m,t}| - \overline{R_m})^2 + \varepsilon_t$ (Bui et al., 2017: BNNT),

where $CSAD_t$ is a cross-sectional absolute deviation of returns at time t, $R_{m,t}$ is an equally weighted portfolio return at time t, and $CSAD_{t-1}$ is a one-day lag of cross-sectional absolute deviation of returns at time t.

The sample interval is from 01/01/1996 to 30/06/2018.

The t-statistics are shown in parentheses which is calculated by using Newey & West (1987)'s heteroscedaticity and autocorrelation consistent standard errors.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

Table 2.3 Panel A (continued)

	AUS						BRA					
	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT
$Intercept$	2.666***	2.654***	1.248***	2.667***	1.238***	1.238***	0.819***	0.820***	0.822***	0.819***	0.821***	0.821***
	(130.24)	(118.36)	(13.43)	(130.33)	(13.33)	(13.33)	(26.57)	(23.60)	(26.74)	(26.58)	(31.39)	(31.37)
$\lvert R_{m,t}\rvert$	0.704***	0.725***	0.503***	0.703***	0.494***	0.494***	1.511***	1.509***	1.510***	1.511***	1.512***	1.512***
	(21.13)	(20.22)	(20.24)	(21.13)	(20.89)	(20.49)	(35.18)	(28.47)	(27.41)	(35.20)	(32.64)	(32.65)
$CSAD_{t-1}$			0.500***		0.505***	0.505***			-0.001		-0.001	-0.001
			(16.48)		(16.55)	(16.57)			(-0.33)		(-0.28)	(-0.28)
$R_{m,t}$		0.093***	0.030**					0.004	0.005			
		(6.12)	(2.53)					(0.12)	(0.13)			
${R_{m,t}}^2$	0.001	0.004	0.007				-0.001***	-0.001**	-0.001**			
	(-0.09)	(1.37)	(1.46)				(-4.21)	(-2.14)	(-2.13)			
$\left(R_{m,t}-\overline{R_m}\right)^2$				0.001	0.006					-0.001***	-0.001***	
				(-0.02)	(1.10)					(-4.21)	(-3.92)	
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$						0.006						-0.001***
						(1.07)						(-3.92)
$Adj.R^2$	0.450	0.460	0.676	0.450	0.675	0.675	0.976	0.976	0.976	0.976	0.976	0.976

Table 2.3 Panel A (continued)

	CAN						CHN					
	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT
$Intercept$	2.792***	2.784***	0.325***	2.792***	0.325***	0.325***	1.353***	1.359***	1.045***	1.354***	1.042***	1.042***
	(46.46)	(42.88)	(8.56)	(46.46)	(8.70)	(8.70)	(37.44)	(36.38)	(7.44)	(37.43)	(7.44)	(7.44)
$\lvert R_{m,t}\rvert$	0.699***	0.702***	0.392***	0.699***	0.392***	0.392***	0.093***	0.088***	0.051**	0.093***	0.057**	0.059**
	(10.19)	(9.61)	(13.47)	(10.20)	(13.55)	(13.56)	(3.54)	(3.24)	(2.09)	(3.53)	(2.47)	(2.55)
$CSAD_{t-1}$			0.829***		0.829***	0.829***			0.234**		0.231**	0.231**
			(64.52)		(65.57)	(65.57)			(2.56)		(2.53)	(2.53)
$R_{m,t}$		0.087***	0.005					-0.023*	-0.029**			
		(3.62)	(0.54)					(-1.71)	(-2.20)			
${R_{m,t}}^2$	-0.015*	-0.007	-0.012***				0.011***	0.012***	0.013***			
	(-1.65)	(-0.74)	(-2.96)				(5.68)	(5.97)	(7.03)			
$\left(R_{m,t}-\overline{R_m}\right)^2$				-0.015*	-0.013***					0.012***	0.012***	
				(-1.66)	(-3.06)					(5.70)	(6.62)	
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$						-0.013***						0.012***
						(-3.06)						(6.58)
$Adj.R^2$	0.124	0.128	0.785	0.124	0.785	0.785	0.520	0.522	0.574	0.520	0.571	0.571

Table 2.3 Panel A (continued)

	FRA						GER					
	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT
$Intercept$	1.423***	1.422***	0.451***	1.423***	0.446***	0.446***	1.863***	1.859***	0.205***	1.868***	0.202***	0.201***
	(72.00)	(73.74)	(18.75)	(72.86)	(18.30)	(18.30)	(26.10)	(27.06)	(9.19)	(26.41)	(9.14)	(9.09)
$\lvert R_{m,t} \rvert$	0.882***	0.864***	0.532***	0.880***	0.538***	0.538***	1.143***	1.133***	0.366***	1.127***	0.360***	0.368***
	(17.61)	(17.71)	(25.97)	(17.73)	(26.48)	(26.43)	(13.86)	(14.18)	(16.44)	(13.76)	(16.19)	(15.58)
$CSAD_{t-1}$			0.623		0.626	0.626			0.833***		0.837***	0.836***
			(40.35)		(40.31)	(40.31)			(86.74)		(88.71)	(88.57)
$R_{m,t}$		0.078***	0.032***					0.137***	0.066***			
		(4.69)	(3.47)					(6.02)	(6.85)			
${R_{m,t}}^2$	-0.034**	-0.010	0.002				-0.100***	-0.075***	0.014**			
	(-2.12)	(-0.63)	(0.18)				(-5.39)	(-3.84)	(2.44)			
$\left(R_{m,t} - \overline{R_m}\right)^2$				-0.033**	-0.008					-0.095***	0.006	
				(-2.08)	(-0.94)					(-5.02)	(0.89)	
$\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$						-0.008						0.003
						(-0.98)						(0.41)
$Adj.R^2$	0.434	0.440	0.771	0.434	0.770	0.770	0.256	0.265	0.869	0.255	0.866	0.866

Table 2.3 Panel A (continued)

	GRE						IND					
	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT
$Intercept$	1.898***	1.898***	0.566***	1.898***	0.569***	0.570***	2.156***	2.155***	0.662***	2.156***	0.662***	0.662***
	(55.52)	(55.77)	(9.16)	(55.61)	(9.28)	(9.29)	(47.47)	(49.58)	(7.11)	(47.47)	(6.66)	(6.66)
$\lvert R_{m,t}\rvert$	0.411***	0.410***	0.325***	0.411***	0.323***	0.323***	1.294***	1.300***	0.658***	1.293***	0.653***	0.653***
	(10.69)	(10.61)	(10.11)	(10.68)	(9.96)	(9.91)	(20.94)	(21.79)	(9.70)	(20.94)	(9.43)	(9.42)
$CSAD_{t-1}$			0.628***		0.627***	0.627***			0.630***		0.631***	0.631***
			(20.57)		(20.63)	(20.62)			(14.27)		(13.54)	(13.54)
$R_{m,t}$		0.004	-0.012*					0.049**	0.041***			
		(0.45)	(-1.73)					(2.01)	(2.66)			
${R_{m,t}}^2$	-0.034***	-0.034***	-0.030***				-0.043***	-0.045***	-0.001			
	(-3.90)	(-3.83)	(-3.88)				(-8.18)	(-9.48)	(-0.13)			
$\left(R_{m,t}-\overline{R_m}\right)^2$				-0.034***	-0.030***					-0.043***	0.001	
				(-3.9)	(-3.76)					(-8.17)	(0.12)	
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$						-0.029***						0.001
						(-3.75)						(0.11)
$Adj. R^2$	0.166	0.166	0.548	0.166	0.548	0.548	0.458	0.459	0.776	0.458	0.775	0.775

Table 2.3 Panel A (continued)

	IRE						ITA					
	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT
$Intercept$	1.365***	1.368***	0.802***	1.365***	0.798***	0.798***	1.316***	1.314***	0.477***	1.317***	0.469***	0.468***
	(32.30)	(31.25)	(13.13)	(32.31)	(13.28)	(13.27)	(88.76)	(77.06)	(8.45)	(88.84)	(8.30)	(8.32)
$\lvert R_{m,t}\rvert$	1.065***	1.054***	0.905***	1.065***	0.912***	0.912***	0.374***	0.366***	0.220***	0.371***	0.220***	0.221***
	(16.22)	(15.81)	(16.45)	(16.25)	(16.50)	(16.52)	(11.20)	(10.30)	(7.48)	(11.09)	(7.68)	(7.62)
$CSAD_{t-1}$			0.298***		0.299***	0.299***			0.593***		0.600***	0.600***
			(10.74)		(10.96)	(10.96)			(16.70)		(16.89)	(16.99)
$R_{m,t}$		0.041***	0.026**					0.061***	0.025***			
		(2.80)	(1.97)					(7.79)	(4.43)			
${R_{m,t}}^2$	0.014	0.018	0.020				0.006	0.014	0.016			
	(0.85)	(1.08)	(1.25)				(0.45)	(1.05)	(1.12)			
$\left(R_{m,t}-\overline{R_m}\right)^2$				0.014	0.017					0.007	0.013	
				(0.85)	(1.07)					(0.54)	(0.94)	
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$						0.017						0.012
						(1.07)						(0.91)
$Adj. R^2$	0.527	0.528	0.608	0.527	0.608	0.608	0.346	0.361	0.669	0.346	0.667	0.667

Table 2.3 Panel A (continued)

	JAP						POR					
	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT
$Intercept$	1.376***	1.374***	0.316***	1.376***	0.318***	0.318***	1.054***	1.052***	0.910***	1.054***	0.911***	0.910***
	(70.38)	(114.64)	(11.60)	(71.71)	(10.98)	(10.98)	(47.60)	(47.64)	(31.56)	(47.47)	(32.23)	(32.33)
$\lvert R_{m,t} \rvert$	0.379***	0.380***	0.254***	0.379***	0.255***	0.255***	0.908***	0.912***	0.891***	0.906***	0.885***	0.883***
	(15.42)	(22.29)	(19.01)	(15.63)	(18.23)	(18.19)	(18.76)	(18.38)	(18.52)	(18.65)	(18.78)	(18.56)
$CSAD_{t-1}$			0.700***		0.698***	0.698***			0.090***		0.091***	0.091***
			(35.36)		(33.14)	(33.13)			(7.12)		(7.20)	(7.21)
$R_{m,t}$		0.022***	-0.011**					0.042**	0.039**			
		(2.64)	(-2.00)					(2.42)	(2.34)			
${R_{m,t}}^2$	0.001	0.002	-0.004**				0.089***	0.089***	0.089***			
	(0.39)	(0.74)	(-2.19)				(4.28)	(4.22)	(4.23)			
$\left(R_{m,t} - \overline{R_m}\right)^2$				0.001	-0.003*					0.090***	0.089***	
				(0.42)	(-1.80)					(4.30)	(4.32)	
$\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$						-0.003*						0.089***
						(-1.78)						(4.31)
$Adj. R^2$	0.343	0.344	0.782	0.343	0.782	0.782	0.661	0.663	0.670	0.661	0.669	0.669

Table 2.3 Panel A (continued)

	RUS						SAF					
	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT
$Intercept$	1.148***	1.149***	1.018***	1.148***	1.017***	1.017***	1.795***	1.795***	0.708***	1.795***	0.708***	0.708***
	(35.71)	(37.00)	(34.18)	(35.77)	(34.05)	(33.58)	(42.44)	(41.12)	(15.01)	(42.44)	(15.14)	(15.15)
$\lvert R_{m,t} \rvert$	1.193***	1.192***	1.161***	1.192***	1.162***	1.165***	0.994***	0.991***	0.785***	0.994***	0.784***	0.783***
	(27.75)	(28.32)	(26.43)	(27.79)	(25.90)	(26.06)	(23.79)	(23.10)	(21.71)	(23.83)	(22.24)	(22.23)
$CSAD_{t-1}$			0.068***		0.068***	0.068***			0.518***		0.518***	0.518***
			(4.25)		(4.22)	(4.19)			(28.91)		(29.02)	(29.03)
$R_{m,t}$		-0.008	-0.010					0.016	-0.001			
		(-0.37)	(-0.48)					(1.07)	(-0.09)			
${R_{m,t}}^2$	0.021***	0.021***	0.023***				-0.047***	-0.045***	-0.043***			
	(5.04)	(5.30)	(5.44)				(-4.04)	(-3.61)	(-5.12)			
$\left(R_{m,t} - \overline{R_m}\right)^2$				0.021***	0.022***					-0.047***	-0.043***	
				(5.07)	(5.14)					(-4.05)	(-5.42)	
$\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$						0.022***						-0.043***
						(5.09)						(-5.42)
$Adj. R^2$	0.821	0.821	0.825	0.821	0.825	0.825	0.313	0.313	0.565	0.313	0.565	0.565

Table 2.3 Panel A (continued)

	SPA						THA					
	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT
$Intercept$	1.136***	1.134***	0.820***	1.136***	0.820***	0.820***	1.361***	1.359***	0.271***	1.361***	0.271***	0.271***
	(29.69)	(29.37)	(5.49)	(29.67)	(5.48)	(5.48)	(67.63)	(66.16)	(5.65)	(67.71)	(5.63)	(5.62)
$\lvert R_{m,t}\rvert$	0.291**	0.292**	0.209**	0.291**	0.209**	0.209**	0.800***	0.801***	0.485***	0.799***	0.486***	0.486***
	(2.48)	(2.48)	(2.26)	(2.48)	(2.26)	(2.27)	(15.79)	(15.55)	(15.96)	(15.79)	(16.06)	(15.97)
$CSAD_{t-1}$			0.258***		0.259***	0.259***			0.683***		0.682***	0.682***
			(2.80)		(2.80)	(2.80)			(25.11)		(24.91)	(24.91)
$R_{m,t}$		0.021	0.010					0.022	-0.006			
		(1.43)	(0.76)					(1.03)	(-0.51)			
${R_{m,t}}^2$	0.106**	0.107**	0.113**				-0.034***	-0.033**	-0.018**			
	(2.30)	(2.33)	(2.54)				(-2.65)	(-2.51)	(-2.02)			
$\left(R_{m,t} - \overline{R_m}\right)^2$				0.106**	0.112**					-0.034***	-0.018**	
				(2.30)	(2.53)					(-2.64)	(-1.99)	
$\left(\lvert R_{m,t}\rvert - \overline{R_m}\right)^2$						0.112**						-0.018**
						(2.53)						(-1.99)
$Adj. R^2$	0.585	0.586	0.649	0.585	0.648	0.648	0.409	0.410	0.816	0.409	0.816	0.816

Table 2.3 Panel A (continued)

	UAE						UK					
	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT
$Intercept$	0.939***	0.938***	0.547***	0.939***	0.546***	0.546***	1.344***	1.341***	0.297***	1.346***	0.295***	0.295***
	(34.35)	(32.03)	(22.14)	(33.84)	(22.69)	(22.69)	(44.02)	(45.49)	(9.69)	(44.54)	(9.60)	(9.58)
$\lvert R_{m,t} \rvert$	1.087***	1.086***	0.903***	1.088***	0.903***	0.902***	0.879***	0.871***	0.476***	0.873***	0.475***	0.479***
	(30.63)	(28.33)	(28.33)	(30.40)	(29.34)	(29.42)	(14.28)	(14.89)	(24.38)	(14.39)	(24.28)	(24.04)
$CSAD_{t-1}$			0.326***		0.327***	0.327***			0.709***		0.712***	0.712***
			(18.51)		(18.94)	(18.95)			(38.03)		(37.97)	(38.01)
$R_{m,t}$		0.035**	0.026*					0.088***	0.033***			
		(1.98)	(1.75)					(3.45)	(3.90)			
${R_{m,t}}^2$	-0.064***	-0.062***	-0.048***				-0.053***	-0.031	-0.014*			
	(-7.56)	(-6.70)	(-4.45)				(-2.89)	(-1.64)	(-1.77)			
$\left(R_{m,t} - \overline{R_m}\right)^2$				-0.064***	-0.049***					-0.051***	-0.021***	
				(-7.58)	(-4.97)					(-2.80)	(-2.78)	
$\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$						-0.049***						-0.022***
						(-4.94)						(-2.91)
$Adj. R^2$	0.618	0.619	0.710	0.618	0.709	0.709	0.383	0.390	0.819	0.382	0.818	0.818

Table 2.3 Panel A (continued)

	USA					
	CCK	CZ	BCF	YMH (1)	YMH (2)	BNNT
$Intercept$	1.365***	1.365***	0.275***	1.365***	0.275***	0.275***
	(94.91)	(87.69)	(12.68)	(94.82)	(12.70)	(12.71)
$\lvert R_{m,t} \rvert$	0.227***	0.225***	0.124***	0.229***	0.124***	0.125***
	(8.89)	(8.35)	(9.96)	(8.96)	(10.16)	(10.27)
$CSAD_{t-1}$			0.757***		0.758***	0.758***
			(53.67)		(53.69)	(53.64)
$R_{m,t}$		0.025***	0.003			
		(3.37)	(0.73)			
${R_{m,t}}^2$	0.023***	0.024***	0.009***			
	(4.61)	(4.90)	(2.61)			
$(R_{m,t} - \overline{R_m})^2$				0.022***	0.009***	
				(4.58)	(2.62)	
$(\lvert R_{m,t} \rvert - \overline{R_m})^2$						0.009***
						(2.61)
$Adj. R^2$	0.317	0.320	0.808	0.316	0.808	0.808

Panel B: Regression results of the daily $CSAD_t$ on four herding equations regardless of jump effect (Asymmetric market condition).

Note: This table reports regression statistics between down markets and other markets from four models which are

$CSAD_t = \propto + \gamma_1 D_d + \gamma_2 |R_{m,t}| + \gamma_3 D_d |R_{m,t}| + \gamma_4 (R_{m,t})^2 + \gamma_5 D_d (R_{m,t})^2 + \varepsilon_t$ (Chang et al., 2000: CCK),

$CSAD_t = \propto + \gamma_1 D_d + \gamma_2 |R_{m,t}| + \gamma_3 D_d |R_{m,t}| + \gamma_4 (R_{m,t} - \overline{R_m})^2 + \gamma_5 D_d (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (Yao et al., 2014: YMH1),

$CSAD_t = \propto + \gamma_1 D_d + \gamma_2 CSAD_{t-1} + \gamma_3 D_d CSAD_{t-1} + \gamma_4 |R_{m,t}| + \gamma_5 D_d |R_{m,t}| + \gamma_6 (R_{m,t} - \overline{R_m})^2 + \gamma_7 D_d (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (Yao et al., 2014: YMH2), and

$CSAD_t = \propto + \gamma_1 D_d + \gamma_2 CSAD_{t-1} + \gamma_3 D_d CSAD_{t-1} + \gamma_4 |R_{m,t}| + \gamma_5 D_d |R_{m,t}| + \gamma_6 (|R_{m,t}| - \overline{R_m})^2 + \gamma_7 D_d (|R_{m,t}| - \overline{R_m})^2 + \varepsilon_t$ (Bui et al., 2017: BNNT),

where D_d is a dummy variable which specifies down markets dates. It is equal to one during the negative market return date, and zero otherwise. $CSAD_t$ is a cross-sectional absolute deviation of returns at time t, $R_{m,t}$ is an equally weighted portfolio return at time t, and $CSAD_{t-1}$ is a one-day lag of cross-sectional absolute deviation of returns at time t.

The sample interval is from 01/01/1996 to 30/06/2018.

The t-statistics are shown in parentheses which is calculated by using Newey & West (1987)'s heteroscedaticity and autocorrelation consistent standard errors.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

Table 2.3 Panel B (continued)

	AUS				BRA				CAN			
	CCK	YMH (1)	YMH (2)	BNNT	CCK	YMH (1)	YMH (2)	BNNT	CCK	YMH (1)	YMH (2)	BNNT
$Intercept$	2.718***	2.718***	1.335***	1.335***	1.159***	1.158***	1.015***	1.015***	2.157***	2.157***	0.422***	0.422***
	(173.59)	(173.60)	(10.08)	(10.08)	(36.45)	(36.93)	(19.58)	(19.58)	(74.62)	(74.62)	(7.40)	(7.40)
D_d	0.074***	0.074***	-0.133	-0.133	0.072*	0.072*	0.076	0.076	0.032	0.032	0.061	0.061
	(3.75)	(3.75)	(-0.93)	(-0.93)	(1.81)	(1.83)	(1.23)	(1.23)	(0.80)	(0.80)	(0.80)	(0.80)
$\lvert R_{m,t} \rvert$	0.891***	0.891***	0.616***	0.616***	0.876***	0.890***	0.865***	0.865***	0.656***	0.656***	0.342***	0.342***
	(26.27)	(26.13)	(15.33)	(15.33)	(8.85)	(9.90)	(9.37)	(9.37)	(8.24)	(8.26)	(15.19)	(15.19)
$D_d \lvert R_{m,t} \rvert$	-0.290***	-0.289***	-0.189***	-0.190***	-0.177	-0.206**	-0.202*	-0.172*	-0.116	-0.117	-0.030	-0.030
	(-7.14)	(-7.12)	(-3.91)	(-3.91)	(-1.63)	(-2.05)	(-1.94)	(-1.66)	(-1.16)	(-1.17)	(-1.02)	(-1.02)
${R_{m,t}}^2$	-0.002				0.068				0.052*			
	(-0.39)				(1.49)				(1.65)			
$D_d(R_{m,t})^2$	0.007				0.003				-0.041			
	(1.30)				(0.07)				(-1.14)			
$(R_{m,t} - \overline{R_m})^2$		-0.002	-0.028			0.068	0.067			0.052*	-0.001	
		(-0.39)	(-1.52)			(1.49)	(1.42)			(1.65)	(-0.19)	
$D_d(R_{m,t} - \overline{R_m})^2$		0.007	0.039*			0.003	0.005			-0.041	0.006	
		(1.30)	(1.96)			(0.07)	(0.11)			(-1.14)	(0.80)	
$CSAD_{t-1}$			0.483***	0.483***			0.090***	0.090***			0.760***	0.760***
			(10.87)	(10.87)			(3.50)	(3.50)			(32.35)	(32.35)
$D_d CSAD_{t-1}$			0.056	0.056			-0.001	-0.001			-0.028	-0.028
			(1.16)	(1.16)			(-0.04)	(-0.04)			(-0.90)	(-0.90)
$(\lvert R_{m,t} \rvert - \overline{R_m})^2$				-0.028				0.067				-0.001
				(-1.52)				(1.42)				(-0.19)
$D_d(\lvert R_{m,t} \rvert - \overline{R_m})^2$				0.039*				0.005				0.006
				(1.96)				(0.11)				(0.80)
$Adj.R^2$	0.534	0.534	0.744	0.744	0.695	0.695	0.703	0.703	0.371	0.371	0.834	0.834

Table 2.3 Panel B (continued)

	CHN				FRA				GER			
	CCK	YMH (1)	YMH (2)	BNNT	CCK	YMH (1)	YMH (2)	BNNT	CCK	YMH (1)	YMH (2)	BNNT
$Intercept$	1.286***	1.286***	0.440***	0.440***	1.530***	1.530***	0.500***	0.500***	2.237***	2.237***	0.381***	0.381***
	(75.91)	(75.95)	(17.56)	(17.56)	(86.35)	(86.35)	(19.54)	(19.54)	(80.63)	(80.71)	(12.04)	(12.04)
D_d	-0.050*	-0.050*	-0.255***	-0.255***	0.019	0.019	0.015	0.015	0.121***	0.121***	0.051	0.051
	(-1.85)	(-1.85)	(-6.43)	(-6.43)	(0.89)	(0.89)	(0.42)	(0.42)	(3.28)	(3.28)	(1.12)	(1.12)
$\left\|R_{m,t}\right\|$	0.190***	0.189***	0.034*	0.034*	0.724***	0.722***	0.472***	0.472***	0.910***	0.909***	0.425***	0.425***
	(8.91)	(9.04)	(1.90)	(1.90)	(9.50)	(9.43)	(11.74)	(11.74)	(11.77)	(11.42)	(11.76)	(11.76)
$D_d\left\|R_{m,t}\right\|$	0.179***	0.183***	0.240***	0.235***	0.063	0.064	0.041	0.041	-0.341***	-0.339***	-0.166***	-0.170***
	(4.95)	(5.02)	(9.32)	(9.31)	(0.75)	(0.76)	(0.91)	(0.91)	(-3.70)	(-3.62)	(-3.61)	(-3.63)
${R_{m,t}}^2$	-0.011**				0.155***				0.020			
	(-2.41)				(2.84)				(0.55)			
$D_d\left(R_{m,t}\right)^2$	-0.009				-0.191***				-0.017			
	(-1.32)				(-3.45)				(-0.44)			
$\left(R_{m,t}-\overline{R_m}\right)^2$		-0.011**	-0.001			0.155***	0.064**			0.020	0.017	
		(-2.41)	(-0.15)			(2.84)	(2.08)			(0.55)	(1.03)	
$D_d\left(R_{m,t}-\overline{R_m}\right)^2$		-0.009	-0.022***			-0.191***	-0.078**			-0.017	0.009	
		(-1.32)	(-4.08)			(-3.45)	(-2.47)			(-0.44)	(0.48)	
$CSAD_{t-1}$			0.629***	0.629***			0.618***	0.618***			0.782***	0.782***
			(37.57)	(37.57)			(42.85)	(42.85)			(63.54)	(63.54)
D_dCSAD_{t-1}			0.156***	0.156***			-0.010	-0.010			-0.015	-0.015
			(5.90)	(5.90)			(-0.49)	(-0.49)			(-0.82)	(-0.82)
$\left(\left\|R_{m,t}\right\|-\overline{R_m}\right)^2$				-0.001				0.064**				0.017
				(-0.15)				(2.08)				(1.03)
$D_d\left(\left\|R_{m,t}\right\|-\overline{R_m}\right)^2$				-0.022***				-0.078**				0.009
				(-4.08)				(-2.47)				(0.48)
$Adj. R^2$	0.265	0.265	0.687	0.687	0.461	0.461	0.779	0.779	0.259	0.259	0.810	0.810

Table 2.3 Panel B (continued)

	GRE				IND				IRE			
	CCK	YMH (1)	YMH (2)	BNNT	CCK	YMH (1)	YMH (2)	BNNT	CCK	YMH (1)	YMH (2)	BNNT
$Intercept$	1.977***	1.978***	0.590***	0.590***	1.995***	1.995***	0.422***	0.422***	1.556***	1.556***	0.884***	0.884***
	(88.27)	(88.28)	(14.97)	(14.97)	(74.04)	(74.04)	(9.62)	(9.62)	(38.30)	(38.30)	(14.22)	(14.22)
D_d	0.044	0.044	-0.095	-0.095	0.047	0.047	-0.055	-0.055	0.098**	0.098**	0.063	0.063
	(1.36)	(1.36)	(-1.52)	(-1.52)	(1.12)	(1.13)	(-1.05)	(-1.05)	(2.00)	(2.00)	(0.75)	(0.75)
$\lvert R_{m,t}\rvert$	0.501***	0.504***	0.405***	0.405***	1.393***	1.394***	0.487***	0.487***	0.903***	0.903***	0.775***	0.775***
	(12.86)	(12.81)	(11.10)	(11.10)	(22.13)	(22.07)	(10.50)	(10.50)	(12.00)	(12.04)	(14.26)	(14.26)
$D_d\lvert R_{m,t}\rvert$	-0.170***	-0.174***	-0.115**	-0.114**	0.282**	0.276**	0.092	0.094	0.006	0.005	-0.030	-0.030
	(-3.06)	(-3.11)	(-2.50)	(-2.45)	(2.16)	(2.13)	(1.30)	(1.32)	(0.07)	(0.06)	(-0.39)	(-0.39)
${R_{m,t}}^2$	-0.063***				-0.022**				0.065***			
	(-6.67)				(-1.99)				(2.95)			
$D_d(R_{m,t})^2$	0.042***				-0.229***				-0.050**			
	(3.29)				(-4.08)				(-2.30)			
$(R_{m,t}-\overline{R_m})^2$		-0.063***	-0.057***			-0.022**	0.031**			0.065***	0.047***	
		(-6.67)	(-6.03)			(-1.99)	(2.10)			(2.95)	(2.82)	
$D_d(R_{m,t}-\overline{R_m})^2$		0.042***	0.036***			-0.229***	-0.088***			-0.050**	-0.028	
		(3.29)	(3.11)			(-4.08)	(-3.17)			(-2.30)	(-1.30)	
$CSAD_{t-1}$			0.623***	0.623***			0.745***	0.745***			0.325***	0.325***
			(34.15)	(34.15)			(37.86)	(37.86)			(12.14)	(12.14)
D_dCSAD_{t-1}			0.055*	0.055*			0.022	0.022			0.015	0.015
			(1.91)	(1.91)			(0.95)	(0.95)			(0.41)	(0.41)
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$				-0.057***				0.031**				0.047***
				(-6.03)				(2.10)				(2.82)
$D_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$				0.036***				-0.088***				-0.028
				(3.11)				(-3.17)				(-1.30)
$Adj.R^2$	0.151	0.151	0.568	0.568	0.437	0.437	0.879	0.879	0.503	0.503	0.601	0.601

Table 2.3 Panel B (continued)

	ITA				JAP				POR			
	CCK	YMH (1)	YMH (2)	BNNT	CCK	YMH (1)	YMH (2)	BNNT	CCK	YMH (1)	YMH (2)	BNNT
$Intercept$	1.354***	1.354***	0.759***	0.759***	1.401***	1.401***	0.282***	0.282***	1.029***	1.029***	0.867***	0.867***
	(88.16)	(88.18)	(4.60)	(4.60)	(95.34)	(95.34)	(10.48)	(10.48)	(37.24)	(37.25)	(24.27)	(24.27)
D_d	0.065*	0.065*	-0.185	-0.185	0.034*	0.034*	0.037	0.037	0.083**	0.083**	0.089*	0.089*
	(1.71)	(1.71)	(-1.25)	(-1.25)	(1.80)	(1.80)	(0.82)	(0.82)	(2.16)	(2.16)	(1.79)	(1.79)
$\|R_{m,t}\|$	0.361***	0.360***	0.279***	0.279***	0.380***	0.380***	0.200***	0.200***	1.003***	0.100***	0.961***	0.961***
	(9.80)	(9.65)	(10.39)	(10.39)	(15.09)	(15.05)	(13.61)	(13.61)	(13.19)	(12.97)	(12.71)	(12.71)
$D_d\|R_{m,t}\|$	-0.237**	-0.234**	-0.238**	-0.243**	-0.057*	-0.057*	0.051	0.051	-0.228**	-0.220**	-0.196*	-0.204**
	(-2.16)	(-2.15)	(-2.03)	(-2.03)	(-1.77)	(-1.76)	(1.51)	(1.51)	(-2.13)	(-2.06)	(-1.92)	(-1.98)
${R_{m,t}}^2$	0.019				0.001				0.077**			
	(1.14)				(0.12)				(2.51)			
$D_d\left(R_{m,t}\right)^2$	0.061				0.006				0.029			
	(1.43)				(0.85)				(0.68)			
$\left(R_{m,t}-\overline{R_m}\right)^2$		0.019	0.007			0.001	-0.008*			0.077**	0.078***	
		(1.14)	(0.59)			(0.12)	(-1.84)			(2.51)	(2.58)	
$D_d\left(R_{m,t}-\overline{R_m}\right)^2$		0.061	0.077*			0.006	0.007			0.029	0.026	
		(1.43)	(1.84)			(0.85)	(0.90)			(0.68)	(0.65)	
$CSAD_{t-1}$			0.408***	0.408***			0.748***	0.748***			0.106***	0.106***
			(3.64)	(3.64)			(44.02)	(44.02)			(6.60)	(6.60)
D_dCSAD_{t-1}			0.163	0.163			-0.045	-0.045			-0.011	-0.011
			(1.54)	(1.54)			(-1.56)	(-1.56)			(-0.43)	(-0.43)
$\left(\|R_{m,t}\|-\overline{R_m}\right)^2$				0.007				-0.008*				0.078***
				(0.59)				(-1.84)				(2.58)
$D_d\left(\|R_{m,t}\|-\overline{R_m}\right)^2$				0.077*				0.007				0.026
				(1.84)				(0.90)				(0.65)
$Adj.R^2$	0.483	0.483	0.691	0.691	0.324	0.324	0.811	0.811	0.660	0.660	0.669	0.669

Table 2.3 Panel B (continued)

	RUS				SAF				SPA			
	CCK	YMH (1)	YMH (2)	BNNT	CCK	YMH (1)	YMH (2)	BNNT	CCK	YMH (1)	YMH (2)	BNNT
$Intercept$	1.483***	1.483***	1.127***	1.127***	2.024***	2.024***	1.267***	1.267***	1.026***	1.026***	0.819***	0.819***
	(27.06)	(27.12)	(13.18)	(13.18)	(86.43)	(86.45)	(22.02)	(22.02)	(81.07)	(81.07)	(6.48)	(6.48)
D_d	0.104	0.104	0.204	0.204	-0.024	-0.024	-0.206***	-0.206***	0.164***	0.164***	-0.093	-0.093
	(1.50)	(1.50)	(1.62)	(1.62)	(-0.75)	(-0.75)	(-2.61)	(-2.61)	(6.20)	(6.20)	(-0.74)	(-0.74)
$\lvert R_{m,t}\rvert$	1.065***	1.070***	0.928***	0.928***	0.552***	0.556***	0.486***	0.486***	0.576***	0.576***	0.516***	0.516***
	(8.34)	(8.65)	(7.49)	(7.49)	(6.71)	(6.88)	(6.39)	(6.39)	(16.07)	(16.10)	(10.88)	(10.88)
$D_d\lvert R_{m,t}\rvert$	-0.177	-0.186	-0.119	-0.109	0.248**	0.245**	0.192**	0.191**	-0.472***	-0.473***	-0.504***	-0.503***
	(-1.21)	(-1.31)	(-0.81)	(-0.74)	(2.55)	(2.53)	(2.06)	(2.06)	(-6.24)	(-6.24)	(-5.42)	(-5.41)
${R_{m,t}}^2$	0.038				0.168***				0.020			
	(1.13)				(2.92)				(1.20)			
$D_d(R_{m,t})^2$	0.001				-0.202***				0.137***			
	(0.01)				(-3.34)				(4.78)			
$(R_{m,t}-\overline{R_m})^2$		0.038	0.045			0.168***	0.134**			0.020	0.021	
		(1.13)	(1.34)			(2.92)	(2.33)			(1.20)	(1.09)	
$D_d(R_{m,t}-\overline{R_m})^2$		0.001	-0.004			-0.202***	-0.158***			0.137***	0.144***	
		(0.01)	(-0.11)			(-3.34)	(-2.60)			(4.78)	(4.87)	
$CSAD_{t-1}$			0.193***	0.193***			0.335***	0.335***			0.176*	0.176*
			(5.49)	(5.49)			(14.60)	(14.60)			(1.67)	(1.67)
D_dCSAD_{t-1}			-0.062	-0.062			0.087***	0.087***			0.199*	0.199*
			(-1.03)	(-1.03)			(2.64)	(2.64)			(1.77)	(1.77)
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$				0.045				0.134**				0.021
				(1.34)				(2.33)				(1.09)
$D_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$				-0.004				-0.158***				0.144***
				(-0.11)				(-2.60)				(4.87)
$Adj.R^2$	0.732	0.732	0.757	0.757	0.316	0.316	0.454	0.454	0.674	0.674	0.733	0.733

Table 2.3 Panel B (continued)

	THA				UAE				UK			
	CCK	YMH (1)	YMH (2)	BNNT	CCK	YMH (1)	YMH (2)	BNNT	CCK	YMH (1)	YMH (2)	BNNT
$Intercept$	1.254***	1.254***	0.260***	0.260***	0.988***	0.988***	0.561***	0.561***	1.464***	1.463***	0.430***	0.430***
	(63.99)	(63.99)	(8.90)	(8.90)	(48.33)	(48.33)	(15.15)	(15.15)	(89.67)	(89.78)	(13.66)	(13.66)
D_d	0.157***	0.157***	0.011	0.011	-0.063**	-0.063**	-0.021	-0.021	0.090***	0.090***	0.021	0.021
	(5.28)	(5.28)	(0.28)	(0.28)	(-2.40)	(-2.40)	(-0.47)	(-0.47)	(4.54)	(4.55)	(0.52)	(0.52)
$\lvert R_{m,t} \rvert$	0.932***	0.932***	0.569***	0.569***	1.060***	1.059***	0.882***	0.882***	0.796***	0.790***	0.525***	0.525***
	(19.02)	(18.93)	(13.92)	(13.92)	(23.41)	(23.49)	(19.21)	(19.21)	(11.07)	(10.65)	(10.79)	(10.79)
$D_d \lvert R_{m,t} \rvert$	-0.129**	-0.129**	-0.058	-0.058	-0.032	-0.031	-0.056	-0.057	-0.151**	-0.146*	-0.120**	-0.119**
	(-2.08)	(-2.09)	(-1.09)	(-1.09)	(-0.53)	(-0.51)	(-0.93)	(-0.95)	(-2.02)	(-1.90)	(-2.42)	(-2.41)
${R_{m,t}}^2$	-0.006				-0.072***				0.123**			
	(-0.37)				(-3.51)				(2.29)			
$D_d (R_{m,t})^2$	-0.014				0.023				-0.135***			
	(-0.86)				(0.91)				(-2.62)			
$(R_{m,t} - \overline{R_m})^2$		-0.006	-0.016			-0.072***	-0.066***			0.123**	0.007	
		(-0.37)	(-1.05)			(-3.51)	(-2.65)			(2.29)	(0.18)	
$D_d (R_{m,t} - \overline{R_m})^2$		-0.014	0.012			0.023	0.029			-0.135***	-0.011	
		(-0.86)	(0.63)			(0.91)	(1.02)			(-2.62)	(-0.28)	
$CSAD_{t-1}$			0.661***	0.661***			0.335***	0.335***			0.647***	0.647***
			(37.78)	(37.78)			(12.49)	(12.49)			(37.12)	(37.12)
$D_d CSAD_{t-1}$			0.019	0.019			-0.009	-0.009			0.008	0.008
			(0.84)	(0.84)			(-0.26)	(-0.26)			(0.35)	(0.35)
$(\lvert R_{m,t} \rvert - \overline{R_m})^2$				-0.016				-0.066***				0.007
				(-1.05)				(-2.65)				(0.18)
$D_d (\lvert R_{m,t} \rvert - \overline{R_m})^2$				0.012				0.029				-0.011
				(0.63)				(1.02)				(-0.28)
$Adj. R^2$	0.469	0.469	0.847	0.847	0.585	0.585	0.696	0.696	0.453	0.453	0.816	0.816

Table 2.3 Panel B (continued)

	USA			
	CCK	YMH (1)	YMH (2)	BNNT
$Intercept$	1.305***	1.305***	0.198***	0.198***
	(77.04)	(77.06)	(7.27)	(7.27)
D_d	0.037*	0.037*	0.105***	0.105***
	(1.67)	(1.67)	(2.86)	(2.86)
$\lvert R_{m,t}\rvert$	0.257***	0.259***	0.157***	0.157***
	(8.17)	(8.34)	(10.09)	(10.09)
$D_d\lvert R_{m,t}\rvert$	-0.024	-0.027	-0.049**	-0.047**
	(-0.64)	(-0.72)	(-2.32)	(-2.28)
${R_{m,t}}^2$	0.030***			
	(3.67)			
$D_d\left(R_{m,t}\right)^2$	-0.012			
	(-1.32)			
$\left(R_{m,t}-\overline{R_m}\right)^2$		0.030***	0.001	
		(3.67)	(0.06)	
$D_d\left(R_{m,t}-\overline{R_m}\right)^2$		-0.012	0.012**	
		(-1.32)	(2.13)	
$CSAD_{t-1}$			0.790***	0.790***
			(45.19)	(45.19)
D_dCSAD_{t-1}			-0.053**	-0.053**
			(-2.20)	(-2.20)
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$				0.001
				(0.06)
$D_d\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$				0.012**
				(2.13)
$Adj.R^2$	0.341	0.341	0.833	0.833

2.5.2 Asymmetric herd behavior

Based on the modification of Chang et al. (2000) by incorporating down market dummy variable, Panel B of Table 2.3 depicts herding analysis regardless of jumps during different market conditions. The Chiang & Zheng (2010)-based models are excluded. As mentioned in the previous section, the non-absolute market return does not provide additional information when an extreme market condition is the main priority. Even though the results are not suggestive, the coefficients of Chiang & Zheng (2010) and Blasco et al. (2017) are almost identical to non-lagged CSAD models (Chang et al., 2000 and the first model of Yao et al., 2014) and lagged CSAD models (the second model of Yao et al., 2014 and Bui et al., 2017) respectively.

Considering the coefficient of absolute market return, results confirm the rational asset pricing theory. Thus, the return variation is higher under extreme market conditions. However, the positive association between return dispersion and absolute market return is diminished when the market turns down in Australia, Brazil, Germany, Greece, Italy, Japan, Portugal, Spain, Thailand, UK, and USA. The negative and significant coefficient of non-linear term is found in China, Greece, Japan, and UAE, while anti-herding is identified in Canada, France, Ireland, Portugal, South Africa, UK, and USA. Interestingly, mixed results are seen in India which lagged CSAD models and non-lagged CSAD models suggest opposite conclusions.

Herd behavior significantly escalates when the market is in a down cycle in China, France, India, Ireland, South Africa, and UK. Yet, anti-herding is stronger during the same market condition in Australia, Greece, Italy, Spain, and USA. Three of them only suggest the evidence of significant non-linear relationship when market condition is considered. The interaction terms between down market dummy variable and the market return squared are significant in eleven countries. Only four markets do not show any sign of either herd behavior or anti-herding which are Brazil, Germany, Russia, and Thailand. Therefore, the findings confirm the disparity of herd behavior between down and others market movements (Chang et al., 2000; Chiang & Zheng, 2010; and Zhou & Lai, 2009). Moreover, investors tend not to make their trading decisions independently under negative market conditions especially in emerging markets confirming Zhou & Lai (2009). The justification is that investors have a tendency to be overconfidence about their success under positive market conditions rather than down movements (Gervais & Odean, 2001 and Chuang & Lee, 2006). The coefficient of determination can be separated into two groups which are non-lagged CSAD and lagged CSAD equations. The latter models generally show higher adjusted R-squared.

2.5.3 Model selection and jump descriptive statistics

In order to identify the best model to analyze jump effect, the information selection criteria to evaluate six models is shown in Table 2.4. The model with the lowest value obtained from such criteria is selected as it can best minimize information lost. The results indicate that Blasco et al. (2017), the second model of Yao et al. (2014), and Bui et al. (2017) offer the most appropriate techniques. It can also be inferred that lagged CSAD variables provide incremental information. When comparing suitability between the three models mentioned above, Blasco et al. (2017) has the lowest average value especially for the whole sample. Therefore, the non-absolute market return also offers incremental information when market condition is ignored. In summary, Blasco et al. (2017), the second model of Yao et al. (2014), and Bui et al. (2017) are the key models for the examination of jump effect.

Panels A and B of Table 2.5 depict jump statistics based on staggered return and non-staggered return bipower variation techniques respectively. The frequency of significant return jump and the jump date ratio are illustrated in both panels. For both cases, the number of jump date from 99% confidence level is higher than 99.9% confidence level which is sensible. Portugal has the highest jump ratio regarding staggered return bipower variation with 99% confidence level, whereas UAE shows the lowest number of jump occurrence. At 99.9% interval, the top and bottom countries are Ireland and China respectively. In terms of non-staggered return bipower variation approach, Ireland has the largest jump proportion, while India has the smallest, for both 99% and 99.9% confidence levels. When examining the difference between staggered- and non-staggered return methods, the result shows that the former has higher jump ratios. This study’s methodology focuses on staggered return bipower variation technique with 99% confidence level, while non-staggered return bipower variation is used to run a robustness check.

Table 2.4 Information selection criteria for different models.

Note: This table represents selection information criteria by using AIC, AICc, BIC, and HQIC. The whole sample (Whole) and asymmetric market (Asym) are considered in the examination. For the whole sample analysis, the six models are compared which are $CSAD_t = \propto + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \varepsilon_t$ (Chang et al., 2000: CCK), $CSAD_t = \propto + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 (R_{m,t})^2 + \varepsilon_t$ (Chiang & Zheng, 2010: CZ), $CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m,t} + \gamma_3 |R_{m,t}| + \gamma_3 (R_{m,t})^2 + \varepsilon_t$ (Blasco et al., 2017: BCF), $CSAD_t = \propto + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (Yao et al., 2014: YMH1), $CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 |R_{m,t}| + \gamma_3 (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (Yao et al., 2014: YMH2), and $CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 |R_{m,t}| + \gamma_6 (|R_{m,t}| - \overline{R_m})^2 + \varepsilon_t$ (Bui et al., 2017: BNNT). For the asymmetric market analysis, the six modification models are compared which are $CSAD_t = \propto + \gamma_1 D_d + \gamma_2 |R_{m,t}| + \gamma_3 D_d |R_{m,t}| + \gamma_4 (R_{m,t})^2 + \gamma_5 D_d (R_{m,t})^2 + \varepsilon_t$ (CCK), $CSAD_t = \propto + \gamma_1 D_d + \gamma_2 R_{m,t} + \gamma_3 D_d R_{m,t} + \gamma_4 |R_{m,t}| + \gamma_5 D_d |R_{m,t}| + \gamma_6 (R_{m,t})^2 + \gamma_7 D_d (R_{m,t})^2 + \varepsilon_t$ (CZ), $CSAD_t = \propto + \gamma_1 D_d + \gamma_2 CSAD_{t-1} + \gamma_3 D_d CSAD_{t-1} + \gamma_4 R_{m,t} + \gamma_5 D_d R_{m,t} + \gamma_6 |R_{m,t}| + \gamma_7 D_d |R_{m,t}| + \gamma_8 (R_{m,t})^2 + \gamma_9 D_d (R_{m,t})^2 + \varepsilon_t$ (BCF), $CSAD_t = \propto + \gamma_1 D_d + \gamma_2 |R_{m,t}| + \gamma_3 D_d |R_{m,t}| + \gamma_4 (R_{m,t} - \overline{R_m})^2 + \gamma_5 D_d (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (YMH, 1), $CSAD_t = \propto + \gamma_1 D_d + \gamma_2 CSAD_{t-1} + \gamma_3 D_d CSAD_{t-1} + \gamma_4 |R_{m,t}| + \gamma_5 D_d |R_{m,t}| + \gamma_6 (R_{m,t} - \overline{R_m})^2 + \gamma_7 D_d (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (YMH, 2), and $CSAD_t = \propto + \gamma_1 D_d + \gamma_2 CSAD_{t-1} + \gamma_3 D_d CSAD_{t-1} + \gamma_4 |R_{m,t}| + \gamma_5 D_d |R_{m,t}| + \gamma_6 (|R_{m,t}| - \overline{R_m})^2 + \gamma_7 D_d (|R_{m,t}| - \overline{R_m})^2 + \varepsilon_t$ (BNNT), where D_d is a dummy variable which specifies down markets dates. It is equal to one during the negative market return date, and zero otherwise. $CSAD_t$ is a cross-sectional absolute deviation of returns at time t, $R_{m,t}$ is an equally weighted portfolio return at time t, and $CSAD_{t-1}$ is a one-day lag of cross-sectional absolute deviation of returns at time t. the sample interval is from 01/01/1996 to 30/06/2018. * indicates the best fit model using AIC, AICc, BIC, HQIC criteria.

Table 2.4 (continued)

AUS	AIC (Whole)	AIC (Asym)	AICc (Whole)	AICc (Asym)	BIC (Whole)	BIC (Asym)	HQIC (Whole)	HQIC (Asym)
CCK	6860.379	6692.167	6860.384	6692.183	6886.743	6738.304	6865.283	6703.976
CZ	6704.660	6692.167	6704.667	6692.194	6737.615	6738.304	6711.866	6712.578
BCF	3566.922*	3483.784*	3566.933*	3483.825	3606.468*	3543.103*	3576.429*	3508.799
YMH (1)	6860.530	6692.167	6860.534	6692.183	6886.894	6738.304	6865.434	6703.976
YMH (2)	3575.325	3483.784*	3575.332	3483.811*	3608.280	3543.103*	3582.531	3500.196*
BNNT	3575.741	3483.784*	3575.748	3483.811*	3608.696	3543.103*	3582.947	3500.196*
Base Value	10802.596	10802.596	10802.596	10802.596	10815.778	10815.778	10802.897	10802.897
BRA								
CCK	8792.585	8737.359	8792.589	8737.374	8819.055	8783.682	8797.508	8749.205
CZ	8745.212	8737.359	8745.219	8737.385	8778.300	8783.682	8752.442	8757.820
BCF	8606.136*	8600.032*	8606.147*	8600.072	8645.842*	8659.590*	8615.675*	8625.108
YMH (1)	8817.857	8737.359	8817.861	8737.374	8844.327	8783.682	8822.779	8749.205
YMH (2)	8670.399	8600.032*	8670.406	8600.058*	8703.487	8659.590*	8677.630	8616.493*
BNNT	8646.056	8600.032*	8646.063	8600.058*	8679.144	8659.590*	8653.286	8616.493*
Base Value	15301.841	15301.841	15301.842	15301.842	15315.077	15315.077	15302.149	15302.149
CAN								
CCK	7286.196	7197.185	7286.202	7197.207	7311.317	7241.147	7290.879	7208.552
CZ	7216.250	7197.185	7216.260	7197.222	7247.651	7241.147	7223.161	7217.007
BCF	1941.891*	1942.709*	1941.907*	1942.765	1979.573	1999.231*	1951.030*	1966.987
YMH (1)	7286.273	7197.185	7286.279	7197.207	7311.394	7241.147	7290.956	7208.552
YMH (2)	1947.686	1942.709*	1947.696	1942.746*	1979.087*	1999.231*	1954.597	1958.531*
BNNT	1947.674	1942.709*	1947.684	1942.746*	1979.075*	1999.231*	1954.585	1958.531*
Base Value	9020.297	9020.297	9020.298	9020.298	9032.857	9032.857	9020.524	9020.524

Table 2.4 (continued)

CHN	AIC (Whole)	AIC (Asym)	AICc (Whole)	AICc (Asym)	BIC (Whole)	BIC (Asym)	HQIC (Whole)	HQIC (Asym)
CCK	7968.518	7703.181	7968.523	7703.197	7994.905	7749.359	7973.427	7714.998
CZ	7705.821	7703.181	7705.828	7703.208	7738.804	7749.359	7713.032	7723.604
BCF	3249.748*	3074.600*	3249.759*	3074.641	3289.329*	3133.971*	3259.262*	3099.628
YMH (1)	7977.319	7703.181	7977.323	7703.197	8003.706	7749.359	7982.227	7714.998
YMH (2)	4157.148	3074.600*	4157.156	3074.627*	4190.132	3133.971*	4164.359	3091.022*
BNNT	4144.834	3074.600*	4144.841	3074.627*	4177.817	3133.971*	4152.045	3091.022*
Base Value	9363.656	9363.656	9363.656	9363.656	9376.849	9376.849	9363.958	9363.958
FRA								
CCK	5318.078	5181.801	5318.083	5181.817	5344.359	5227.793	5322.968	5193.580
CZ	5260.089	5181.801	5260.097	5181.828	5292.941	5227.793	5267.276	5202.174
BCF	502.419*	480.602*	502.430*	480.644	541.841*	539.735*	511.902*	505.568
YMH (1)	5318.634	5181.801	5318.639	5181.817	5344.916	5227.793	5323.524	5193.580
YMH (2)	525.850	480.602*	525.858	480.629*	558.702	539.735*	533.037	496.975*
BNNT	525.661	480.602*	525.668	480.629*	558.513	539.735*	532.847	496.975*
Base Value	8438.679	8438.679	8438.680	8438.680	8451.820	8451.820	8438.976	8438.976
GER								
CCK	11090.454	10986.940	11090.459	10986.957	11116.500	11032.521	11095.303	10998.637
CZ	11003.276	10986.940	11003.284	10986.969	11035.834	11032.521	11010.407	11007.203
BCF	4220.298*	4224.277*	4220.310*	4224.321	4259.367*	4282.881*	4229.712*	4249.106
YMH (1)	11093.057	10986.940	11093.062	10986.957	11119.104	11032.521	11097.906	10998.637
YMH (2)	4328.076	4224.277*	4328.084	4224.306*	4360.634	4282.881*	4335.208	4240.540*
BNNT	4330.532	4224.277*	4330.540	4224.306*	4363.090	4282.881*	4337.663	4240.540*
Base Value	12469.339	12469.339	12469.340	12469.340	12482.362	12482.362	12469.622	12469.622

Table 2.4 (continued)

GRE	AIC (Whole)	AIC (Asym)	AICc (Whole)	AICc (Asym)	BIC (Whole)	BIC (Asym)	HQIC (Whole)	HQIC (Asym)
CCK	11145.877	11098.054	11145.881	11098.070	11172.358	11144.395	11150.802	11109.904
CZ	11147.649	11098.054	11147.656	11098.081	11180.750	11144.395	11154.882	11118.520
BCF	7443.614*	7360.499*	7443.625*	7360.538	7483.335*	7420.080*	7453.155*	7385.581
YMH (1)	11145.713	11098.054	11145.717	11098.070	11172.193	11144.395	11150.637	11109.904
YMH (2)	7461.689	7360.499*	7461.697	7360.525*	7494.790	7420.080*	7468.922	7376.964*
BNNT	7464.322	7360.499*	7464.329	7360.525*	7497.422	7420.080*	7471.555	7376.964*
Base Value	12000.751	12000.751	12000.752	12000.752	12013.991	12013.991	12001.059	12001.059
IND								
CCK	14602.314	14465.752	14602.318	14465.767	14628.775	14512.059	14607.235	14477.594
CZ	14583.631	14465.752	14583.638	14465.778	14616.707	14512.059	14590.859	14486.209
BCF	6075.071*	6004.306*	6075.082*	6004.346	6114.762*	6063.843*	6084.606*	6029.377
YMH (1)	14602.906	14465.752	14602.911	14465.767	14629.367	14512.059	14607.828	14477.594
YMH (2)	6095.972	6004.306*	6095.980	6004.332*	6129.049	6063.843*	6103.201	6020.763*
BNNT	6096.751	6004.306*	6096.759	6004.332*	6129.827	6063.843*	6103.980	6020.763*
Base Value	17633.227	17633.227	17633.228	17633.228	17646.458	17646.458	17633.534	17633.534
IRE								
CCK	16365.048	16305.784	16365.052	16305.799	16391.572	16352.201	16369.980	16317.648
CZ	16346.559	16305.784	16346.566	16305.809	16379.714	16352.201	16353.802	16326.269
BCF	15103.651*	15083.497*	15103.661*	15083.536	15143.437*	15143.176*	15113.204*	15108.604
YMH (1)	16365.190	16305.784	16365.195	16305.799	16391.715	16352.201	16370.123	16317.648
YMH (2)	15110.874	15083.497*	15110.881	15083.522*	15144.030	15143.176*	15118.117	15099.982*
BNNT	15110.762	15083.497*	15110.770	15083.522*	15143.918	15143.176*	15118.005	15099.982*
Base Value	20222.701	20222.701	20222.702	20222.702	20235.963	20235.963	20223.012	20223.012

Table 2.4 (continued)

ITA	AIC (Whole)	AIC (Asym)	AICc (Whole)	AICc (Asym)	BIC (Whole)	BIC (Asym)	HQIC (Whole)	HQIC (Asym)
CCK	690.659	646.674	690.670	646.710	713.634	686.880	694.940	657.236
CZ	660.145	646.674	660.163	646.736	688.864	686.880	666.520	665.424
BCF	-453.894*	-535.083*	-453.868*	-534.988	-419.431	-483.390*	-445.425*	-512.146
YMH (1)	687.280	646.674	687.290	646.710	710.255	686.880	691.561	657.236
YMH (2)	-449.830	-535.083*	-449.813	-535.021*	-421.112*	-483.390*	-443.455	-520.333*
BNNT	-447.535	-535.083*	-447.517	-535.021*	-418.816	-483.390*	-441.160	-520.333*
Base Value	2164.263	2164.263	2164.265	2164.265	2175.751	2175.751	2164.357	2164.357
JAP								
CCK	6026.606	6026.460	6026.610	6026.475	6053.049	6072.736	6031.524	6038.296
CZ	6026.230	6026.460	6026.238	6026.486	6059.285	6072.736	6033.455	6046.908
BCF	-913.238*	-958.620*	-913.227*	-958.580	-873.573*	-899.122*	-903.708*	-933.560
YMH (1)	6026.568	6026.460	6026.572	6026.475	6053.011	6072.736	6031.486	6038.296
YMH (2)	-865.710	-958.620*	-865.702	-958.594*	-832.655	-899.122*	-858.485	-942.172*
BNNT	-865.636	-958.620*	-865.628	-958.594*	-832.581	-899.122*	-858.411	-942.172*
Base Value	8174.943	8174.943	8174.944	8174.944	8188.165	8188.165	8175.249	8175.249
POR								
CCK	10371.550	10339.984	10371.554	10340.001	10397.805	10385.931	10376.435	10351.754
CZ	10345.553	10339.984	10345.561	10340.011	10378.373	10385.931	10352.734	10360.344
BCF	10194.867*	10192.751*	10194.878*	10192.793	10234.250*	10251.826*	10204.342*	10217.702
YMH (1)	10367.584	10339.984	10367.589	10340.001	10393.840	10385.931	10372.469	10351.754
YMH (2)	10213.546	10192.751*	10213.554	10192.779*	10246.366	10251.826*	10220.727	10209.112*
BNNT	10217.268	10192.751*	10217.276	10192.779*	10250.088	10251.826*	10224.449	10209.112*
Base Value	15978.720	15978.720	15978.721	15978.721	15991.848	15991.848	15979.015	15979.015

Table 2.4 (continued)

RUS	AIC (Whole)	AIC (Asym)	AICc (Whole)	AICc (Asym)	BIC (Whole)	BIC (Asym)	HQIC (Whole)	HQIC (Asym)
CCK	8478.021	8445.636	8478.028	8445.661	8502.635	8488.710	8482.612	8456.817
CZ	8450.256	8445.636	8450.267	8445.678	8481.023	8488.710	8457.043	8465.211
BCF	8127.845*	8113.406*	8127.862*	8113.469	8164.765*	8168.786*	8136.829*	8137.374
YMH (1)	8482.435	8445.636	8482.442	8445.661	8507.048	8488.710	8487.026	8456.817
YMH (2)	8159.056	8113.406*	8159.068	8113.447*	8189.823	8168.786*	8165.844	8128.981*
BNNT	8153.902	8113.406*	8153.913	8113.447*	8184.668	8168.786*	8160.689	8128.981*
Base Value	13021.801	13021.801	13021.802	13021.802	13034.108	13034.108	13021.998	13021.998
SAF								
CCK	5991.284	5975.294	5991.290	5975.316	6016.305	6019.081	5995.949	5986.624
CZ	5992.844	5975.294	5992.854	5975.332	6024.120	6019.081	5999.730	5995.068
BCF	5132.281	5108.740*	5132.297	5108.798	5169.813	5165.038*	5141.390	5132.957
YMH (1)	5991.233	5975.294	5991.239	5975.316	6016.254	6019.081	5995.898	5986.624
YMH (2)	5130.997	5108.740*	5131.008	5108.778*	5162.274*	5165.038*	5137.884	5124.514*
BNNT	5130.963*	5108.740*	5130.973*	5108.778*	5162.240*	5165.038*	5137.850*	5124.514*
Base Value	7433.030	7433.030	7433.031	7433.031	7445.541	7445.541	7433.252	7433.252
SPA								
CCK	4526.230	4106.729	4526.234	4106.744	4552.797	4153.221	4531.170	4118.608
CZ	4510.260	4106.729	4510.267	4106.754	4543.468	4153.221	4517.513	4127.234
BCF	3628.472*	2969.037*	3628.482*	2969.076	3668.322*	3028.812*	3638.038*	2994.169
YMH (1)	4526.851	4106.729	4526.855	4106.744	4553.417	4153.221	4531.790	4118.608
YMH (2)	3635.914	2969.037*	3635.921	2969.062*	3669.123	3028.812*	3643.167	2985.542*
BNNT	3635.419	2969.037*	3635.426	2969.062*	3668.628	3028.812*	3642.672	2985.542*
Base Value	10448.871	10448.871	10448.872	10448.872	10462.155	10462.155	10449.185	10449.185

Table 2.4 (continued)

THA	AIC (Whole)	AIC (Asym)	AICc (Whole)	AICc (Asym)	BIC (Whole)	BIC (Asym)	HQIC (Whole)	HQIC (Asym)
CCK	10930.581	10868.911	10930.585	10868.926	10956.942	10915.042	10935.485	10880.718
CZ	10919.785	10868.911	10919.793	10868.937	10952.737	10915.042	10926.990	10889.321
BCF	4194.709	4190.093*	4194.720	4190.134	4234.251	4249.405*	4204.216	4215.105
YMH (1)	10930.933	10868.911	10930.938	10868.926	10957.294	10915.042	10935.837	10880.718
YMH (2)	4194.162*	4190.093*	4194.170*	4190.120*	4227.113*	4249.405*	4201.367*	4206.503*
BNNT	4194.254	4190.093*	4194.261	4190.120*	4227.205	4249.405*	4201.459	4206.503*
Base Value	14271.998	14271.998	14271.999	14271.999	14285.178	14285.178	14272.299	14272.299
UAE								
CCK	3059.861	3043.725	3059.870	3043.754	3083.769	3085.564	3064.321	3054.644
CZ	3057.304	3043.725	3057.317	3043.775	3087.188	3085.564	3063.916	3062.950
BCF	2148.831*	2140.931*	2148.852*	2141.006	2184.693	2194.723*	2157.597	2164.462
YMH (1)	3059.576	3043.725	3059.585	3043.754	3083.484	3085.564	3064.036	3054.644
YMH (2)	2149.974	2140.931*	2149.988	2140.980*	2179.859*	2194.723*	2156.587*	2156.156*
BNNT	2150.215	2140.931*	2150.229	2140.980*	2180.100	2194.723*	2156.828	2156.156*
Base Value	5603.141	5603.141	5603.142	5603.142	5615.095	5615.095	5603.294	5603.294
UK								
CCK	5984.202	5766.757	5984.207	5766.772	6010.759	5813.230	5989.140	5778.633
CZ	5867.132	5766.757	5867.139	5766.783	5900.328	5813.230	5874.383	5787.258
BCF	-384.841*	-396.551*	-384.830*	-396.512	-345.006*	-336.799*	-375.278*	-371.425
YMH (1)	5989.085	5766.757	5989.089	5766.772	6015.641	5813.230	5994.023	5778.633
YMH (2)	-320.131	-396.551*	-320.124	-396.525*	-286.936	-336.799*	-312.881	-380.050*
BNNT	-322.640	-396.551*	-322.633	-396.525*	-289.445	-336.799*	-315.390	-380.050*
Base Value	9170.298	9170.298	9170.299	9170.299	9183.576	9183.576	9170.610	9170.610

Table 2.4 (continued)

USA	AIC (Whole)	AIC (Asym)	AICc (Whole)	AICc (Asym)	BIC (Whole)	BIC (Asym)	HQIC (Whole)	HQIC (Asym)
CCK	7361.645	7325.526	7361.649	7325.541	7388.191	7371.981	7366.581	7337.398
CZ	7343.744	7325.526	7343.751	7325.552	7376.926	7371.981	7350.992	7346.022
BCF	-363.839	-399.659*	-363.828	-399.620	-324.021	-339.932*	-354.279	-374.539
YMH (1)	7363.794	7325.526	7363.798	7325.541	7390.339	7371.981	7368.730	7337.398
YMH (2)	-365.584	-399.659*	-365.577	-399.633*	-332.402	-339.932*	-358.336	-383.163*
BNNT	-365.741*	-399.659*	-365.734*	-399.633*	-332.559*	-339.932*	-358.493*	-383.163*
Base Value	9670.931	9670.931	9670.932	9670.932	9684.204	9684.204	9671.243	9671.243

Table 2.5 Descriptive statistics of jump's occurrence.

Note: This table represents jump date statistics based on the occurrence of jump by using staggered and non-staggered return bipower variation. Number of jump date at 99% and 99.9% confidence levels, proportion of jump date at 99% and 99.9% confidence levels to trading day, and trading day are shown.

Panel A: Descriptive statistics of jump's occurrence by employing staggered return bipower variation.

Staggered Return	AUS	BRA	CAN	CHN	FRA	GER	GRE	IND	IRE	ITA	JAP	POR	RUS	SAF	SPA	THA	UAE	UK	USA
Jump Days (99%)	3,778	4,256	2,966	2,253	4,522	4,722	3,352	3,443	4,935	2,050	3,163	4,696	2,899	3,429	4,883	3,415	1,308	5,002	4,202
Jump Ratio (99%)	0.603	0.769	0.731	0.415	0.856	0.830	0.605	0.621	0.873	0.889	0.575	0.896	0.813	0.857	0.862	0.624	0.320	0.882	0.706
Jump Days (99.9%)	1453	1692	1567	346	2227	2747	1198	843	3391	1028	744	2568	2034	1639	2596	972	588	2677	1695
Jump Ratio (99.9%)	0.232	0.306	0.386	0.064	0.422	0.483	0.216	0.152	0.600	0.446	0.135	0.490	0.570	0.410	0.458	0.178	0.144	0.472	0.285
Trading Days	6,261	5,532	4,059	5,430	5,281	5,691	5,545	5,546	5,650	2,307	5,499	5,243	3,567	4,002	5,666	5,469	4,092	5,670	5,952

Panel B: Descriptive statistics of jump's occurrence by employing non-staggered return bipower variation.

Non-Staggered Return	AUS	BRA	CAN	CHN	FRA	GER	GRE	IND	IRE	ITA	JAP	POR	RUS	SAF	SPA	THA	UAE	UK	USA
Jump Days (99%)	1,294	596	1,380	478	670	825	671	393	1,970	255	1,154	807	1,001	461	845	636	1,185	958	812
Jump Ratio (99%)	0.207	0.108	0.340	0.088	0.127	0.145	0.121	0.071	0.349	0.111	0.210	0.154	0.281	0.115	0.149	0.116	0.290	0.169	0.136
Jump Days (99.9%)	801	293	1020	203	295	413	316	157	1498	113	599	489	610	218	403	290	900	534	436
Jump Ratio (99.9%)	0.128	0.053	0.251	0.037	0.056	0.073	0.057	0.028	0.265	0.049	0.109	0.093	0.171	0.054	0.071	0.053	0.220	0.094	0.073
Trading Days	6,261	5,532	4,059	5,430	5,281	5,691	5,545	5,546	5,650	2,307	5,499	5,243	3,567	4,002	5,666	5,469	4,092	5,670	5,952

2.5.4 Influence of jump on herd behavior

Panel A of Table 2.6 demonstrates the effect of jumps on herd behavior. Staggered return bipower variation with 99% confidence level is used in order to detect the occurrence of jumps. The modification of the second model of Yao et al. (2014), Bui et al. (2017), and Blasco et al. (2017) are applied to all sample data. The second model of Yao et al. (2014) and Bui et al. (2017) deliver identical results. In consideration of the coefficient of absolute market return, the rational asset pricing theory is confirmed in every country except for Spain. The positive association between return dispersion and market return is reduced upon the occurrence of jumps in Australia, India, Ireland, Russia, and USA. On the other hand, such positive association increases in France, Portugal, and Spain. Thus, return jumps affect the validity of rational asset pricing theory. When considering non-linear terms, herd behavior is detected in Australia, China, Greece, Ireland, South Africa, and UAE, whereas, anti-herding is identified in Brazil, France, Germany, Portugal, Russia, and Spain.

The impact of jumps on herd behavior is represented by the interaction term between jump dummy variable and the squared market return. The effect is significant in ten countries. Therefore, investor behavior generally changes during the existence of jumps. Moreover, herding is enhanced upon the existence of jumps in Brazil, France, Portugal, and Spain. The coefficient is significantly positive indicating the presence of anti-herding in Australia, China, India, Ireland, Italy, and South Africa. All of those countries are either developed markets or members of BRICS. However, the signs of original coefficient of non-linear term are mostly opposite to the signs of the interaction term between squared return and jump dummy in every country except for Canada, Russia, Thailand, UK, and USA. It is possible to conclude that herd behavior is sensitive as it extremely changes during jump dates (Bikhchandani et al., 1992). Also, the evidence strengthens the importance of understanding jumps so as to better explain aggregate market herding. The coefficients of determination with the value higher than 0.451 suggest that the proposed models suit the samples very well. Hence, the new models offer additional information and foster better understanding of herd behavior on aggregate level.

There are some justifications for the case that a discontinuous jump is not so convincing that encourages individuals to follow. First, return jump is considered as the sign of illiquidity, asymmetric information, and uncertainty which are market inefficiency indications during the period of non-jump. However, jumps can also be considered as an improvement of price discovery (Glosten & Milgrom, 1985 and Buckley et al., 2014) as asymmetric information is partially reduced after the occurrence of jump. These cut a propensity of information cascade. Moreover, discontinuous jumps attract investors' attention and encourage them to search for more information (Barber & Odean, 2008 and Li et al., 2017). The improvement of investor's private information improves their decision-making processes.

Table 2.6 Regression results for the effect of jump on herd behavior by using staggered return bipower variation with 99% confidence level.

Panel A: Regression results for the effect of jump on herd behavior by using staggered return bipower variation with 99% confidence level (Whole sample).

Note: This table reports regression statistics of the whole sample by using three equations which are

$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 CSAD_{t-1} + \gamma_3 D_j CSAD_{t-1} + \gamma_4 |R_{m,t}| + \gamma_5 D_j |R_{m,t}| + \gamma_6 (R_{m,t} - \overline{R_m})^2 + \gamma_7 D_j (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (Yao et al., 2014: YMH2),

$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 CSAD_{t-1} + \gamma_3 D_j CSAD_{t-1} + \gamma_4 |R_{m,t}| + \gamma_5 D_j |R_{m,t}| + \gamma_6 (|R_{m,t}| - \overline{R_m})^2 + \gamma_7 D_j (|R_{m,t}| - \overline{R_m})^2 + \varepsilon_t$ (Bui et al., 2017: BNNT), and

$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 CSAD_{t-1} + \gamma_3 D_j CSAD_{t-1} + \gamma_4 R_{m,t} + \gamma_5 D_j R_{m,t} + \gamma_6 |R_{m,t}| + \gamma_7 D_j |R_{m,t}| + \gamma_8 (R_{m,t})^2 + \gamma_9 D_j (R_{m,t})^2 + \varepsilon_t$ (Blasco et al., 2017: BCF),

where $CSAD_t$ is a cross-sectional absolute deviation of returns at time t, $R_{m,t}$ is an equally weighted portfolio return at time t, and $CSAD_{t-1}$ is a one-day lag of cross-sectional absolute deviation of returns at time t. D_j is a dummy variable which specifies jump date. It is equal to one in the jump date, and zero otherwise.

The sample interval is from 01/01/1996 to 30/06/2018.

The t-statistics are shown in parentheses which is calculated by using Newey & West (1987)'s heteroscedaticity and autocorrelation consistent standard errors.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

Table 2.6 Panel A (continued)

	AUS			BRA		
Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	1.143***	1.142***	1.160***	1.019***	1.020***	1.019***
	(13.78)	(13.80)	(13.63)	(16.96)	(17.03)	(17.17)
D_j	0.214	0.214	0.206	-0.016	-0.010	-0.006
	(1.42)	(1.42)	(1.38)	(-0.21)	(-0.13)	(-0.08)
$CSAD_{t-1}$	0.544***	0.543***	0.535***	0.093**	0.092**	0.093**
	(19.12)	(19.14)	(17.99)	(2.40)	(2.38)	(2.45)
$D_j CSAD_{t-1}$	-0.050	-0.050	-0.046	0.001	0.002	-0.003
	(-1.01)	(-1.01)	(-0.94)	(0.02)	(0.04)	(-0.06)
$\lvert R_{m,t} \rvert$	0.549***	0.551***	0.568***	0.814***	0.827***	0.816***
	(19.24)	(18.95)	(16.39)	(9.93)	(10.06)	(9.64)
$D_j \lvert R_{m,t} \rvert$	-0.107***	-0.109***	-0.117***	0.079	0.054	0.055
	(-2.95)	(-2.97)	(-2.79)	(0.74)	(0.51)	(0.50)
$\left(R_{m,t} - \overline{R_m}\right)^2$	-0.010*			0.069***		
	(-1.94)			(12.27)		
$D_j\left(R_{m,t} - \overline{R_m}\right)^2$	0.019***			-0.050*		
	(2.70)			(-1.71)		
$\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$		-0.010**			0.070***	
		(-1.96)			(12.32)	
$D_j\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$		0.019***			-0.046	
		(2.70)			(-1.50)	
$R_{m,t}$			0.028*			-0.020
			(1.88)			(-0.39)
$D_j R_{m,t}$			-0.010			0.087
			(-0.42)			(1.48)
${R_{m,t}}^2$			-0.011*			0.069***
			(-1.67)			(11.34)
$D_j {R_{m,t}}^2$			0.021***			-0.038
			(2.66)			(-1.22)
$Adj. R^2$	0.741	0.741	0.741	0.705	0.705	0.708

Table 2.6 Panel A (continued)

	CAN			CHN		
Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.456***	0.456***	0.458***	0.407***	0.400***	0.369***
	(6.11)	(6.11)	(6.05)	(14.64)	(14.49)	(13.91)
D_j	-0.001	-0.001	-0.001	-0.077*	-0.077*	-0.073*
	(-0.02)	(-0.02)	(-0.00)	(-1.76)	(-1.77)	(-1.72)
$CSAD_{t-1}$	0.738***	0.738***	0.736***	0.655***	0.655***	0.673***
	(22.99)	(22.99)	(22.40)	(36.90)	(36.87)	(39.59)
D_jCSAD_{t-1}	0.011	0.011	0.010	0.026	0.026	0.030
	(0.31)	(0.31)	(0.28)	(0.88)	(0.89)	(1.07)
$\lvert R_{m,t}\rvert$	0.333***	0.333***	0.333***	0.127***	0.137***	0.166***
	(12.51)	(12.51)	(12.56)	(7.06)	(7.93)	(9.32)
$D_j\lvert R_{m,t}\rvert$	-0.015	-0.016	-0.011	-0.009	-0.008	-0.023
	(-0.46)	(-0.46)	(-0.32)	(-0.37)	(-0.32)	(-0.85)
$\left(R_{m,t}-\overline{R_m}\right)^2$	0.002			-0.007*		
	(0.79)			(-1.89)		
$D_j\left(R_{m,t}-\overline{R_m}\right)^2$	0.001			0.009**		
	(0.12)			(1.98)		
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		0.002			-0.009**	
		(0.79)			(-2.46)	
$D_j\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		0.001			0.009*	
		(0.12)			(1.95)	
$R_{m,t}$			0.014			-0.075***
			(0.89)			(-14.92)
$D_jR_{m,t}$			0.003			-0.004
			(0.17)			(-0.43)
${R_{m,t}}^2$			0.003			-0.017***
			(1.07)			(-4.61)
$D_j{R_{m,t}}^2$			0.001			0.010*
			(0.07)			(1.70)
$Adj.R^2$	0.834	0.834	0.834	0.622	0.622	0.680

Table 2.6 Panel A (continued)

	FRA			GER		
Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.488***	0.488***	0.503***	0.201***	0.200***	0.201***
	(9.96)	(9.95)	(10.37)	(5.59)	(5.58)	(5.57)
D_j	0.002	0.003	-0.010	0.316***	0.312***	0.326***
	(0.04)	(0.05)	(-0.19)	(6.60)	(6.54)	(6.85)
$CSAD_{t-1}$	0.631***	0.631***	0.623***	0.830***	0.830***	0.830***
	(21.76)	(21.76)	(21.54)	(42.51)	(42.49)	(42.26)
D_jCSAD_{t-1}	-0.013	-0.013	-0.007	-0.084***	-0.084***	-0.090***
	(-0.42)	(-0.43)	(-0.23)	(-3.66)	(-3.66)	(-3.93)
$\lvert R_{m,t}\rvert$	0.448***	0.449***	0.436***	0.296***	0.297***	0.292***
	(9.37)	(9.37)	(9.20)	(6.78)	(6.69)	(6.73)
$D_j\lvert R_{m,t}\rvert$	0.095*	0.095*	0.103**	0.041	0.053	0.056
	(1.85)	(1.84)	(2.03)	(0.82)	(1.04)	(1.12)
$\left(R_{m,t}-\overline{R_m}\right)^2$	0.041**			0.032**		
	(2.07)			(2.49)		
$D_j\left(R_{m,t}-\overline{R_m}\right)^2$	-0.061***			-0.020		
	(-2.94)			(-1.18)		
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		0.040**			0.031**	
		(2.05)			(2.42)	
$D_j\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		-0.060***			-0.024	
		(-2.93)			(-1.42)	
$R_{m,t}$			0.047**			0.034
			(2.36)			(1.63)
$D_jR_{m,t}$			-0.019			0.048**
			(-0.87)			(2.05)
${R_{m,t}}^2$			0.057***			0.040***
			(2.78)			(2.85)
$D_j{R_{m,t}}^2$			-0.068***			-0.018
			(-3.20)			(-1.04)
$Adj.R^2$	0.778	0.778	0.779	0.810	0.810	0.815

Table 2.6 Panel A (continued)

	GRE			IND		
Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.555***	0.557***	0.546***	0.417***	0.417***	0.415***
	(10.83)	(10.84)	(10.81)	(10.43)	(10.41)	(10.37)
D_j	0.006	0.005	0.014	-0.026	-0.026	-0.023
	(0.10)	(0.09)	(0.22)	(-0.48)	(-0.48)	(-0.43)
$CSAD_{t-1}$	0.651***	0.651***	0.655***	0.752***	0.752***	0.751***
	(28.26)	(28.25)	(28.69)	(48.11)	(48.12)	(48.33)
$D_j CSAD_{t-1}$	-0.004	-0.004	-0.007	0.019	0.019	0.018
	(-0.15)	(-0.15)	(-0.25)	(0.86)	(0.87)	(0.82)
$\lvert R_{m,t} \rvert$	0.292***	0.291***	0.296***	0.512***	0.513***	0.528***
	(8.99)	(8.89)	(9.56)	(11.46)	(11.27)	(11.21)
$D_j \lvert R_{m,t} \rvert$	0.040	0.041	0.037	-0.109*	-0.111*	-0.111*
	(0.91)	(0.92)	(0.85)	(-1.81)	(-1.81)	(-1.79)
$\left(R_{m,t} - \overline{R_m}\right)^2$	-0.035***			-0.007		
	(-4.55)			(-0.49)		
$D_j \left(R_{m,t} - \overline{R_m}\right)^2$	0.012			0.054**		
	(1.07)			(2.47)		
$\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$		-0.034***			-0.008	
		(-4.49)			(-0.51)	
$D_j \left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$		0.011			0.054**	
		(1.05)			(2.46)	
$R_{m,t}$			-0.025**			0.032*
			(-2.54)			(1.82)
$D_j R_{m,t}$			0.020			0.002
			(1.39)			(0.10)
${R_{m,t}}^2$			-0.036***			-0.013
			(-5.00)			(-0.85)
$D_j {R_{m,t}}^2$			0.012			0.054**
			(1.17)			(2.49)
$Adj. R^2$	0.569	0.569	0.570	0.878	0.878	0.878

Table 2.6 Panel A (continued)

	IRE			ITA		
Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.589***	0.589***	0.590***	0.535***	0.535***	0.548***
	(6.05)	(6.05)	(6.08)	(10.90)	(10.91)	(11.23)
D_j	0.354***	0.354***	0.357***	0.183	0.183	0.173
	(3.37)	(3.37)	(3.40)	(1.19)	(1.19)	(1.12)
$CSAD_{t-1}$	0.277***	0.277***	0.278***	0.552***	0.552***	0.543***
	(4.90)	(4.90)	(4.89)	(18.00)	(18.02)	(17.84)
D_jCSAD_{t-1}	0.062	0.062	0.060	-0.086	-0.086	-0.080
	(1.07)	(1.07)	(1.02)	(-0.93)	(-0.92)	(-0.86)
$\lvert R_{m,t}\rvert$	1.224***	1.223***	1.213***	0.251***	0.253***	0.246***
	(12.77)	(12.77)	(12.34)	(5.45)	(5.50)	(5.37)
$D_j\lvert R_{m,t}\rvert$	-0.484***	-0.484***	-0.477***	-0.143	-0.147	-0.139
	(-4.27)	(-4.27)	(-4.14)	(-1.50)	(-1.53)	(-1.46)
$\left(R_{m,t}-\overline{R_m}\right)^2$	-0.061***			-0.007		
	(-3.53)			(-0.40)		
$D_j\left(R_{m,t}-\overline{R_m}\right)^2$	0.093***			0.077*		
	(3.89)			(1.80)		
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		-0.061***			-0.008	
		(-3.52)			(-0.46)	
$D_j\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		0.093***			0.078*	
		(3.89)			(1.83)	
$R_{m,t}$			0.021			0.019
			(0.50)			(1.28)
$D_jR_{m,t}$			0.001			-0.006
			(0.03)			(-0.31)
${R_{m,t}}^2$			-0.057***			-0.001
			(-2.97)			(-0.03)
$D_j{R_{m,t}}^2$			0.091***			0.073*
			(3.61)			(1.67)
$Adj.R^2$	0.604	0.604	0.605	0.680	0.680	0.681

Table 2.6 Panel A (continued)

	JAP			POR		
Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.379***	0.379***	0.367***	0.986***	0.984***	0.976***
	(8.81)	(8.82)	(9.28)	(13.45)	(13.31)	(12.84)
D_j	-0.134***	-0.134***	-0.123***	-0.078	-0.076	-0.069
	(-2.70)	(-2.70)	(-2.64)	(-1.00)	(-0.98)	(-0.86)
$CSAD_{t-1}$	0.679***	0.680***	0.691***	0.126***	0.126***	0.122***
	(27.54)	(27.56)	(30.60)	(3.57)	(3.57)	(3.54)
D_jCSAD_{t-1}	0.082***	0.082***	0.071***	-0.027	-0.027	-0.024
	(2.93)	(2.93)	(2.70)	(-0.72)	(-0.73)	(-0.66)
$\lvert R_{m,t}\rvert$	0.218***	0.218***	0.208***	0.547***	0.544***	0.595***
	(6.19)	(6.14)	(6.87)	(4.64)	(4.48)	(4.55)
$D_j\lvert R_{m,t}\rvert$	0.008	0.009	0.018	0.331**	0.332**	0.289**
	(0.20)	(0.21)	(0.51)	(2.56)	(2.50)	(2.05)
$\left(R_{m,t}-\overline{R_m}\right)^2$	0.006			0.180***		
	(0.62)			(3.56)		
$D_j\left(R_{m,t}-\overline{R_m}\right)^2$	-0.015			-0.093*		
	(-1.28)			(-1.71)		
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		0.006			0.178***	
		(0.63)			(3.48)	
$D_j\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		-0.015			-0.092*	
		(-1.28)			(-1.67)	
$R_{m,t}$			-0.034***			0.068
			(-3.32)			(1.40)
$D_jR_{m,t}$			0.024**			-0.028
			(1.99)			(-0.52)
${R_{m,t}}^2$			0.006			0.168***
			(0.68)			(3.00)
$D_j{R_{m,t}}^2$			-0.015			-0.081
			(-1.49)			(-1.36)
$Adj.R^2$	0.812	0.812	0.814	0.668	0.668	0.669

Table 2.6 Panel A (continued)

	RUS			SAF		
Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	1.161***	1.162***	1.162***	0.982***	0.981***	0.979***
	(11.78)	(11.79)	(11.97)	(10.09)	(10.08)	(10.04)
D_j	-0.011	-0.011	-0.015	0.192*	0.193*	0.194*
	(-0.07)	(-0.07)	(-0.10)	(1.75)	(1.76)	(1.77)
$CSAD_{t-1}$	0.070**	0.070**	0.071**	0.428***	0.428***	0.427***
	(1.97)	(1.97)	(2.01)	(9.76)	(9.75)	(9.75)
$D_j CSAD_{t-1}$	0.190***	0.189***	0.186***	-0.059	-0.059	-0.059
	(3.13)	(3.13)	(3.12)	(-1.20)	(-1.20)	(-1.19)
$\lvert R_{m,t} \rvert$	1.175***	1.177***	1.168***	0.818***	0.821***	0.844***
	(13.60)	(13.62)	(12.94)	(7.50)	(7.55)	(7.43)
$D_j \lvert R_{m,t} \rvert$	-0.538***	-0.533***	-0.516***	-0.171	-0.173	-0.194
	(-3.84)	(-3.85)	(-3.55)	(-1.47)	(-1.50)	(-1.61)
$\left(R_{m,t} - \overline{R_m}\right)^2$	0.025***			-0.090*		
	(7.41)			(-1.70)		
$D_j\left(R_{m,t} - \overline{R_m}\right)^2$	0.040			0.091		
	(1.27)			(1.63)		
$\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$		0.025***			-0.092*	
		(7.35)			(-1.74)	
$D_j\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$		0.041			0.093*	
		(1.26)			(1.66)	
$R_{m,t}$			0.029			-0.035
			(0.59)			(-0.93)
$D_j R_{m,t}$			0.019			0.029
			(0.28)			(0.70)
${R_{m,t}}^2$			0.026***			-0.109*
			(5.68)			(-1.96)
$D_j {R_{m,t}}^2$			0.037			0.108*
			(1.10)			(1.84)
$Adj. R^2$	0.769	0.769	0.770	0.451	0.451	0.451

Table 2.6 Panel A (continued)

	SPA			THA		
Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	1.139***	1.139***	1.133***	0.292***	0.292***	0.289***
	(14.70)	(14.70)	(14.78)	(9.55)	(9.55)	(10.02)
D_j	-0.577***	-0.577***	-0.572***	-0.053	-0.054	-0.050
	(-6.93)	(-6.93)	(-6.94)	(-1.39)	(-1.40)	(-1.36)
$CSAD_{t-1}$	0.067	0.067	0.062	0.665***	0.665***	0.669***
	(1.24)	(1.24)	(1.17)	(34.75)	(34.76)	(36.37)
D_jCSAD_{t-1}	0.332***	0.332***	0.336***	0.011	0.011	0.006
	(5.60)	(5.60)	(5.73)	(0.46)	(0.46)	(0.26)
$\lvert R_{m,t}\rvert$	0.019	0.020	0.036	0.513***	0.513***	0.508***
	(0.27)	(0.28)	(0.49)	(17.07)	(17.02)	(16.59)
$D_j\lvert R_{m,t}\rvert$	0.409***	0.408***	0.394***	0.060	0.061	0.067
	(5.28)	(5.27)	(4.92)	(1.40)	(1.43)	(1.59)
$\left(R_{m,t} - \overline{R_m}\right)^2$	0.177***			-0.004		
	(16.55)			(-0.66)		
$D_j\left(R_{m,t} - \overline{R_m}\right)^2$	-0.158***			-0.016		
	(-8.37)			(-1.38)		
$\left(\lvert R_{m,t}\rvert - \overline{R_m}\right)^2$		0.177***			-0.004	
		(16.57)			(-0.65)	
$D_j\left(\lvert R_{m,t}\rvert - \overline{R_m}\right)^2$		-0.158***			-0.016	
		(-8.37)			(-1.40)	
$R_{m,t}$			0.082			-0.034
			(1.44)			(-1.64)
$D_jR_{m,t}$			-0.067			0.047**
			(-1.15)			(2.05)
${R_{m,t}}^2$			0.183***			-0.005
			(16.79)			(-0.86)
$D_j{R_{m,t}}^2$			-0.163***			-0.014
			(-8.49)			(-1.23)
$Adj.R^2$	0.772	0.772	0.774	0.847	0.847	0.847

Table 2.6 Panel A (continued)

	UAE			UK		
Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.504***	0.504***	0.504***	0.412***	0.412***	0.412***
	(20.08)	(20.09)	(20.05)	(8.65)	(8.63)	(8.64)
D_j	0.132***	0.132***	0.129***	0.017	0.016	0.023
	(3.03)	(3.03)	(3.00)	(0.32)	(0.31)	(0.43)
$CSAD_{t-1}$	0.351***	0.351***	0.351***	0.643***	0.642***	0.639***
	(17.69)	(17.69)	(17.66)	(21.38)	(21.35)	(21.21)
D_jCSAD_{t-1}	-0.052*	-0.053*	-0.052*	0.019	0.019	0.017
	(-1.81)	(-1.81)	(-1.80)	(0.57)	(0.58)	(0.52)
$\left\|R_{m,t}\right\|$	0.862***	0.862***	0.862***	0.470***	0.474***	0.478***
	(21.79)	(21.88)	(21.56)	(8.98)	(8.84)	(9.87)
$D_j\left\|R_{m,t}\right\|$	-0.018	-0.019	-0.010	0.004	0.005	-0.002
	(-0.24)	(-0.25)	(-0.13)	(0.08)	(0.09)	(-0.03)
$\left(R_{m,t} - \overline{R_m}\right)^2$	-0.054***			-0.001		
	(-3.47)			(-0.05)		
$D_j\left(R_{m,t} - \overline{R_m}\right)^2$	0.007			-0.021		
	(0.21)			(-0.88)		
$\left(\left\|R_{m,t}\right\| - \overline{R_m}\right)^2$		-0.054***			-0.002	
		(-3.48)			(-0.10)	
$D_j\left(\left\|R_{m,t}\right\| - \overline{R_m}\right)^2$		0.007			-0.021	
		(0.21)			(-0.88)	
$R_{m,t}$			0.005			0.053***
			(0.34)			(2.72)
$D_jR_{m,t}$			0.028			-0.009
			(0.90)			(-0.41)
${R_{m,t}}^2$			-0.054***			0.012
			(-3.33)			(0.53)
$D_j{R_{m,t}}^2$			0.007			-0.023
			(0.20)			(-1.01)
$Adj. R^2$	0.696	0.696	0.697	0.815	0.815	0.817

Table 2.6 Panel A (continued)

	USA		
Staggered Return	YMH (2)	BNNT	BCF
$Intercept$	0.197***	0.196***	0.195***
	(5.56)	(5.54)	(5.47)
D_j	0.072*	0.073*	0.075*
	(1.74)	(1.76)	(1.80)
$CSAD_{t-1}$	0.774***	0.774***	0.776***
	(31.60)	(31.57)	(31.30)
$D_j CSAD_{t-1}$	-0.013	-0.013	-0.015
	(-0.46)	(-0.46)	(-0.54)
$\lvert R_{m,t} \rvert$	0.180***	0.181***	0.180***
	(7.41)	(7.50)	(7.89)
$D_j \lvert R_{m,t} \rvert$	-0.069**	-0.069**	-0.070***
	(-2.52)	(-2.56)	(-2.69)
$\left(R_{m,t} - \overline{R_m}\right)^2$	0.001		
	(0.16)		
$D_j \left(R_{m,t} - \overline{R_m}\right)^2$	0.010		
	(1.42)		
$\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$		0.001	
		(0.14)	
$D_j \left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$		0.010	
		(1.45)	
$R_{m,t}$			-0.010
			(-1.05)
$D_j R_{m,t}$			0.015
			(1.42)
${R_{m,t}}^2$			0.001
			(0.19)
$D_j {R_{m,t}}^2$			0.010
			(1.60)
$Adj. R^2$	0.832	0.832	0.833

Panel B: Regression results for the effect of jump on herd behavior by using staggered return bipower variation with 99% confidence level (Asymmetric market condition).

Note: This table reports regression statistics comparing between down markets and other markets by using two equations which are

$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 D_d + \gamma_3 D_j D_d + \gamma_4 CSAD_{t-1} + \gamma_5 D_j CSAD_{t-1} + \gamma_6 D_d CSAD_{t-1} + \gamma_7 D_j D_d CSAD_{t-1} + \gamma_8 |R_{m,t}| + \gamma_9 D_j |R_{m,t}| + \gamma_{10} D_d |R_{m,t}| + \gamma_{11} D_j D_d |R_{m,t}| + \gamma_{12} (R_{m,t} - \overline{R_m})^2 + \gamma_{13} D_j (R_{m,t} - \overline{R_m})^2 + \gamma_{14} D_d (R_{m,t} - \overline{R_m})^2 + \gamma_{15} D_j D_d (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (Yao et al., 2014: YMH2), and

$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 D_d + \gamma_3 D_j D_d + \gamma_4 CSAD_{t-1} + \gamma_5 D_j CSAD_{t-1} + \gamma_6 D_d CSAD_{t-1} + \gamma_7 D_j D_d CSAD_{t-1} + \gamma_8 |R_{m,t}| + \gamma_9 D_j |R_{m,t}| + \gamma_{10} D_d |R_{m,t}| + \gamma_{11} D_j D_d |R_{m,t}| + \gamma_{12} (|R_{m,t}| - \overline{R_m})^2 + \gamma_{13} D_j (|R_{m,t}| - \overline{R_m})^2 + \gamma_{14} D_d (|R_{m,t}| - \overline{R_m})^2 + \gamma_{15} D_j D_d (|R_{m,t}| - \overline{R_m})^2 + \varepsilon_t$ (Bui et al., 2017: BNNT),

where $CSAD_t$ is a cross-sectional absolute deviation of returns at time t, $R_{m,t}$ is an equally weighted portfolio return at time t, and $CSAD_{t-1}$ is a one-day lag of cross-sectional absolute deviation of returns at time t. D_j is a dummy variable which specifies jump date. It is equal to one in the jump date, and zero otherwise. D_d is a dummy variable which specifies down markets dates. It is equal to one during the negative market return date, and zero otherwise.

The sample interval is from 01/01/1996 to 30/06/2018.

The t-statistics are shown in parentheses which is calculated by using Newey & West (1987)'s heteroscedaticity and autocorrelation consistent standard errors.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

Table 2.6 Panel B (continued)

	AUS		BRA		CAN	
Staggered Return	YMH (2)	BNNT	YMH (2)	BNNT	YMH (2)	BNNT
$Intercept$	1.146***	1.146***	1.032***	1.032***	0.482***	0.482***
	(8.52)	(8.52)	(12.17)	(12.17)	(3.78)	(3.78)
D_j	0.119	0.119	-0.022	-0.022	-0.073	-0.073
	(0.66)	(0.66)	(-0.21)	(-0.21)	(-0.52)	(-0.52)
D_d	0.006	0.006	-0.053	-0.053	-0.040	-0.040
	(0.04)	(0.04)	(-0.46)	(-0.46)	(-0.27)	(-0.27)
$D_j D_d$	-0.049	-0.049	0.082	0.082	0.129	0.129
	(-0.23)	(-0.23)	(0.58)	(0.58)	(0.75)	(0.75)
$CSAD_{t-1}$	0.533***	0.533***	0.087*	0.087*	0.720***	0.720***
	(11.20)	(11.20)	(1.86)	(1.86)	(13.50)	(13.50)
$D_j CSAD_{t-1}$	-0.035	-0.035	0.003	0.003	0.051	0.051
	(-0.56)	(-0.56)	(0.06)	(0.06)	(0.87)	(0.87)
$D_d CSAD_{t-1}$	0.015	0.015	0.020	0.020	0.032	0.032
	(0.28)	(0.28)	(0.34)	(0.34)	(0.52)	(0.52)
$D_j D_d CSAD_{t-1}$	0.024	0.024	-0.024	-0.024	-0.078	-0.078
	(0.33)	(0.33)	(-0.32)	(-0.32)	(-1.08)	(-1.08)
$\|R_{m,t}\|$	0.655***	0.655***	0.836***	0.836***	0.364***	0.364***
	(11.08)	(11.08)	(6.52)	(6.52)	(9.20)	(9.20)
$D_j\|R_{m,t}\|$	0.124	0.124	0.038	0.038	-0.036	-0.036
	(1.19)	(1.19)	(0.23)	(0.23)	(-0.75)	(-0.75)
$D_d\|R_{m,t}\|$	-0.202***	-0.203***	-0.005	0.024	-0.070	-0.070
	(-2.95)	(-2.95)	(-0.03)	(0.13)	(-1.28)	(-1.28)
$D_j D_d\|R_{m,t}\|$	-0.166	-0.167	-0.033	-0.055	0.052	0.052
	(-1.42)	(-1.42)	(-0.14)	(-0.24)	(0.80)	(0.80)
$(R_{m,t} - \overline{R_m})^2$	-0.023***		0.056		0.006	
	(-4.21)		(0.82)		(0.40)	
$D_j(R_{m,t} - \overline{R_m})^2$	-0.111**		0.016		-0.008	
	(-2.29)		(0.18)		(-0.43)	
$D_d(R_{m,t} - \overline{R_m})^2$	0.033***		0.013		-0.001	
	(3.11)		(0.18)		(-0.08)	
$D_j D_d(R_{m,t} - \overline{R_m})^2$	0.113**		-0.069		0.009	
	(2.20)		(-0.72)		(0.48)	
$(\|R_{m,t}\| - \overline{R_m})^2$		-0.023***		0.056		0.006
		(-4.21)		(0.82)		(0.40)
$D_j(\|R_{m,t}\| - \overline{R_m})^2$		-0.111**		0.016		-0.008
		(-2.29)		(0.18)		(-0.43)
$D_d(\|R_{m,t}\| - \overline{R_m})^2$		0.033***		0.013		-0.001
		(3.11)		(0.18)		(-0.08)
$D_j D_d(\|R_{m,t}\| - \overline{R_m})^2$		0.113**		-0.069		0.009
		(2.20)		(-0.72)		(0.48)
$Adj. R^2$	0.750	0.750	0.710	0.710	0.834	0.834

Table 2.6 Panel B (continued)

	CHN		FRA		GER	
Staggered Return	YMH (2)	BNNT	YMH (2)	BNNT	YMH (2)	BNNT
$Intercept$	0.484***	0.484***	0.592***	0.592***	0.270***	0.270***
	(14.50)	(14.50)	(8.60)	(8.60)	(5.09)	(5.09)
D_j	-0.095**	-0.095**	-0.109	-0.109	0.216***	0.216***
	(-1.96)	(-1.96)	(-1.49)	(-1.49)	(3.19)	(3.19)
D_d	-0.266***	-0.266***	-0.150	-0.150	-0.134*	-0.134*
	(-5.30)	(-5.30)	(-1.48)	(-1.48)	(-1.72)	(-1.72)
D_jD_d	0.039	0.039	0.195*	0.195*	0.219**	0.219**
	(0.51)	(0.51)	(1.82)	(1.82)	(2.27)	(2.27)
$CSAD_{t-1}$	0.612***	0.612***	0.584***	0.584***	0.809***	0.809***
	(27.80)	(27.80)	(14.81)	(14.81)	(37.69)	(37.69)
D_jCSAD_{t-1}	0.038	0.038	0.041	0.041	-0.059**	-0.059**
	(1.11)	(1.11)	(0.97)	(0.97)	(-2.21)	(-2.21)
D_dCSAD_{t-1}	0.156***	0.156***	0.072	0.072	0.042	0.042
	(4.59)	(4.59)	(1.27)	(1.27)	(1.06)	(1.06)
$D_jD_dCSAD_{t-1}$	-0.010	-0.010	-0.096	-0.096	-0.065	-0.065
	(-0.19)	(-0.19)	(-1.59)	(-1.59)	(-1.48)	(-1.48)
$\lvert R_{m,t}\rvert$	0.039**	0.039**	0.363***	0.363***	0.238**	0.238**
	(2.07)	(2.07)	(3.41)	(3.41)	(2.18)	(2.18)
$D_j\lvert R_{m,t}\rvert$	-0.023	-0.023	0.128	0.128	0.215*	0.215*
	(-0.79)	(-0.79)	(1.12)	(1.12)	(1.84)	(1.84)
$D_d\lvert R_{m,t}\rvert$	0.237***	0.232***	0.058	0.057	0.046	0.042
	(7.85)	(7.84)	(0.47)	(0.46)	(0.38)	(0.33)
$D_jD_d\lvert R_{m,t}\rvert$	0.007	0.008	-0.029	-0.028	-0.245*	-0.243*
	(0.15)	(0.19)	(-0.21)	(-0.21)	(-1.84)	(-1.82)
$(R_{m,t}-\overline{R_m})^2$	-0.004		0.147**		0.092	
	(-0.94)		(2.05)		(1.16)	
$D_j(R_{m,t}-\overline{R_m})^2$	0.011*		-0.100		-0.081	
	(1.68)		(-1.28)		(-1.00)	
$D_d(R_{m,t}-\overline{R_m})^2$	-0.020***		-0.111		-0.058	
	(-3.42)		(-1.44)		(-0.74)	
$D_jD_d(R_{m,t}-\overline{R_m})^2$	-0.004		0.045		0.073	
	(-0.44)		(0.54)		(0.90)	
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.004		0.147**		0.092
		(-0.94)		(2.05)		(1.16)
$D_j(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.011*		-0.100		-0.081
		(1.68)		(-1.28)		(-1.00)
$D_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.020***		-0.111		-0.058
		(-3.42)		(-1.44)		(-0.74)
$D_jD_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.004		0.045		0.073
		(-0.44)		(0.54)		(0.90)
$Adj.R^2$	0.690	0.690	0.780	0.780	0.815	0.815

Table 2.6 Panel B (continued)

	GRE		IND		IRE	
Staggered Return	YMH (2)	BNNT	YMH (2)	BNNT	YMH (2)	BNNT
$Intercept$	0.610***	0.610***	0.475***	0.475***	0.570***	0.570***
	(9.55)	(9.55)	(7.38)	(7.38)	(4.09)	(4.09)
D_j	-0.005	-0.005	-0.082	-0.082	0.375**	0.375**
	(-0.06)	(-0.06)	(-0.97)	(-0.97)	(2.55)	(2.55)
D_d	-0.134	-0.134	-0.122	-0.122	0.132	0.132
	(-1.32)	(-1.32)	(-1.56)	(-1.56)	(0.70)	(0.70)
$D_j D_d$	0.032	0.032	0.106	0.106	-0.103	-0.103
	(0.24)	(0.24)	(1.03)	(1.03)	(-0.51)	(-0.51)
$CSAD_{t-1}$	0.615***	0.615***	0.723***	0.723***	0.348***	0.348***
	(20.60)	(20.60)	(27.45)	(27.45)	(4.86)	(4.86)
$D_j CSAD_{t-1}$	0.006	0.006	0.039	0.039	-0.030	-0.030
	(0.17)	(0.17)	(1.05)	(1.05)	(-0.41)	(-0.41)
$D_d CSAD_{t-1}$	0.067	0.067	0.037	0.037	-0.138	-0.138
	(1.47)	(1.47)	(1.16)	(1.16)	(-1.30)	(-1.30)
$D_j D_d CSAD_{t-1}$	-0.017	-0.017	-0.027	-0.027	0.176	0.176
	(-0.29)	(-0.29)	(-0.61)	(-0.61)	(1.60)	(1.60)
$\lvert R_{m,t} \rvert$	0.394***	0.394***	0.546***	0.546***	0.873***	0.873***
	(11.01)	(11.01)	(10.35)	(10.35)	(4.81)	(4.81)
$D_j \lvert R_{m,t} \rvert$	-0.024	-0.024	-0.107	-0.107	-0.122	-0.122
	(-0.34)	(-0.34)	(-1.31)	(-1.31)	(-0.64)	(-0.64)
$D_d \lvert R_{m,t} \rvert$	-0.139***	-0.138***	0.149**	0.154**	0.428*	0.426*
	(-2.69)	(-2.64)	(2.04)	(2.09)	(1.89)	(1.89)
$D_j D_d \lvert R_{m,t} \rvert$	0.093	0.093	-0.074	-0.078	-0.495**	-0.493**
	(1.08)	(1.07)	(-0.66)	(-0.69)	(-2.03)	(-2.03)
$\left(R_{m,t} - \overline{R_m}\right)^2$	-0.063***		0.003		0.051	
	(-8.29)		(0.44)		(0.83)	
$D_j\left(R_{m,t} - \overline{R_m}\right)^2$	0.030		0.050**		-0.001	
	(1.54)		(2.34)		(-0.02)	
$D_d\left(R_{m,t} - \overline{R_m}\right)^2$	0.043***		-0.110***		-0.123*	
	(3.58)		(-6.38)		(-1.93)	
$D_j D_d\left(R_{m,t} - \overline{R_m}\right)^2$	-0.029		0.030		0.105	
	(-1.31)		(0.82)		(1.54)	
$\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$		-0.063***		0.003		0.051
		(-8.29)		(0.44)		(0.83)
$D_j\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$		0.030		0.050**		-0.001
		(1.54)		(2.34)		(-0.02)
$D_d\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$		0.043***		-0.110***		-0.123*
		(3.58)		(-6.38)		(-1.93)
$D_j D_d\left(\lvert R_{m,t} \rvert - \overline{R_m}\right)^2$		-0.029		0.030		0.105
		(-1.31)		(0.82)		(1.54)
$Adj.R^2$	0.576	0.576	0.880	0.880	0.607	0.607

Table 2.6 Panel B (continued)

	ITA		JAP		POR	
Staggered Return	YMH (2)	BNNT	YMH (2)	BNNT	YMH (2)	BNNT
$Intercept$	0.619***	0.619***	0.338***	0.338***	0.868***	0.868***
	(8.63)	(8.63)	(7.47)	(7.47)	(10.40)	(10.40)
D_j	0.154	0.154	-0.094*	-0.094*	0.001	0.001
	(0.82)	(0.82)	(-1.72)	(-1.72)	(0.01)	(0.01)
D_d	-0.123	-0.123	0.050	0.050	0.212	0.212
	(-1.23)	(-1.23)	(0.71)	(0.71)	(1.52)	(1.52)
D_jD_d	-0.077	-0.077	-0.039	-0.039	-0.131	-0.131
	(-0.41)	(-0.41)	(-0.47)	(-0.47)	(-0.88)	(-0.88)
$CSAD_{t-1}$	0.516***	0.516***	0.714***	0.714***	0.157***	0.157***
	(11.69)	(11.69)	(25.77)	(25.77)	(3.20)	(3.20)
D_jCSAD_{t-1}	-0.119	-0.119	0.064*	0.064*	-0.056	-0.056
	(-0.94)	(-0.94)	(1.89)	(1.89)	(-1.09)	(-1.09)
D_dCSAD_{t-1}	0.053	0.053	-0.035	-0.035	-0.055	-0.055
	(0.85)	(0.85)	(-0.81)	(-0.81)	(-0.86)	(-0.86)
$D_jD_dCSAD_{t-1}$	0.123	0.123	0.003	0.003	0.048	0.048
	(0.96)	(0.96)	(0.06)	(0.06)	(0.69)	(0.69)
$\lvert R_{m,t}\rvert$	0.158	0.158	0.209***	0.209***	0.788***	0.788***
	(1.44)	(1.44)	(9.71)	(9.71)	(4.64)	(4.64)
$D_j\lvert R_{m,t}\rvert$	0.126	0.126	-0.041	-0.041	0.181	0.181
	(1.10)	(1.10)	(-1.08)	(-1.08)	(0.98)	(0.98)
$D_d\lvert R_{m,t}\rvert$	0.101	0.101	-0.021	-0.022	-0.422*	-0.440*
	(0.83)	(0.84)	(-0.45)	(-0.47)	(-1.65)	(-1.69)
$D_jD_d\lvert R_{m,t}\rvert$	-0.350**	-0.356**	0.105*	0.106*	0.244	0.254
	(-2.05)	(-2.06)	(1.74)	(1.75)	(0.89)	(0.91)
$(R_{m,t}-\overline{R_m})^2$	0.062		-0.009*		0.121**	
	(1.06)		(-1.67)		(2.32)	
$D_j(R_{m,t}-\overline{R_m})^2$	-0.057		0.013		-0.044	
	(-0.96)		(0.80)		(-0.73)	
$D_d(R_{m,t}-\overline{R_m})^2$	-0.075		0.028**		0.107	
	(-1.24)		(2.50)		(1.05)	
$D_jD_d(R_{m,t}-\overline{R_m})^2$	0.157**		-0.043**		-0.085	
	(2.11)		(-2.17)		(-0.78)	
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.062		-0.009*		0.121**
		(1.06)		(-1.67)		(2.32)
$D_j(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.057		0.013		-0.044
		(-0.96)		(0.80)		(-0.73)
$D_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.075		0.028**		0.107
		(-1.24)		(2.50)		(1.05)
$D_jD_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.157**		-0.043**		-0.085
		(2.11)		(-2.17)		(-0.78)
$Adj.R^2$	0.693	0.693	0.819	0.819	0.669	0.669

Table 2.6 Panel B (continued)

	RUS		SAF		SPA	
Staggered Return	YMH (2)	BNNT	YMH (2)	BNNT	YMH (2)	BNNT
$Intercept$	1.194***	1.194***	1.099***	1.099***	1.028***	1.028***
	(11.96)	(11.96)	(8.85)	(8.85)	(19.59)	(19.59)
D_j	-0.142	-0.142	0.198	0.198	-0.519***	-0.519***
	(-0.94)	(-0.94)	(1.43)	(1.43)	(-8.40)	(-8.40)
D_d	0.141	0.141	-0.216	-0.216	-0.328**	-0.328**
	(0.83)	(0.83)	(-1.11)	(-1.11)	(-2.36)	(-2.36)
$D_j D_d$	0.092	0.092	0.006	0.006	0.440***	0.440***
	(0.35)	(0.35)	(0.03)	(0.03)	(2.94)	(2.94)
$CSAD_{t-1}$	0.117***	0.117***	0.385***	0.385***	0.033	0.033
	(2.74)	(2.74)	(7.01)	(7.01)	(0.94)	(0.94)
$D_j CSAD_{t-1}$	0.141**	0.141**	-0.058	-0.058	0.400***	0.400***
	(1.99)	(1.99)	(-0.97)	(-0.97)	(9.70)	(9.70)
$D_d CSAD_{t-1}$	-0.062	-0.062	0.083	0.083	0.401***	0.401***
	(-1.06)	(-1.06)	(0.96)	(0.96)	(4.15)	(4.15)
$D_j D_d CSAD_{t-1}$	0.062	0.062	0.003	0.003	-0.474***	-0.474***
	(0.54)	(0.54)	(0.04)	(0.04)	(-4.45)	(-4.45)
$\lvert R_{m,t}\rvert$	0.749***	0.749***	0.658***	0.658***	0.592***	0.592***
	(8.27)	(8.27)	(3.61)	(3.61)	(7.78)	(7.78)
$D_j\lvert R_{m,t}\rvert$	0.139	0.139	-0.206	-0.206	-0.149*	-0.149*
	(1.00)	(1.00)	(-1.03)	(-1.03)	(-1.73)	(-1.73)
$D_d\lvert R_{m,t}\rvert$	0.366**	0.372**	0.250	0.244	-0.770***	-0.768***
	(2.16)	(2.21)	(1.04)	(1.02)	(-7.28)	(-7.27)
$D_j D_d\lvert R_{m,t}\rvert$	-0.969***	-0.944***	-0.048	-0.042	0.746***	0.745***
	(-4.36)	(-4.31)	(-0.18)	(-0.16)	(6.43)	(6.42)
$(R_{m,t} - \overline{R_m})^2$	0.118***		0.012		-0.002	
	(7.99)		(0.09)		(-0.13)	
$D_j(R_{m,t} - \overline{R_m})^2$	-0.084**		0.145		0.023	
	(-2.48)		(0.98)		(0.76)	
$D_d(R_{m,t} - \overline{R_m})^2$	-0.093***		-0.142		0.199***	
	(-5.94)		(-0.97)		(10.64)	
$D_j D_d(R_{m,t} - \overline{R_m})^2$	0.184***		-0.028		-0.202***	
	(4.18)		(-0.17)		(-5.82)	
$(\lvert R_{m,t}\rvert - \overline{R_m})^2$		0.118***		0.012		-0.002
		(7.99)		(0.09)		(-0.13)
$D_j(\lvert R_{m,t}\rvert - \overline{R_m})^2$		-0.084**		0.145		0.023
		(-2.48)		(0.98)		(0.76)
$D_d(\lvert R_{m,t}\rvert - \overline{R_m})^2$		-0.093***		-0.142		0.199***
		(-5.94)		(-0.97)		(10.64)
$D_j D_d(\lvert R_{m,t}\rvert - \overline{R_m})^2$		0.184***		-0.028		-0.202***
		(4.18)		(-0.17)		(-5.82)
$Adj.R^2$	0.781	0.781	0.455	0.455	0.785	0.785

Table 2.6 Panel B (continued)

	THA		UAE		UK	
Staggered Return	YMH (2)	BNNT	YMH (2)	BNNT	YMH (2)	BNNT
$Intercept$	0.292***	0.292***	0.489***	0.489***	0.357***	0.357***
	(7.09)	(7.09)	(12.48)	(12.48)	(4.75)	(4.75)
D_j	-0.042	-0.042	0.220***	0.220***	0.087	0.087
	(-0.76)	(-0.76)	(3.39)	(3.39)	(1.05)	(1.05)
D_d	-0.021	-0.021	0.027	0.027	0.143	0.143
	(-0.38)	(-0.38)	(0.57)	(0.57)	(1.50)	(1.50)
D_jD_d	0.013	0.013	-0.167*	-0.167*	-0.146	-0.146
	(0.17)	(0.17)	(-1.90)	(-1.90)	(-1.43)	(-1.43)
$CSAD_{t-1}$	0.642***	0.642***	0.355***	0.355***	0.665***	0.665***
	(26.68)	(26.68)	(11.35)	(11.35)	(13.80)	(13.80)
D_jCSAD_{t-1}	0.033	0.033	-0.061	-0.061	-0.022	-0.022
	(1.06)	(1.06)	(-1.29)	(-1.29)	(-0.42)	(-0.42)
D_dCSAD_{t-1}	0.052	0.052	-0.006	-0.006	-0.064	-0.064
	(1.48)	(1.48)	(-0.15)	(-0.15)	(-1.08)	(-1.08)
$D_jD_dCSAD_{t-1}$	-0.056	-0.056	0.009	0.009	0.084	0.084
	(-1.28)	(-1.28)	(0.14)	(0.14)	(1.34)	(1.34)
$\lvert R_{m,t}\rvert$	0.575***	0.575***	0.941***	0.941***	0.504***	0.504***
	(8.76)	(8.76)	(19.69)	(19.69)	(5.12)	(5.12)
$D_j\lvert R_{m,t}\rvert$	-0.054	-0.054	-0.160	-0.160	0.019	0.019
	(-0.68)	(-0.68)	(-1.50)	(-1.50)	(0.17)	(0.17)
$D_d\lvert R_{m,t}\rvert$	-0.091	-0.091	-0.163**	-0.164**	-0.094	-0.095
	(-1.18)	(-1.18)	(-2.41)	(-2.42)	(-0.82)	(-0.83)
$D_jD_d\lvert R_{m,t}\rvert$	0.173*	0.175*	0.301**	0.300**	-0.022	-0.020
	(1.82)	(1.83)	(2.16)	(2.16)	(-0.18)	(-0.16)
$(R_{m,t}-\overline{R_m})^2$	-0.025		-0.091***		0.046	
	(-1.05)		(-6.72)		(0.78)	
$D_j(R_{m,t}-\overline{R_m})^2$	0.030		0.064		-0.039	
	(1.10)		(1.18)		(-0.54)	
$D_d(R_{m,t}-\overline{R_m})^2$	0.029		0.071***		-0.031	
	(1.17)		(3.28)		(-0.50)	
$D_jD_d(R_{m,t}-\overline{R_m})^2$	-0.068**		-0.113*		0.016	
	(-2.23)		(-1.76)		(0.21)	
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.025		-0.091***		0.046
		(-1.05)		(-6.72)		(0.78)
$D_j(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.030		0.064		-0.039
		(1.10)		(1.18)		(-0.54)
$D_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.029		0.071***		-0.031
		(1.17)		(3.28)		(-0.50)
$D_jD_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.068**		-0.113*		0.016
		(-2.23)		(-1.76)		(0.21)
$Adj. R^2$	0.849	0.849	0.699	0.699	0.817	0.817

Table 2.6 Panel B (continued)

	USA	
Staggered Return	YMH (2)	BNNT
$Intercept$	0.123**	0.123**
	(2.36)	(2.36)
D_j	0.111*	0.111*
	(1.87)	(1.87)
D_d	0.172***	0.172***
	(2.74)	(2.74)
D_jD_d	-0.099	-0.099
	(-1.32)	(-1.32)
$CSAD_{t-1}$	0.811***	0.811***
	(21.62)	(21.62)
D_jCSAD_{t-1}	-0.031	-0.031
	(-0.74)	(-0.74)
D_dCSAD_{t-1}	-0.080*	-0.080*
	(-1.77)	(-1.77)
$D_jD_dCSAD_{t-1}$	0.039	0.039
	(0.76)	(0.76)
$\lvert R_{m,t}\rvert$	0.204***	0.204***
	(9.17)	(9.17)
$D_j\lvert R_{m,t}\rvert$	-0.077***	-0.077***
	(-2.77)	(-2.77)
$D_d\lvert R_{m,t}\rvert$	-0.077**	-0.075**
	(-2.20)	(-2.17)
$D_jD_d\lvert R_{m,t}\rvert$	0.050	0.050
	(1.21)	(1.22)
$(R_{m,t}-\overline{R_m})^2$	-0.007	
	(-1.41)	
$D_j(R_{m,t}-\overline{R_m})^2$	0.014**	
	(2.07)	
$D_d(R_{m,t}-\overline{R_m})^2$	0.022***	
	(3.07)	
$D_jD_d(R_{m,t}-\overline{R_m})^2$	-0.017*	
	(-1.79)	
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.007
		(-1.41)
$D_j(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.014**
		(2.07)
$D_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.022***
		(3.07)
$D_jD_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.017*
		(-1.79)
$Adj.R^2$	0.834	0.834

2.5.5 Asymmetric effect of jump on herd behavior

Panel B of Table 2.6 shows the effect of jump on herd behavior under different market conditions. Down market dummy variables are used to identify such effect. Since absolute and non-absolute market return variables deliver similar results in this case, Blasco et al. (2017) is excluded from the analysis. Even the results from Blasco et al. (2017) are not presented in the panel, it also delivers almost identical result to especially Yao et al. (2014) and Bui et al. (2017). The small differences are caused by the inclusion of demean techniques in Yao et al. (2014) and Bui et al. (2017). When considering the coefficient of absolute market return, the return variation is higher under extreme market conditions in every country except for Italy. Thus, it confirms the rational asset pricing theory. While such theory holds in Germany upon the occurrence of jump, it offers the opposite result in Spain and USA. In terms of market condition effect, the violation of such theory is detected during the period of negative market return in Australia, Greece, Portugal, Spain, and UAE, unlike China, India, Ireland, Russia, and USA which indicate a steeper slope. In view of both the occurrence of jump and market condition, the association between return dispersion and market return is negative when there are jumps on negative return dates in Germany, Ireland, Italy, and Russia. Yet, results are opposite in Japan, Spain, Thailand, and UAE.

When taking the coefficient of non-linear terms into consideration, herd behavior is identified in Australia, Greece, Japan, and UAE while the anti-herding is found in France, Portugal, and Russia. Independent decision-making decreases during jump dates in Australia, and Russia, while it increases in China, India, and USA. Also, the existence of jump mostly alters herd behavior as suggested by the reverse of signs between the coefficient of return squared and its interaction with jump dummy variables. This confirms the conclusion from the last section. In view of the impact of market condition on herd behavior, herding is reinforced during the period of down market in China, India, Ireland, and Russia, while anti-herding is more pronounced in Australia, Greece, Japan, Spain, UAE, and USA. In consideration of both jump and market condition effects, herd behavior is enhanced when jumps occur during dates with negative market return in Japan, Spain, Thailand, UAE, and USA. The inverse conclusion is discovered in Australia, Italy, and Russia. Therefore, the effect of jump on herd behavior is higher during the period of down market than the others. In conclusion, the hypothesis is confirmed when considering both jump and market condition supporting the argument that overconfidence bias is stronger during up-market periods (Gervais & Odean, 2001 and Chuang & Lee, 2006). As down-market periods are more likely to be perceived as periods of high uncertainty (Zhou & Lai, 2009), the occurrence of jump intensifies herd behavior.

2.5.6 Robustness

In order to check for robustness, Table 2.7 shows herd behavior which takes jump effect into consideration. Non-staggered return bipower variation with 99% confidence level is also used to detect the occurrence of jump. Moreover, the second model of Yao et al. (2014), Bui et al. (2017) and Blasco et al. (2017) are applied to identify herding as suggested by the information selection criteria. Panel A demonstrates jump effect on herd behavior regarding the whole sample. In general, the results are in line with staggered return methodology. The rational asset pricing theory is confirmed as the coefficients of absolute market return are positive and significant in every country except for Italy. The theory also holds during dates where there are jumps in Brazil, Portugal, and Spain, with the exception of USA. Herd behavior is found in six countries which are Australia, China, France, Greece, UAE, and UK whereas anti-herding is detected in Brazil, Canada, Germany, India, Italy, Portugal, Russia, Spain, and USA. Most of those countries are developed markets. When comparing the detection power, the main technique indicates a smaller number of significant non-linear terms than the robustness method. The result shows that the impact of jump on investor behavior is significant in nine markets. The existence of jump mostly alters herd behavior as suggested by the reverse of signs between the coefficient of return squared and its interaction with jump dummy variables. Herd behavior is stronger during the period of jumps in Brazil, Germany, Portugal, Russia, and Spain while it is not the case for Australia, China, Ireland, and South Africa. Therefore, not only changes during the period of jump, herd behavior is also more pronounced during such period. After all, the models used have proven effective as the coefficient of determination is higher than 0.450 in all countries.

Panel B of Table 2.7 is the asymmetric market analysis. The two equations applied provide identical outcomes. The rational asset pricing theory is confirmed by such outcomes from every market. The interaction term between absolute market return and jump dummy is significantly positive in Australia, Germany, and Ireland implying that a return variation is higher where jump dates occur during the period of extreme market. However, China, Greece, and Thailand show the opposite results. In view of the market movement impact, the rational asset pricing theory does not hold during the period of negative market return in Australia, Brazil, Germany, Greece, Italy, Portugal, Spain, UK, and USA, whereas China and South Africa indicate the reverse conclusion. Christie & Huang (1995) propose that the negative linear relationship between CSAD and market return determines herd behavior. Thus, the rational asset pricing theory is more likely to be violated when markets go down. In consideration of both jump and market direction effects, such violation occurs upon the existence of jump during negative market return period in Australia, and Germany. However, the opposite results are illustrated for Brazil, China, Greece, Portugal, Spain, and Thailand as the steeper slope is discovered. In view of coefficient of non-linear term, herding is found in Australia, Greece, and UAE. Conversely, France, Germany, India, Ireland, Portugal, South Africa, and Spain show the occurrence of anti-herding. The imitation across trader behavior is stronger during jump dates in Australia, Germany, and Spain whereas Brazil, China, Greece, and Thailand show the sign of stronger anti-herding. Again, jumps lead to the dramatically change in investor behavior in most countries confirming the impact of jump and the fragility of herd behavior. The interaction term between market return squared and asymmetric market dummy is negative in China, France, India, and South Africa suggesting that herd behavior is strengthened during the period of negative market return. Still, the reverse results are presented for Australia, Greece, Italy, Spain, and USA. When taking into account both effects, herding is severe when jumps occur on dates of negative market return in Brazil, China, Greece, Portugal, Spain, and Thailand. Nevertheless, herd behavior is less pronounced in Australia and Germany under the same market condition. Therefore, the robustness results support the main methodology, the staggered return bipower variation method, that herd behavior is stronger when jumps occur during the period of negative market return. In general, the findings of the non-staggered return approach are in line with the staggered return bipower variation method’s. Conclusively, the behavioral change upon the occurrence of jump is mostly confirmed.

Table 2.7 Regression results for the effect of jump on herd behavior by using non-staggered return bipower variation with 99% confidence level.

Panel A: Regression results for the effect of jump on herd behavior by using non-staggered return bipower variation with 99% confidence level (Whole sample).
Note: This table reports regression statistics by using three equations which are
$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 CSAD_{t-1} + \gamma_3 D_j CSAD_{t-1} + \gamma_4 |R_{m,t}| + \gamma_5 D_j |R_{m,t}| + \gamma_6 (R_{m,t} - \overline{R_m})^2 + \gamma_7 D_j (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (Yao et al., 2014: YMH2),
$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 CSAD_{t-1} + \gamma_3 D_j CSAD_{t-1} + \gamma_4 |R_{m,t}| + \gamma_5 D_j |R_{m,t}| + \gamma_6 (|R_{m,t}| - \overline{R_m})^2 + \gamma_7 D_j (|R_{m,t}| - \overline{R_m})^2 + \varepsilon_t$ (Bui et al., 2017: BNNT), and
$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 CSAD_{t-1} + \gamma_3 D_j CSAD_{t-1} + \gamma_4 R_{m,t} + \gamma_5 D_j R_{m,t} + \gamma_6 |R_{m,t}| + \gamma_7 D_j |R_{m,t}| + \gamma_8 (R_{m,t})^2 + \gamma_9 D_j (R_{m,t})^2 + \varepsilon_t$ (Blasco et al., 2017: BCF),
where $CSAD_t$ is a cross-sectional absolute deviation of returns at time t, $R_{m,t}$ is an equally weighted portfolio return at time t, and $CSAD_{t-1}$ is a one-day lag of cross-sectional absolute deviation of returns at time t. D_j is a dummy variable which specifies jump date. It is equal to one in the jump date, and zero otherwise.
The sample interval is from 01/01/1996 to 30/06/2018.
The t-statistics are shown in parentheses which is calculated by using Newey & West (1987)'s heteroscedaticity and autocorrelation consistent standard errors.
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

Table 2.7 Panel A (continued)

	AUS			BRA		
Non-Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	1.169***	1.169***	1.181***	1.065***	1.067***	1.069***
	(17.08)	(17.09)	(17.11)	(29.76)	(30.23)	(30.63)
D_j	0.392*	0.392*	0.390*	-0.262***	-0.258***	-0.255***
	(1.65)	(1.65)	(1.72)	(-3.36)	(-3.30)	(-3.34)
$CSAD_{t-1}$	0.543***	0.543***	0.538***	0.091***	0.090***	0.087***
	(23.36)	(23.36)	(22.78)	(4.37)	(4.33)	(4.26)
D_jCSAD_{t-1}	-0.115	-0.115	-0.114	0.026	0.026	0.030
	(-1.49)	(-1.49)	(-1.57)	(0.60)	(0.61)	(0.71)
$\|R_{m,t}\|$	0.502***	0.503***	0.514***	0.749***	0.758***	0.744***
	(30.69)	(30.43)	(28.41)	(23.47)	(24.47)	(24.33)
$D_j\|R_{m,t}\|$	-0.040	-0.041	-0.045	0.460***	0.423***	0.403**
	(-0.98)	(-1.02)	(-1.03)	(2.99)	(2.75)	(2.49)
$(R_{m,t} - \overline{R_m})^2$	-0.005**			0.067***		
	(-2.23)			(8.75)		
$D_j(R_{m,t} - \overline{R_m})^2$	0.016***			-0.131*		
	(3.18)			(-1.67)		
$(\|R_{m,t}\| - \overline{R_m})^2$		-0.005**			0.069***	
		(-2.25)			(9.26)	
$D_j(\|R_{m,t}\| - \overline{R_m})^2$		0.016***			-0.128	
		(3.18)			(-1.48)	
$R_{m,t}$			0.023***			0.045*
			(2.63)			(1.83)
$D_jR_{m,t}$			-0.006			0.041
			(-0.16)			(0.74)
${R_{m,t}}^2$			-0.005*			0.072***
			(-1.73)			(9.75)
$D_j{R_{m,t}}^2$			0.016***			-0.111
			(3.27)			(-1.34)
$Adj. R^2$	0.743	0.743	0.743	0.702	0.703	0.705

Table 2.7 Panel A (continued)

	CAN			CHN		
Non-Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.443***	0.443***	0.445***	0.365***	0.358***	0.328***
	(10.62)	(10.62)	(10.49)	(17.38)	(17.17)	(15.75)
D_j	0.053	0.053	0.053	0.042	0.037	0.046
	(0.67)	(0.67)	(0.68)	(0.54)	(0.48)	(0.75)
$CSAD_{t-1}$	0.743***	0.743***	0.741***	0.670***	0.670***	0.691***
	(42.02)	(42.02)	(40.80)	(48.86)	(48.83)	(51.37)
D_jCSAD_{t-1}	0.004	0.004	0.003	-0.017	-0.017	-0.034
	(0.12)	(0.12)	(0.08)	(-0.32)	(-0.32)	(-0.79)
$\lvert R_{m,t}\rvert$	0.322***	0.322***	0.325***	0.134***	0.143***	0.164***
	(19.67)	(19.68)	(19.59)	(8.94)	(9.95)	(10.44)
$D_j\lvert R_{m,t}\rvert$	-0.012	-0.012	-0.010	-0.070	-0.062	-0.027
	(-0.38)	(-0.38)	(-0.29)	(-1.59)	(-1.47)	(-0.61)
$(R_{m,t}-\overline{R_m})^2$	0.005**			-0.006*		
	(2.46)			(-1.94)		
$D_j(R_{m,t}-\overline{R_m})^2$	-0.004			0.016*		
	(-0.58)			(1.96)		
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.005**			-0.008***	
		(2.47)			(-2.59)	
$D_j(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.004			0.015*	
		(-0.58)			(1.91)	
$R_{m,t}$			0.013			-0.072***
			(1.34)			(-15.53)
$D_jR_{m,t}$			0.004			-0.044***
			(0.29)			(-4.15)
${R_{m,t}}^2$			0.006***			-0.015***
			(2.70)			(-4.40)
$D_j{R_{m,t}}^2$			-0.004			0.006
			(-0.54)			(0.63)
$Adj.R^2$	0.835	0.835	0.835	0.619	0.620	0.679

Table 2.7 Panel A (continued)

	FRA			GER		
Non-Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.483***	0.482***	0.487***	0.395***	0.392***	0.401***
	(28.18)	(28.18)	(28.19)	(16.88)	(16.76)	(17.20)
D_j	0.066	0.066	0.059	0.004	-0.004	-0.005
	(1.24)	(1.25)	(1.14)	(0.05)	(-0.06)	(-0.07)
$CSAD_{t-1}$	0.624***	0.624***	0.620***	0.780***	0.779***	0.775***
	(60.56)	(60.55)	(59.68)	(86.06)	(85.98)	(85.41)
D_jCSAD_{t-1}	-0.038	-0.038	-0.033	0.012	0.012	0.012
	(-1.16)	(-1.16)	(-1.03)	(0.39)	(0.41)	(0.39)
$\lvert R_{m,t}\rvert$	0.537***	0.538***	0.533***	0.332***	0.341***	0.336***
	(27.82)	(27.84)	(27.11)	(13.30)	(13.28)	(13.75)
$D_j\lvert R_{m,t}\rvert$	-0.018	-0.019	-0.009	0.081	0.113	0.099
	(-0.37)	(-0.39)	(-0.18)	(1.11)	(1.52)	(1.33)
$\left(R_{m,t}-\overline{R_m}\right)^2$	-0.013*			0.015		
	(-1.67)			(1.62)		
$D_j\left(R_{m,t}-\overline{R_m}\right)^2$	-0.008			-0.052		
	(-0.49)			(-1.50)		
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		-0.013*			0.011	
		(-1.72)			(1.23)	
$D_j\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		-0.007			-0.067**	
		(-0.46)			(-2.03)	
$R_{m,t}$			0.036***			0.070***
			(4.04)			(7.55)
$D_jR_{m,t}$			-0.050**			0.031
			(-1.99)			(1.19)
${R_{m,t}}^2$			-0.003			0.025***
			(-0.31)			(2.83)
$D_j{R_{m,t}}^2$			-0.022			-0.054
			(-1.23)			(-1.39)
$Adj.R^2$	0.777	0.777	0.779	0.806	0.806	0.810

Table 2.7 Panel A (continued)

	GRE			IND		
Non-Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.560***	0.562***	0.553***	0.404***	0.403***	0.403***
	(15.41)	(15.43)	(15.43)	(13.90)	(13.88)	(13.94)
D_j	-0.027	-0.028	-0.016	-0.038	-0.038	-0.033
	(-0.36)	(-0.37)	(-0.21)	(-0.54)	(-0.54)	(-0.46)
$CSAD_{t-1}$	0.649***	0.649***	0.651***	0.762***	0.762***	0.760***
	(40.46)	(40.45)	(40.91)	(62.63)	(62.63)	(62.65)
D_jCSAD_{t-1}	0.016	0.016	0.012	0.011	0.011	0.013
	(0.45)	(0.46)	(0.34)	(0.32)	(0.32)	(0.38)
$\lvert R_{m,t}\rvert$	0.321***	0.320***	0.324***	0.441***	0.442***	0.457***
	(10.05)	(9.97)	(10.50)	(13.80)	(13.68)	(14.29)
$D_j\lvert R_{m,t}\rvert$	-0.053	-0.052	-0.059	0.173	0.172	0.124
	(-0.95)	(-0.94)	(-1.04)	(1.50)	(1.48)	(1.05)
$\left(R_{m,t}-\overline{R_m}\right)^2$	-0.033***			0.026**		
	(-4.35)			(2.01)		
$D_j\left(R_{m,t}-\overline{R_m}\right)^2$	0.018			-0.037		
	(1.24)			(-1.04)		
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		-0.032***			0.025**	
		(-4.31)			(1.98)	
$D_j\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		0.018			-0.036	
		(1.24)			(-1.01)	
$R_{m,t}$			-0.022***			0.037***
			(-3.01)			(3.02)
$D_jR_{m,t}$			0.033			-0.069
			(1.04)			(-1.30)
${R_{m,t}}^2$			-0.034***			0.019
			(-4.71)			(1.56)
$D_j{R_{m,t}}^2$			0.021			-0.017
			(1.31)			(-0.40)
$Adj.R^2$	0.560	0.560	0.562	0.877	0.877	0.877

Table 2.7 Panel A (continued)

	IRE			ITA		
Non-Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.872***	0.872***	0.877***	0.720***	0.719***	0.723***
	(18.72)	(18.72)	(18.70)	(4.99)	(4.99)	(4.98)
D_j	0.071	0.071	0.071	-0.231	-0.233	-0.231
	(0.84)	(0.84)	(0.83)	(-1.40)	(-1.42)	(-1.39)
$CSAD_{t-1}$	0.378***	0.378***	0.377***	0.465***	0.465***	0.462***
	(17.31)	(17.31)	(17.20)	(5.39)	(5.40)	(5.29)
D_jCSAD_{t-1}	-0.117***	-0.117***	-0.119***	0.137	0.137	0.138
	(-3.20)	(-3.20)	(-3.21)	(1.36)	(1.37)	(1.36)
$\lvert R_{m,t}\rvert$	0.752***	0.752***	0.745***	0.107	0.106	0.107
	(19.86)	(19.85)	(19.30)	(1.28)	(1.24)	(1.27)
$D_j\lvert R_{m,t}\rvert$	0.054	0.054	0.059	0.105	0.112	0.087
	(0.63)	(0.64)	(0.71)	(1.01)	(1.06)	(0.85)
$(R_{m,t}-\overline{R_m})^2$	0.010			0.069*		
	(1.11)			(1.78)		
$D_j(R_{m,t}-\overline{R_m})^2$	0.051**			-0.052		
	(2.05)			(-1.09)		
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.010			0.069*	
		(1.12)			(1.78)	
$D_j(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.051**			-0.054	
		(2.05)			(-1.13)	
$R_{m,t}$			0.027			0.012
			(1.56)			(1.28)
$D_jR_{m,t}$			0.006			0.037*
			(0.20)			(1.71)
${R_{m,t}}^2$			0.013			0.071*
			(1.40)			(1.80)
$D_j{R_{m,t}}^2$			0.050**			-0.036
			(2.10)			(-0.75)
$Adj.R^2$	0.608	0.608	0.609	0.680	0.679	0.681

Table 2.7 Panel A (continued)

	JAP			POR		
Non-Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.315***	0.315***	0.310***	0.919***	0.919***	0.917***
	(11.19)	(11.19)	(11.57)	(29.81)	(29.97)	(29.29)
D_j	-0.035	-0.036	-0.030	-0.081	-0.083	-0.075
	(-0.75)	(-0.75)	(-0.65)	(-1.37)	(-1.41)	(-1.31)
$CSAD_{t-1}$	0.716***	0.716***	0.721***	0.103***	0.103***	0.102***
	(38.45)	(38.44)	(40.69)	(7.54)	(7.56)	(7.41)
D_jCSAD_{t-1}	0.029	0.029	0.023	-0.022	-0.022	-0.024
	(0.95)	(0.95)	(0.77)	(-0.74)	(-0.75)	(-0.81)
$\|R_{m,t}\|$	0.223***	0.223***	0.219***	0.851***	0.848***	0.858***
	(10.93)	(10.84)	(10.64)	(15.24)	(15.14)	(15.38)
$D_j\|R_{m,t}\|$	-0.010	-0.009	-0.006	0.212*	0.224*	0.196*
	(-0.27)	(-0.26)	(-0.17)	(1.72)	(1.81)	(1.76)
$(R_{m,t} - \overline{R_m})^2$	-0.001			0.097***		
	(-0.14)			(4.47)		
$D_j(R_{m,t} - \overline{R_m})^2$	0.009			-0.106**		
	(0.71)			(-2.17)		
$(\|R_{m,t}\| - \overline{R_m})^2$		-0.001			0.096***	
		(-0.13)			(4.50)	
$D_j(\|R_{m,t}\| - \overline{R_m})^2$		0.009			-0.108**	
		(0.70)			(-2.25)	
$R_{m,t}$			-0.026***			0.033
			(-4.72)			(1.44)
$D_jR_{m,t}$			0.034***			0.070
			(2.73)			(1.38)
${R_{m,t}}^2$			-0.002			0.096***
			(-0.37)			(4.35)
$D_j{R_{m,t}}^2$			0.011			-0.098**
			(0.86)			(-2.31)
$Adj.R^2$	0.808	0.808	0.810	0.670	0.670	0.672

Table 2.7 Panel A (continued)

	RUS			SAF		
Non-Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	1.251***	1.252***	1.254***	1.126***	1.126***	1.126***
	(17.37)	(17.43)	(17.99)	(27.53)	(27.52)	(27.53)
D_j	-0.153	-0.149	-0.146	0.155	0.155	0.142
	(-0.90)	(-0.88)	(-0.87)	(1.40)	(1.39)	(1.28)
$CSAD_{t-1}$	0.124***	0.124***	0.122***	0.383***	0.383***	0.383***
	(3.16)	(3.17)	(3.23)	(21.55)	(21.55)	(21.59)
D_jCSAD_{t-1}	0.130	0.130	0.132	-0.050	-0.050	-0.045
	(1.56)	(1.56)	(1.58)	(-1.10)	(-1.11)	(-1.00)
$\lvert R_{m,t}\rvert$	0.925***	0.928***	0.921***	0.701***	0.701***	0.704***
	(13.38)	(13.49)	(13.89)	(16.81)	(16.89)	(16.38)
$D_j\lvert R_{m,t}\rvert$	-0.012	-0.025	-0.040	-0.147	-0.144	-0.124
	(-0.11)	(-0.24)	(-0.38)	(-1.60)	(-1.57)	(-1.28)
$\left(R_{m,t}-\overline{R_m}\right)^2$	0.038***			-0.028		
	(6.63)			(-1.25)		
$D_j\left(R_{m,t}-\overline{R_m}\right)^2$	-0.038*			0.069**		
	(-1.77)			(2.28)		
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		0.038***			-0.028	
		(6.58)			(-1.26)	
$D_j\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		-0.036			0.069**	
		(-1.62)			(2.28)	
$R_{m,t}$			0.060			-0.004
			(1.22)			(-0.22)
$D_jR_{m,t}$			-0.022			-0.055
			(-0.38)			(-1.31)
${R_{m,t}}^2$			0.040***			-0.030
			(6.88)			(-1.27)
$D_j{R_{m,t}}^2$			-0.031			0.054
			(-1.38)			(1.64)
$Adj.R^2$	0.758	0.758	0.760	0.451	0.451	0.451

Table 2.7 Panel A (continued)

	SPA			THA		
Non-Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.875***	0.875***	0.874***	0.265***	0.265***	0.265***
	(6.27)	(6.27)	(6.27)	(12.43)	(12.42)	(12.56)
D_j	-0.210	-0.210	-0.209	-0.017	-0.017	-0.015
	(-1.34)	(-1.34)	(-1.34)	(-0.24)	(-0.23)	(-0.21)
$CSAD_{t-1}$	0.227**	0.227**	0.225**	0.671***	0.671***	0.671***
	(2.13)	(2.13)	(2.12)	(53.34)	(53.34)	(54.01)
D_jCSAD_{t-1}	0.075	0.075	0.076	0.002	0.002	0.002
	(0.62)	(0.62)	(0.62)	(0.05)	(0.05)	(0.04)
$\lvert R_{m,t}\rvert$	0.150***	0.151***	0.153***	0.532***	0.532***	0.531***
	(2.58)	(2.59)	(2.63)	(26.89)	(26.76)	(26.72)
$D_j\lvert R_{m,t}\rvert$	0.280***	0.280***	0.280***	0.073	0.073	0.078
	(4.15)	(4.15)	(4.12)	(0.73)	(0.72)	(0.78)
$\left(R_{m,t}-\overline{R_m}\right)^2$	0.149***			-0.007		
	(5.81)			(-1.41)		
$D_j\left(R_{m,t}-\overline{R_m}\right)^2$	-0.138***			-0.028		
	(-5.08)			(-0.75)		
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		0.149***			-0.007	
		(5.81)			(-1.40)	
$D_j\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		-0.138***			-0.027	
		(-5.08)			(-0.74)	
$R_{m,t}$			0.025			-0.006
			(1.54)			(-0.48)
$D_jR_{m,t}$			-0.016			-0.023
			(-0.67)			(-0.68)
${R_{m,t}}^2$			0.151***			-0.008
			(5.83)			(-1.42)
$D_j{R_{m,t}}^2$			-0.140***			-0.033
			(-5.05)			(-0.87)
$Adj.R^2$	0.721	0.721	0.721	0.847	0.847	0.847

Table 2.7 Panel A (continued)

	UAE			UK		
Non-Staggered Return	YMH (2)	BNNT	BCF	YMH (2)	BNNT	BCF
$Intercept$	0.561***	0.561***	0.561***	0.425***	0.424***	0.430***
	(20.42)	(20.40)	(20.28)	(20.99)	(20.97)	(21.18)
D_j	-0.034	-0.034	-0.034	0.037	0.036	0.039
	(-0.74)	(-0.74)	(-0.75)	(0.54)	(0.52)	(0.56)
$CSAD_{t-1}$	0.311***	0.311***	0.311***	0.664***	0.664***	0.658***
	(15.19)	(15.19)	(15.11)	(56.34)	(56.35)	(55.71)
D_jCSAD_{t-1}	0.058*	0.058*	0.058*	-0.045	-0.045	-0.047
	(1.81)	(1.81)	(1.82)	(-1.10)	(-1.10)	(-1.13)
$\lvert R_{m,t}\rvert$	0.866***	0.865***	0.862***	0.465***	0.469***	0.470***
	(23.36)	(23.40)	(21.79)	(26.44)	(26.23)	(26.90)
$D_j\lvert R_{m,t}\rvert$	-0.014	-0.014	-0.012	0.077	0.084	0.076
	(-0.21)	(-0.21)	(-0.17)	(1.18)	(1.27)	(1.18)
$\left(R_{m,t} - \overline{R_m}\right)^2$	-0.050***			-0.016**		
	(-3.05)			(-2.15)		
$D_j\left(R_{m,t} - \overline{R_m}\right)^2$	-0.013			-0.029		
	(-0.43)			(-0.69)		
$\left(\lvert R_{m,t}\rvert - \overline{R_m}\right)^2$		-0.049***			-0.017**	
		(-3.03)			(-2.32)	
$D_j\left(\lvert R_{m,t}\rvert - \overline{R_m}\right)^2$		-0.013			-0.032	
		(-0.43)			(-0.78)	
$R_{m,t}$			0.026			0.046***
			(1.40)			(5.25)
$D_jR_{m,t}$			-0.028			-0.004
			(-1.06)			(-0.15)
${R_{m,t}}^2$			-0.047***			-0.006
			(-2.61)			(-0.74)
$D_j{R_{m,t}}^2$			-0.016			-0.034
			(-0.51)			(-0.77)
$Adj. R^2$	0.696	0.696	0.696	0.814	0.814	0.816

Table 2.7 Panel A (continued)

	USA		
Non-Staggered Return	YMH (2)	BNNT	BCF
$Intercept$	0.252***	0.252***	0.252***
	(12.56)	(12.55)	(12.59)
D_j	-0.008	-0.008	-0.004
	(-0.17)	(-0.15)	(-0.08)
$CSAD_{t-1}$	0.759***	0.759***	0.760***
	(57.66)	(57.62)	(57.94)
D_jCSAD_{t-1}	0.030	0.030	0.029
	(0.90)	(0.90)	(0.89)
$\lvert R_{m,t}\rvert$	0.135***	0.135***	0.135***
	(10.60)	(10.74)	(10.64)
$D_j\lvert R_{m,t}\rvert$	-0.029	-0.030	-0.040*
	(-1.24)	(-1.32)	(-1.74)
$\left(R_{m,t}-\overline{R_m}\right)^2$	0.008**		
	(2.45)		
$D_j\left(R_{m,t}-\overline{R_m}\right)^2$	-0.003		
	(-0.54)		
$\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		0.008**	
		(2.43)	
$D_j\left(\lvert R_{m,t}\rvert-\overline{R_m}\right)^2$		-0.002	
		(-0.46)	
$R_{m,t}$			-0.002
			(-0.40)
$D_jR_{m,t}$			0.019*
			(1.71)
${R_{m,t}}^2$			0.008**
			(2.41)
$D_j{R_{m,t}}^2$			0.001
			(0.13)
$Adj.R^2$	0.832	0.832	0.832

Panel B: Regression results for the effect of jump on herd behavior by using non-staggered return bipower variation with 99% confidence level (Asymmetric market condition).

Note: This table reports regression statistics comparing between down markets and other markets by using two equations which are

$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 D_d + \gamma_3 D_j D_d + \gamma_4 CSAD_{t-1} + \gamma_5 D_j CSAD_{t-1} + \gamma_6 D_d CSAD_{t-1} + \gamma_7 D_j D_d CSAD_{t-1} + \gamma_8 |R_{m,t}| + \gamma_9 D_j |R_{m,t}| + \gamma_{10} D_d |R_{m,t}| + \gamma_{11} D_j D_d |R_{m,t}| + \gamma_{12} (R_{m,t} - \overline{R_m})^2 + \gamma_{13} D_j (R_{m,t} - \overline{R_m})^2 + \gamma_{14} D_d (R_{m,t} - \overline{R_m})^2 + \gamma_{15} D_j D_d (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (Yao et al., 2014: YMH2), and

$CSAD_t = \propto + \gamma_1 D_j + \gamma_2 D_d + \gamma_3 D_j D_d + \gamma_4 CSAD_{t-1} + \gamma_5 D_j CSAD_{t-1} + \gamma_6 D_d CSAD_{t-1} + \gamma_7 D_j D_d CSAD_{t-1} + \gamma_8 |R_{m,t}| + \gamma_9 D_j |R_{m,t}| + \gamma_{10} D_d |R_{m,t}| + \gamma_{11} D_j D_d |R_{m,t}| + \gamma_{12} (|R_{m,t}| - \overline{R_m})^2 + \gamma_{13} D_j (|R_{m,t}| - \overline{R_m})^2 + \gamma_{14} D_d (|R_{m,t}| - \overline{R_m})^2 + \gamma_{15} D_j D_d (|R_{m,t}| - \overline{R_m})^2 + \varepsilon_t$ (Bui et al., 2017: BNNT),

where *$CSAD_t$* is a cross-sectional absolute deviation of returns at time t, *$R_{m,t}$* is an equally weighted portfolio return at time t, and *$CSAD_{t-1}$* is a one-day lag of cross-sectional absolute deviation of returns at time t. *D_j* is a dummy variable which specifies jump date. It is equal to one in the jump date, and zero otherwise. *D_d* is a dummy variable which specifies down markets dates. It is equal to one during the negative market return date, and zero otherwise.

The sample interval is from 01/01/1996 to 30/06/2018.

The t-statistics are shown in parentheses which is calculated by using Newey & West (1987)'s heteroscedaticity and autocorrelation consistent standard errors.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

Table 2.7 Panel B (continued)

	AUS		BRA		CAN	
Non-Staggered Return	YMH (2)	BNNT	YMH (2)	BNNT	YMH (2)	BNNT
$Intercept$	1.187***	1.187***	1.034***	1.034***	0.501***	0.501***
	(10.56)	(10.56)	(19.44)	(19.44)	(7.23)	(7.23)
D_j	0.229	0.229	-0.156*	-0.156*	-0.158	-0.158
	(1.27)	(1.27)	(-1.65)	(-1.65)	(-1.36)	(-1.36)
D_d	-0.031	-0.031	0.064	0.064	-0.104	-0.104
	(-0.23)	(-0.23)	(0.99)	(0.99)	(-1.17)	(-1.17)
D_jD_d	-0.140	-0.140	-0.033	-0.033	0.408***	0.408***
	(-0.59)	(-0.59)	(-0.26)	(-0.26)	(2.60)	(2.60)
$CSAD_{t-1}$	0.532***	0.532***	0.086***	0.086***	0.720***	0.720***
	(13.71)	(13.71)	(3.33)	(3.33)	(25.74)	(25.74)
D_jCSAD_{t-1}	-0.098	-0.098	0.084	0.084	0.091*	0.091*
	(-1.55)	(-1.55)	(1.52)	(1.52)	(1.91)	(1.91)
D_dCSAD_{t-1}	0.015	0.015	0.005	0.005	0.040	0.040
	(0.33)	(0.33)	(0.13)	(0.13)	(1.07)	(1.07)
$D_jD_dCSAD_{t-1}$	0.083	0.083	-0.125	-0.125	-0.168***	-0.168***
	(1.00)	(1.00)	(-1.57)	(-1.57)	(-2.63)	(-2.63)
$\lvert R_{m,t}\rvert$	0.576***	0.576***	0.843***	0.843***	0.324***	0.324***
	(18.06)	(18.06)	(8.85)	(8.85)	(10.71)	(10.71)
$D_j\lvert R_{m,t}\rvert$	0.369***	0.369***	-0.133	-0.133	-0.018	-0.018
	(3.50)	(3.50)	(-0.83)	(-0.83)	(-0.40)	(-0.40)
$D_d\lvert R_{m,t}\rvert$	-0.106***	-0.106***	-0.191*	-0.160	-0.015	-0.014
	(-2.84)	(-2.83)	(-1.79)	(-1.50)	(-0.39)	(-0.39)
$D_jD_d\lvert R_{m,t}\rvert$	-0.441***	-0.443***	0.668***	0.605***	0.005	0.006
	(-3.64)	(-3.64)	(2.89)	(2.77)	(0.09)	(0.09)
$(R_{m,t}-\overline{R_m})^2$	-0.016***		0.068		0.016	
	(-2.86)		(1.41)		(1.05)	
$D_j(R_{m,t}-\overline{R_m})^2$	-0.144***		0.178*		-0.019	
	(-3.17)		(1.72)		(-1.11)	
$D_d(R_{m,t}-\overline{R_m})^2$	0.016**		0.006		-0.011	
	(2.37)		(0.13)		(-0.71)	
$D_jD_d(R_{m,t}-\overline{R_m})^2$	0.159***		-0.328***		0.021	
	(3.39)		(-2.66)		(1.11)	
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.016***		0.068		0.016
		(-2.86)		(1.41)		(1.05)
$D_j(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.144***		0.178*		-0.019
		(-3.17)		(1.72)		(-1.11)
$D_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.016**		0.006		-0.011
		(2.37)		(0.13)		(-0.71)
$D_jD_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.159***		-0.328***		0.021
		(3.39)		(-2.66)		(1.11)
$Adj.R^2$	0.751	0.751	0.707	0.707	0.836	0.836

Table 2.7 Panel B (continued)

	CHN		FRA		GER	
Non-Staggered Return	YMH (2)	BNNT	YMH (2)	BNNT	YMH (2)	BNNT
$Intercept$	0.433***	0.433***	0.495***	0.495***	0.378***	0.378***
	(16.29)	(16.29)	(18.16)	(18.16)	(11.52)	(11.52)
D_j	0.080	0.080	0.007	0.007	-0.031	-0.031
	(1.22)	(1.22)	(0.10)	(0.10)	(-0.28)	(-0.28)
D_d	-0.248***	-0.248***	0.013	0.013	0.055	0.055
	(-5.90)	(-5.90)	(0.36)	(0.36)	(1.13)	(1.13)
D_jD_d	-0.042	-0.042	0.060	0.060	0.017	0.017
	(-0.38)	(-0.38)	(0.60)	(0.60)	(0.11)	(0.11)
$CSAD_{t-1}$	0.632***	0.632***	0.621***	0.621***	0.783***	0.783***
	(35.71)	(35.71)	(41.36)	(41.36)	(60.94)	(60.94)
D_jCSAD_{t-1}	-0.025	-0.025	-0.015	-0.015	0.009	0.009
	(-0.51)	(-0.51)	(-0.38)	(-0.38)	(0.21)	(0.21)
D_dCSAD_{t-1}	0.154***	0.154***	-0.009	-0.009	-0.018	-0.018
	(5.49)	(5.49)	(-0.43)	(-0.43)	(-0.92)	(-0.92)
$D_jD_dCSAD_{t-1}$	-0.015	-0.015	-0.025	-0.025	0.014	0.014
	(-0.19)	(-0.19)	(-0.40)	(-0.40)	(0.25)	(0.25)
$\lvert R_{m,t}\rvert$	0.045**	0.045**	0.474***	0.474***	0.397***	0.397***
	(2.45)	(2.45)	(10.79)	(10.79)	(10.35)	(10.35)
$D_j\lvert R_{m,t}\rvert$	-0.149***	-0.149***	0.103	0.103	0.316**	0.316**
	(-3.17)	(-3.17)	(0.87)	(0.87)	(2.54)	(2.54)
$D_d\lvert R_{m,t}\rvert$	0.225***	0.220***	0.037	0.037	-0.130***	-0.134***
	(8.28)	(8.26)	(0.76)	(0.76)	(-2.66)	(-2.68)
$D_jD_d\lvert R_{m,t}\rvert$	0.191***	0.191***	-0.086	-0.086	-0.377**	-0.379**
	(2.73)	(2.78)	(-0.63)	(-0.63)	(-2.46)	(-2.42)
$(R_{m,t}-\overline{R_m})^2$	-0.002		0.069**		0.029*	
	(-0.52)		(2.09)		(1.71)	
$D_j(R_{m,t}-\overline{R_m})^2$	0.023**		-0.152		-0.160**	
	(2.54)		(-1.56)		(-2.33)	
$D_d(R_{m,t}-\overline{R_m})^2$	-0.020***		-0.082**		-0.004	
	(-3.58)		(-2.42)		(-0.20)	
$D_jD_d(R_{m,t}-\overline{R_m})^2$	-0.022*		0.144		0.174**	
	(-1.75)		(1.45)		(2.15)	
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.002		0.069**		0.029*
		(-0.52)		(2.09)		(1.71)
$D_j(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.023**		-0.152		-0.160**
		(2.54)		(-1.56)		(-2.33)
$D_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.020***		-0.082**		-0.004
		(-3.58)		(-2.42)		(-0.20)
$D_jD_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.022*		0.144		0.174**
		(-1.75)		(1.45)		(2.15)
$Adj.R^2$	0.689	0.689	0.780	0.780	0.810	0.810

Table 2.7 Panel B (continued)

	GRE		IND		IRE	
Non-Staggered Return	YMH (2)	BNNT	YMH (2)	BNNT	YMH (2)	BNNT
$Intercept$	0.593***	0.593***	0.434***	0.434***	0.882***	0.882***
	(14.13)	(14.13)	(9.40)	(9.40)	(11.58)	(11.58)
D_j	-0.030	-0.030	-0.182**	-0.182**	0.006	0.006
	(-0.33)	(-0.33)	(-2.02)	(-2.02)	(0.05)	(0.05)
D_d	-0.105	-0.105	-0.073	-0.073	0.031	0.031
	(-1.50)	(-1.50)	(-1.34)	(-1.34)	(0.32)	(0.32)
D_jD_d	0.088	0.088	0.299**	0.299**	0.101	0.101
	(0.58)	(0.58)	(2.20)	(2.20)	(0.61)	(0.61)
$CSAD_{t-1}$	0.617***	0.617***	0.739***	0.739***	0.368***	0.368***
	(31.11)	(31.11)	(35.58)	(35.58)	(12.74)	(12.74)
D_jCSAD_{t-1}	0.062	0.062	0.089*	0.089*	-0.122**	-0.122**
	(1.54)	(1.54)	(1.88)	(1.88)	(-2.34)	(-2.34)
D_dCSAD_{t-1}	0.065**	0.065**	0.031	0.031	0.015	0.015
	(2.07)	(2.07)	(1.29)	(1.29)	(0.36)	(0.36)
$D_jD_dCSAD_{t-1}$	-0.093	-0.093	-0.142**	-0.142**	0.010	0.010
	(-1.38)	(-1.38)	(-2.16)	(-2.16)	(0.13)	(0.13)
$\lvert R_{m,t}\rvert$	0.436***	0.436***	0.493***	0.493***	0.695***	0.695***
	(15.68)	(15.68)	(10.34)	(10.34)	(8.19)	(8.19)
$D_j\lvert R_{m,t}\rvert$	-0.306***	-0.306***	-0.057	-0.057	0.204*	0.204*
	(-2.60)	(-2.60)	(-0.34)	(-0.34)	(1.90)	(1.90)
$D_d\lvert R_{m,t}\rvert$	-0.149***	-0.148***	0.069	0.071	0.019	0.019
	(-3.48)	(-3.42)	(0.95)	(0.98)	(0.19)	(0.20)
$D_jD_d\lvert R_{m,t}\rvert$	0.330**	0.331**	0.305	0.306	-0.223	-0.222
	(2.52)	(2.52)	(1.17)	(1.15)	(-1.37)	(-1.36)
$(R_{m,t}-\overline{R_m})^2$	-0.065***		0.031**		0.044*	
	(-9.96)		(2.06)		(1.67)	
$D_j(R_{m,t}-\overline{R_m})^2$	0.088**		-0.008		0.017	
	(2.34)		(-0.20)		(0.58)	
$D_d(R_{m,t}-\overline{R_m})^2$	0.044***		-0.084***		-0.037	
	(4.41)		(-2.99)		(-1.35)	
$D_jD_d(R_{m,t}-\overline{R_m})^2$	-0.092**		-0.021		0.045	
	(-2.37)		(-0.16)		(1.00)	
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.065***		0.031**		0.044*
		(-9.96)		(2.06)		(1.67)
$D_j(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.088**		-0.008		0.017
		(2.34)		(-0.20)		(0.58)
$D_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.044***		-0.084***		-0.037
		(4.41)		(-2.99)		(-1.35)
$D_jD_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.092**		-0.021		0.045
		(-2.37)		(-0.16)		(1.00)
$Adj.R^2$	0.572	0.572	0.879	0.879	0.610	0.610

Table 2.7 Panel B (continued)

	ITA		JAP		POR	
Non-Staggered Return	YMH (2)	BNNT	YMH (2)	BNNT	YMH (2)	BNNT
$Intercept$	0.774***	0.774***	0.296***	0.296***	0.863***	0.863***
	(4.54)	(4.54)	(9.57)	(9.57)	(23.20)	(23.20)
D_j	-0.282	-0.282	-0.063	-0.063	0.024	0.024
	(-1.40)	(-1.40)	(-0.96)	(-0.96)	(0.26)	(0.26)
D_d	-0.202	-0.202	0.019	0.019	0.123**	0.123**
	(-1.32)	(-1.32)	(0.35)	(0.35)	(2.25)	(2.25)
D_jD_d	0.216	0.216	0.085	0.085	-0.188	-0.188
	(1.00)	(1.00)	(0.90)	(0.90)	(-1.58)	(-1.58)
$CSAD_{t-1}$	0.397***	0.397***	0.740***	0.740***	0.106***	0.106***
	(3.43)	(3.43)	(38.28)	(38.28)	(6.38)	(6.38)
D_jCSAD_{t-1}	0.206	0.206	0.047	0.047	-0.008	-0.008
	(1.52)	(1.52)	(1.17)	(1.17)	(-0.15)	(-0.15)
D_dCSAD_{t-1}	0.175	0.175	-0.034	-0.034	-0.010	-0.010
	(1.59)	(1.59)	(-1.01)	(-1.01)	(-0.38)	(-0.38)
$D_jD_dCSAD_{t-1}$	-0.184	-0.184	-0.057	-0.057	-0.026	-0.026
	(-1.24)	(-1.24)	(-0.96)	(-0.96)	(-0.40)	(-0.40)
$\lvert R_{m,t}\rvert$	0.280***	0.280***	0.192***	0.192***	0.970***	0.970***
	(9.69)	(9.69)	(11.50)	(11.50)	(12.45)	(12.45)
$D_j\lvert R_{m,t}\rvert$	-0.083	-0.083	-0.007	-0.007	-0.032	-0.032
	(-0.78)	(-0.78)	(-0.13)	(-0.13)	(-0.18)	(-0.18)
$D_d\lvert R_{m,t}\rvert$	-0.241*	-0.246*	0.059	0.059	-0.243**	-0.252**
	(-1.96)	(-1.96)	(1.60)	(1.59)	(-2.36)	(-2.42)
$D_jD_d\lvert R_{m,t}\rvert$	0.193	0.197	-0.007	-0.007	0.377*	0.389*
	(1.09)	(1.09)	(-0.10)	(-0.10)	(1.70)	(1.75)
$(R_{m,t}-\overline{R_m})^2$	0.005		-0.008		0.078**	
	(0.47)		(-1.58)		(2.47)	
$D_j(R_{m,t}-\overline{R_m})^2$	0.059		0.023		-0.008	
	(0.98)		(0.97)		(-0.11)	
$D_d(R_{m,t}-\overline{R_m})^2$	0.080*		0.007		0.043	
	(1.86)		(0.78)		(1.06)	
$D_jD_d(R_{m,t}-\overline{R_m})^2$	-0.113		-0.018		-0.150*	
	(-1.39)		(-0.67)		(-1.77)	
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.005		-0.008		0.078**
		(0.47)		(-1.58)		(2.47)
$D_j(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.059		0.023		-0.008
		(0.98)		(0.97)		(-0.11)
$D_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.080*		0.007		0.043
		(1.86)		(0.78)		(1.06)
$D_jD_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.113		-0.018		-0.150*
		(-1.39)		(-0.67)		(-1.77)
$Adj.R^2$	0.692	0.692	0.812	0.812	0.673	0.673

Table 2.7 Panel B (continued)

	RUS		SAF		SPA	
Non-Staggered Return	YMH (2)	BNNT	YMH (2)	BNNT	YMH (2)	BNNT
$Intercept$	1.136***	1.136***	1.255***	1.255***	0.851***	0.851***
	(12.42)	(12.42)	(20.17)	(20.17)	(7.06)	(7.06)
D_j	-0.003	-0.003	0.143	0.143	-0.434***	-0.434***
	(-0.01)	(-0.01)	(0.86)	(0.86)	(-3.44)	(-3.44)
D_d	0.215*	0.215*	-0.220***	-0.220***	-0.193	-0.193
	(1.67)	(1.67)	(-2.58)	(-2.58)	(-1.63)	(-1.63)
D_jD_d	-0.229	-0.229	-0.039	-0.039	0.593***	0.593***
	(-0.72)	(-0.72)	(-0.17)	(-0.17)	(4.20)	(4.20)
$CSAD_{t-1}$	0.161***	0.161***	0.340***	0.340***	0.158	0.158
	(4.43)	(4.43)	(13.63)	(13.63)	(1.57)	(1.57)
D_jCSAD_{t-1}	0.106	0.106	-0.049	-0.049	0.337***	0.337***
	(1.05)	(1.05)	(-0.79)	(-0.79)	(3.18)	(3.18)
D_dCSAD_{t-1}	-0.063	-0.063	0.087**	0.087**	0.273***	0.273***
	(-1.06)	(-1.06)	(2.46)	(2.46)	(2.62)	(2.62)
$D_jD_dCSAD_{t-1}$	0.036	0.036	0.018	0.018	-0.567***	-0.567***
	(0.23)	(0.23)	(0.21)	(0.21)	(-4.68)	(-4.68)
$\lvert R_{m,t}\rvert$	0.984***	0.984***	0.481***	0.481***	0.498***	0.498***
	(6.77)	(6.77)	(5.58)	(5.58)	(9.42)	(9.42)
$D_j\lvert R_{m,t}\rvert$	-0.247	-0.247	-0.074	-0.074	-0.038	-0.038
	(-1.34)	(-1.34)	(-0.37)	(-0.37)	(-0.60)	(-0.60)
$D_d\lvert R_{m,t}\rvert$	-0.143	-0.132	0.239**	0.237**	-0.500***	-0.499***
	(-0.82)	(-0.76)	(2.38)	(2.36)	(-5.99)	(-5.99)
$D_jD_d\lvert R_{m,t}\rvert$	0.360	0.344	-0.018	-0.014	0.398***	0.398***
	(1.49)	(1.45)	(-0.08)	(-0.06)	(3.80)	(3.79)
$(R_{m,t} - \overline{R_m})^2$	0.041		0.149**		0.037*	
	(1.16)		(2.21)		(1.65)	
$D_j(R_{m,t} - \overline{R_m})^2$	0.034		-0.039		-0.049**	
	(0.65)		(-0.33)		(-2.14)	
$D_d(R_{m,t} - \overline{R_m})^2$	-0.001		-0.199***		0.136***	
	(-0.02)		(-2.85)		(4.73)	
$D_jD_d(R_{m,t} - \overline{R_m})^2$	-0.095		0.111		-0.090***	
	(-1.62)		(0.91)		(-2.62)	
$(\lvert R_{m,t}\rvert - \overline{R_m})^2$		0.041		0.149**		0.037*
		(1.16)		(2.21)		(1.65)
$D_j(\lvert R_{m,t}\rvert - \overline{R_m})^2$		0.034		-0.039		-0.049**
		(0.65)		(-0.33)		(-2.14)
$D_d(\lvert R_{m,t}\rvert - \overline{R_m})^2$		-0.001		-0.199***		0.136***
		(-0.02)		(-2.85)		(4.73)
$D_jD_d(\lvert R_{m,t}\rvert - \overline{R_m})^2$		-0.095		0.111		-0.090***
		(-1.62)		(0.91)		(-2.62)
$Adj.R^2$	0.761	0.761	0.455	0.455	0.750	0.750

Table 2.7 Panel B (continued)

	THA		UAE		UK	
Non-Staggered Return	YMH (2)	BNNT	YMH (2)	BNNT	YMH (2)	BNNT
$Intercept$	0.265***	0.265***	0.576***	0.576***	0.434***	0.434***
	(8.72)	(8.72)	(12.75)	(12.75)	(13.39)	(13.39)
D_j	-0.003	-0.003	-0.044	-0.044	0.018	0.018
	(-0.03)	(-0.03)	(-0.68)	(-0.68)	(0.19)	(0.19)
D_d	-0.002	-0.002	-0.027	-0.027	0.010	0.010
	(-0.05)	(-0.05)	(-0.51)	(-0.51)	(0.23)	(0.23)
D_jD_d	0.045	0.045	0.051	0.051	0.060	0.060
	(0.31)	(0.31)	(0.61)	(0.61)	(0.39)	(0.39)
$CSAD_{t-1}$	0.655***	0.655***	0.310***	0.310***	0.651***	0.651***
	(36.44)	(36.44)	(9.57)	(9.57)	(35.79)	(35.79)
D_jCSAD_{t-1}	0.070	0.070	0.079*	0.079*	-0.038	-0.038
	(1.28)	(1.28)	(1.66)	(1.66)	(-0.70)	(-0.70)
D_dCSAD_{t-1}	0.031	0.031	-0.001	-0.001	0.010	0.010
	(1.31)	(1.31)	(-0.01)	(-0.01)	(0.44)	(0.44)
$D_jD_dCSAD_{t-1}$	-0.123	-0.123	-0.045	-0.045	-0.024	-0.024
	(-1.42)	(-1.42)	(-0.76)	(-0.76)	(-0.28)	(-0.28)
$\lvert R_{m,t}\rvert$	0.580***	0.580***	0.896***	0.896***	0.507***	0.507***
	(13.46)	(13.46)	(16.47)	(16.47)	(11.39)	(11.39)
$D_j\lvert R_{m,t}\rvert$	-0.357***	-0.357***	-0.058	-0.058	0.082	0.082
	(-3.15)	(-3.15)	(-0.69)	(-0.69)	(0.57)	(0.57)
$D_d\lvert R_{m,t}\rvert$	-0.080	-0.080	-0.068	-0.069	-0.104**	-0.103**
	(-1.53)	(-1.53)	(-0.94)	(-0.95)	(-2.15)	(-2.13)
$D_jD_d\lvert R_{m,t}\rvert$	0.534***	0.536***	-0.007	-0.006	-0.009	-0.005
	(3.22)	(3.22)	(-0.06)	(-0.05)	(-0.05)	(-0.03)
$(R_{m,t}-\overline{R_m})^2$	-0.018		-0.058*		0.018	
	(-1.12)		(-1.93)		(0.53)	
$D_j(R_{m,t}-\overline{R_m})^2$	0.155**		-0.024		-0.040	
	(2.29)		(-0.71)		(-0.35)	
$D_d(R_{m,t}-\overline{R_m})^2$	0.016		0.020		-0.021	
	(0.89)		(0.58)		(-0.61)	
$D_jD_d(R_{m,t}-\overline{R_m})^2$	-0.201***		0.060		0.002	
	(-2.64)		(1.30)		(0.01)	
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.018		-0.058*		0.018
		(-1.12)		(-1.93)		(0.53)
$D_j(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.155**		-0.024		-0.040
		(2.29)		(-0.71)		(-0.35)
$D_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.016		0.020		-0.021
		(0.89)		(0.58)		(-0.61)
$D_jD_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.201***		0.060		0.002
		(-2.64)		(1.30)		(0.01)
$Adj.R^2$	0.848	0.848	0.698	0.698	0.817	0.817

Table 2.7 Panel B (continued)

	USA	
Non-Staggered Return	YMH (2)	BNNT
$Intercept$	0.197***	0.197***
	(6.65)	(6.65)
D_j	-0.005	-0.005
	(-0.08)	(-0.08)
D_d	0.109***	0.109***
	(2.73)	(2.73)
D_jD_d	-0.011	-0.011
	(-0.11)	(-0.11)
$CSAD_{t-1}$	0.787***	0.787***
	(41.46)	(41.46)
D_jCSAD_{t-1}	0.026	0.026
	(0.56)	(0.56)
D_dCSAD_{t-1}	-0.056**	-0.056**
	(-2.14)	(-2.14)
$D_jD_dCSAD_{t-1}$	0.012	0.012
	(0.19)	(0.19)
$\lvert R_{m,t}\rvert$	0.160***	0.160***
	(9.58)	(9.58)
$D_j\lvert R_{m,t}\rvert$	-0.007	-0.007
	(-0.15)	(-0.15)
$D_d\lvert R_{m,t}\rvert$	-0.042*	-0.041*
	(-1.86)	(-1.82)
$D_jD_d\lvert R_{m,t}\rvert$	-0.048	-0.048
	(-0.81)	(-0.81)
$(R_{m,t}-\overline{R_m})^2$	0.001	
	(0.06)	
$D_j(R_{m,t}-\overline{R_m})^2$	-0.004	
	(-0.24)	
$D_d(R_{m,t}-\overline{R_m})^2$	0.012**	
	(1.99)	
$D_jD_d(R_{m,t}-\overline{R_m})^2$	0.004	
	(0.19)	
$(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.001
		(0.06)
$D_j(\lvert R_{m,t}\rvert-\overline{R_m})^2$		-0.004
		(-0.24)
$D_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.012**
		(1.99)
$D_jD_d(\lvert R_{m,t}\rvert-\overline{R_m})^2$		0.004
		(0.19)
$Adj.R^2$	0.833	0.833

2.6 Conclusion

This chapter examines the effect of jump on herd behavior which is one of the most prominent investor's behaviors. A suitability comparison between aggregate herding detection models is done by using the information criteria. The results indicate that lagged CSAD models are the most appropriate techniques for herding detection. Leaving out the occurrence of jump, the outcomes suggest that there are differences in terms of herd behavior intensity between the period of negative market return and the others. However, when taking the existence of jump into account in order to examine the imitation across trader behavior when jumps occur and other dates, it appears that herd behavior generally changes during the occurrence of jump. Such result confirms the sensitivity of the herding (Bikhchandani et al., 1992). Also, as market return jumps are market-wide distinctive events that bring about market uncertainty (Merton, 1976), investors' attention increases significantly (Barber & Odean, 2008 and Li et al., 2017). Previous literatures also suggest that herding should be stronger upon the occurrence of jump (Park, 2011). According to the results, the significantly negative figures indicate the reduction of independent trading behavior. Such findings mostly support the hypothesis during the period of negative market return.

CHAPTER 3
DOES CORPORATE TRANSPARENCY AFFECT AGGREGATE MARKET HERDING?

3.1 Introduction

Corporate transparency denotes quality and quantity of firm information that reveal to outside investors. It signifies an accessibility to a firm information. Information disclosure, clarity, and accuracy are three primary dimensions of corporate transparency. To put it another way, corporate transparency characterizes a clarity of firm information environment. With corporate transparency, Healy & Palepu (2001) suggest that the investors ability to distinguish between good and bad investments is advanced. As firms improve their disclosure quality, the information asymmetry should be reduced (Brown & Hillegeist, 2007). Thus, the gap between investors and managers is lessen with corporate transparency.

The opacity indicates an information gap between corporate insiders and outside investors. Because less quantity and low-quality information mean less certainty for investors to evaluate a firm value. Comparing with managers, investors are informational disadvantage. Hence, the information uncertainty increases an informativeness of informed trade. Considering the information cascade, it is the fundamental of rational herd behavior. The notion suggests that individuals are more likely to follow an observed trade during uncertainty period. As the information uncertainty is worsen among opaque firms, the declining of independence decision is expected. In contrast, the improvement of corporate transparency decreases the uncertainty. Additionally, it also improves an accuracy of investors' assessment (Healy & Palepu, 2001). Therefore, corporate transparency is expected to reduce an information-based herding.

Even the explanation of the association between corporate transparency and herd behavior is quite clear, prior study is limited. With inconclusive evidences, literature concentrates on institutional investor herding. Besides, they mostly incorporate accounting measure and country-level index which have some drawbacks.

To the best of my knowledge, Wang & Huang (2018) is the only paper that investigates the relationship by considering aggregate market herding. This chapter distinguishes from Wang & Huang (2018) as follows. First, the stock return synchronicity is used as corporate transparency proxy. The synchronicity is measured by coefficient of determination (R-squared) from the market model. Unlike Information Disclosure and Transparency Ranking System (IDTRs) that has been applied by Wang & Huang (2018), return synchronicity is unrestricted to Taiwanese stocks and opens for international study. Also, the IDTRs is a country-level index which rates annually. The short research interval of Wang & Huang (2018) also worsens the inferences of annualized sample. Second, the two-portfolio construction of Wang & Huang (2018) does not effectively provide the insight of the association between corporate transparency and aggregate market herding. As IDTRs index is rated by central authority, Wang & Huang (2018) cannot control number of stocks in each transparency rating which affects the unequal size of portfolios. Moreover, low rating firms are sometime not publicly announced. As a result, number of transparent stocks are normally higher than opaque firms which is biased.

The justification of stock return synchronicity as a proxy of corporate transparency is initiated by Dasgupta et al. (2010). Because prices of transparent companies should reveal more of firm-specific information. Corporate transparency subsequently increases security return predictability. On the other hand, stock prices of transparent firms are more informative regarding the power to capture information of upcoming events. Hence, surprised trade and volatility of transparent stocks should be lower when the events actually happen (Lee & Chung, 1998). Alternatively, actual incidents provide less additional information to investors and stock price. To sum up, the improvement of transparency implies higher synchronicity between stock return and market return.

As corporate transparency is a firm characteristic, this chapter contributes to the literature regarding the firm attribute effect of aggregate market herding. Because corporate transparency emphasizes reliability and attainability of firm information. This chapter offers the supporting evidence that the enhancement of corporate transparency strengthens the independence of investors’ trading decision. The confirmation should energize the promotion of corporate transparency which lowers the information asymmetry. The effective functioning of security market is expected to develop with the equality of information accessibility.

3.2 Literature review

Corporate transparency represents an accessibility of investors to firm information. With corporate transparency, investors and managers can make a decision by using a comparable information. This implies that information is equally distributed between investors and managers. Thus, the gap between managers and investors is reduced. The possibility is higher for investors and managers to have similar perception about the company. Because the uncertainty is related to the availability of information (Kremer & Nautz, 2013). The advancement of corporate transparency lessens the uncertainty. As herd behavior is stronger during uncertainty period (Bikhchandani & Sharma, 2001), market participants are more likely to make the independent decision regarding the transparent stock (Kremer & Nautz, 2013).

Moreover, corporate transparency decreases price volatility (Lee & Chung, 1998). A tendency of occupying the same information increases a chance of parallel valuation, subsequently leading to a similar trade (IMF, 2001). Still, the association between corporate transparency and volatility may not straight forward. Mohtadi & Ruediger (2012) show an inverted-u shape relationship between corporate transparency and volatility. The negative correlation between corporate transparency and volatility is established among moderate and high corporate transparency which aligns with IMF (2001). However, the positive relationship is also found in a low transparency circumstance. Because the frequency of reactions to incoming information is higher at this state which supports Furman & Stiglitz (1998).

The transparency and opacity have been extensively studied by financial scholars. The two are interrelated. As opacity is a state of being dark, opaque companies disclose lower quantity and quality data. Without transparency, investors cannot be sure about firm information, underlying risk, and fundamental value. Thus, the informational uncertainty heightens with the increasing of corporate opacity. Besides, transparent companies reveal less complicated information. Alternatively, information asymmetry between managers and external shareholders is lesser for the transparent firms (Jensen & Meckling, 1976). Karolyi (2015) proposes that corporate opacity implies circumstances of the lack of corporate transparency. Transparency International (2014) signifies that corporate misconducts are energized by the opacity of firm structure and the oversea operation within weak-rule-of-law countries. The corruption activities, operational mistakes, and tax evasion are linked with the lack of transparency reporting. IMF (2008) supports this notion. The paper points that conflict of interest between managers and shareholders rises with information asymmetry resulting the unmaximizing owners' wealth. Uygur (2018) indicates that low-ability managers prefer opaque structure which conceals their performance. In contrast, high-ability CEOs have an incentive to signal their achievements to the market which is supported by the improvement of corporate transparency. In short, corporate opacity is the opposite side of corporate transparency. Plenty of transparency and opacity proxies are widely proposed. They can be separated into two groups which are opacity and transparency measures.

First, earnings management is measured by accounting information from financial statement. Healy (1985), DeAngelo (1986), Jones (1991), Dechow & Sloan (1991), and Hutton et al. (2009) introduce earnings management detection models which signify a corporate opacity from discretionary accruals. On the other hand, earnings smoothing is evaluated by various techniques, for instance; earnings predictability, variability of net income, and correlation between the change in operating cash flow and change in accruals (Bhattacharya et al., 2003; Leuz et al., 2003; Francis et al., 2004; and Lang et al., 2006). Besides, Schrand & Zechman (2012) employ an executive overconfidence index which is calculated from an exercise timing of managements' options. Insincere managing decision is another sub-group of corporate opacity measure. Financial statement restatements and weakness of internal control depict misreporting and reliability of financial report. They have been used by Hennes et al. (2008) and Kim & Zhang (2014). Because country-wide indicators are publicly available. They are widely applied among country-level studies. In order to construct opacity measure, Gelos & Wei (2005) utilize the survey of financial disclosure and availability of information about companies from World Economic Forum's Global Competitiveness Report. They also consider the survey of data compilation from International Monetary Fund. Additionally, PricewaterhouseCoopers

(2001) analyzes surveys from 35 countries which leads to an introduction of Global Opacity Index. The latter is one of the key elements of Gelos & Wei (2005). On the other hand, Andrade et al. (2014) employ CreditGrades model which is developed by Goldman Sachs, JP Morgan, and Deutsche Bank. The model represents an opacity of debt security by examining a standard deviation of default boundary. Sun and Ibikunle (2016) investigate informed trade and information asymmetry by servicing PIN model suggesting the corporate opacity.

Second, auditor and analyst activities have long been the key measurement of transparency. Saudagaran & Diga (1997) use number of professional auditors per population as a measure of country auditing standard. Jin & Myers (2006) analyze an informativeness of firm-specific information by using a standard deviation of analysts' forecasts of firm earnings. Low variation implies high corporate transparency. Alternatively, Kothari et al. (2009) examine a voluntary disclosure of firms' earnings forecast by comparing release timing of good and bad news. The smaller gap signifies the firm transparency. Considering the country level measures, La Porta et al. (1998), La Porta et al. (2006), and Lang & Maffett (2011) study details of accounting standard in each market. Besides, Bushman et al. (2004) recommend a transparency indicator which is constructed by using factor analysis of country information mechanism. On the other hand, Lang & Maffett (2011) explore a precision of accounting data from auditor reputation, analysts' forecast accuracy, and number of analysts following. Alternatively, Kremer & Nautz (2013) propose that larger firms have higher transparency than smaller firms. Level of media penetration from World Bank's World Development Indicator has been utilized as a measure of firm-specific information-flow (Maffett, 2012). Miceli (2013) studies sovereign wealth funds' transparency via Linaburg-Maduell Transparency Index from Sovereign Wealth Funds Institute.

Considering the literature regarding the stock return synchronicity, Roll (1988) indicates that an equity price movement is contributed by market-wide information and firm-specific information. By studying a coefficient of determination (R-squared) from market model, Morck et al. (2000) propose that a stock price asynchronicity is found among high gross domestic product countries. As those markets have superior information disclosure and shareholder protection policy, the developments encourage informed risk arbitrageurs and discourage noise traders. The growth of the former improves a price discovery. As a result, stock price reflects firm-specific information more than market-wide factor. This is the pioneer study that use stock return synchronicity as a proxy of stock price informativeness. Chan & Hameed (2006) state that there is a positive relationship between stock return synchronicity and analysts' coverage. It implies that analysts' decisions mostly contain market-wide information. Brockman & Yan (2009) signify that blockholders enhance firm-specific information to impound in stock price resulting low return synchronicity. Crawford et al. (2012) denote that the first analyst to initiate the stock coverage mostly provide industry- and market-wide information rather than firm-specific information resulting high stock return synchronicity. Dong et al. (2016) suggest that the adoption of eXtensible Business Reporting Language (XBRL) lowers information-processing cost. The implementation reduces stock return synchronicity implying that stock price captures more of firm-specific information. Analyzing credit default swaps (CDS), Bai et al. (2017) propose that stock return synchronicity is decreasing with the amount of firm-specific information. Vo (2017) study the association between foreign investor and stock price informativeness in Vietnam stock market. Interestingly, Vo (2017) suggests that stock return variation is negatively correlated with stock price informativeness. The paper applies the logarithmic transformation of coefficient of determination as a proxy of stock price informativeness.

Jin & Myers (2006) are the first to link synchronized stock return with corporate opacity. They show that underdeveloped countries, based on financial system and corporate governance, have higher coefficient of determination and crash risk. Because the opaqueness, that implies asymmetric information between managers and investors, persuades noise traders to follow overall market consensus. The implication is confirmed by firm-level study of Ferreira & Luax (2007) that use the idiosyncratic volatility which is the transformation of coefficient of determination as a proxy of opacity. Also, Haggard et al. (2008) support Jin & Myers (2006) by examining an association between voluntary disclosure and stock return asynchronicity. In contrast, recent studies, such as Dasgupta et al. (2010), Kelly (2014), and Bramante et al. (2015), propose that stock price asynchronicity is driven by other motives rather than private information. Dasgupta et al. (2010) investigate a relationship between firm-level transparency and stock return synchronicity. They propose that security price of high transparent company should be more informative regarding firm-specific information. As a result, investors can effectively predict the future events of firm. Furthermore, they trade based on that information. Since stock price already absorbs the information, security price will less likely to respond when the events actually happen. As market index is consisted of individual securities, market return also reflect that information. Kelly (2014) concludes that low R-squared stocks are small, young, and illiquid companies rather than high transparency enterprises. Hence, corporate transparency links with the synchronicity between security return and market return. Bramante et al. (2015) found that market model R-squared is negatively correlated with the delay of price discovery. This supports the view that high R-squared represents price efficiency. In contrast, Xing & Anderson (2011) show u-shape relationship between coefficient of determination and firm-specific public information. Because security price combines both private and public information. Together with market consensus, return synchronicity is driven by both of them. Hence, the disclosure of firm public information also increases the synchronicity. Conflicting with Jin & Myers (2006), the recent finding supports Dasgupta et al. (2010).

Prior study, that examines the association between corporate transparency and herd behavior, is limited. Furthermore, literature exclusively concentrate on investor type herding. Gelos & Wei (2005) emphasize a positive correlation between opacity of emerging market fund and institutional herding. Ro & Gallimore (2014) study real estate mutual funds. They indicate that there is a negative relationship between transparency and REITs' institutional herding. Nevertheless, Miceli (2013) cannot confirm an evidence of institutional herding in sovereign wealth funds. For an equity market, Kremer & Nautz (2013) cannot indicate a relationship between institutional herding and corporate transparency which is measured by size of stock. However, Cai et al. (2012) specify an increasing of institutional herding during transparency period which is the period that the Financial Industry Regulatory Authority (FINRA) introduces the Trade Reporting and Compliance Engine (TRACE). Moreover, they also illustrate an asymmetric herd behavior between buy and sell. While, Choi & Skiba (2015) investigate the association between institutional herding and information asymmetry. Corporate transparency is one of the five dimensions of information asymmetry that have been considered in the paper. They emphasize that there is a negative relationship between opacity and institutional herding.

Wang & Huang (2018) is the only paper that investigate the association between corporate transparency and aggregate market herding. However, they use country-specific index which is the Information Disclosure and Transparency Ranking System (IDTRs). The index is an ordinal scale that is solely constructed for Taiwanese firms. Thus, their methodology cannot utilize with international study. Besides, the section of market-level event study employs the implement period of IDTRs as a window of the change of country transparency which is questionable. For corporate-level analysis, they categorize stocks into two groups which are high and low transparency companies based on IDTRs index. The coefficients of nonlinear terms are compared between the two portfolios. As IDTRs has been rated annually since 2003, the paper roughly examines the association. The complete perspective of the effect of corporate transparency level on aggregate market herding is undiscovered. However, Wang & Huang (2018) suggest that corporate transparency reduces herd behavior.

In order to examine the association between corporate transparency and aggregate market herd behavior, this is the first paper that employs stock return synchronicity as a proxy of corporate transparency. There are some advantages to use coefficient of determination as a corporate transparency substitute rather than other proxies that have been used by prior studies, for examples, the survey of government opacity by International Monetary Fund (Gelos & Wei, 2005), the survey of the level of financial disclosure and the availability of firms' information by World Economic Forum (Gelos & Wei, 2005), the Opacity index by PricewaterhouseCoopers (Gelos & Wei, 2005), firm size (Kremer & Nautz, 2013), event of regulation implementation (Cai et al., 2012 and Wang & Huang, 2018), specific investment strategy (Ro & Gallimore, 2014), accounting measures (Choi & Skiba, 2015), and individual country standard (Wang & Huang, 2018).

First, return synchronicity is not the country-wide statistics that focus on a country governance rather than corporate transparency. Hence, Gelos & Wei (2005) analyze country-level indices for the study of country institutional herd behavior. Second, market capitalization, that has been used by Kremer & Nautz (2013), is a point-in-time statistic that is highly impacted by market condition. As the measure has higher volatility than stock return synchronicity which is a longer period quantification, it is prone to reflect other characteristic rather than corporate transparency. Most importantly, it does not guarantee that big firms are always transparent such as the case of Enron and Tyco. Also, Transparency International (2014) suggests that 80% of the 124 world largest listed companies score under 50% of the maximum value regarding the transparency of financial reporting. Third, the various announcement dates and the grace period of the regulation implementation influence the precision of event window. It affects the accuracy of event study of Cai et al. (2012) and Wang & Huang (2018). Forth, the fund manager investment strategy, that has been used by Ro & Gallimore (2014), is not applicable for aggregate market herding study. Fifth, stock return synchronicity does not rely on accounting information which is subjected to different rule and regulation across countries. Sixth, stock return synchronicity can easily be constructed with shorter rebalancing window. Conversely, country-wide indices are generally provided by central authority annually. Last but not least, IDTRs index from Wang & Huang (2018) is tailored for Taiwanese stock and does not available for other equity markets. Moreover, county specific indices are subjected to different standards that are inappropriate for comparative analysis.

3.3 Data

Daily equity prices being used are obtained from Thomson Reuters Datastream. The period of the study starts from January 1, 1991 to November 2, 2018. Samples include 19 countries representing each continent, i.e., Australia (Australian Securities Exchange), Brazil (Bovespa), Canada (Toronto Stock Exchange), China (Shanghai Stock Exchange), France (Euronext Paris), Germany (Deutsche Börse AG), Greece (Athens Exchange), India (Bombay Stock Exchange), Ireland (Euronext Dublin), Italy (Borsa Italiana), Japan (Tokyo Stock Exchange), Portugal (Euronext Lisbon), Russia (Moscow Exchange), South Africa (Johannesburg Stock Exchange), Spain (Bolsa de Madrid and Mercado Continuo Espanol), Thailand (Stock Exchange of Thailand and Market for Alternative Investment), the United Arab Emirates (Abu Dhabi Securities Exchange), the United Kingdom (London Stock Exchange), and the United States (New York Stock Exchange).

Table 3.1 represents the data description of this chapter. The 21 equity markets from 19 countries are considered. For Spain, the Mercado Continuo Espanol is included in the study as the representative together with the Bolsa de Madrid, as the latter has the small number of active stocks especially for portfolio construction. On the other hand, the Stock Exchange of Thailand and the Market for Alternative Investment are the first and second-leading stock exchange in Thailand. The former is the main market, while the latter is the market for small and medium enterprises. This study includes both exchanges as they represent all listed companies in Thailand. In general, the research interval starts from January 1, 1991 to November 2, 2018. However, as Russia and UAE have a shorter study period than other countries, the intervals, thus, start from September 6, 1995 and January 1, 2004 respectively. As a result, the number of observations for Russia and UAE, which are the 60-day rebalancing period, are also smaller than other countries. Based on the availability of RIC in Thomson Reuters Datastream, Ireland and India have the smallest and largest number of stocks respectively. Consequently, Ireland is excluded form decile portfolio examination.

Table 3.2 explains the descriptive statistics of 60-day CSAD and equally weighted portfolio returns from the R-squared ranking. Quintile portfolio construction's results are also shown in the table. The least transparent companies are represented via a group of stocks that have the smallest return synchronicity. Such group of stocks is in the fifth portfolio. With regard to average CSAD, it is higher for portfolios of companies with lower corporate transparency in most countries. Interestingly, the opposite results are found in Ireland and Portugal. In relation to average 60-day equally weighted portfolio returns, the outcomes are mixed. Portfolios of companies with high corporate transparency provide higher 60-day portfolio returns in Australia, Brazil, Canada, France, Germany, India, Russia, South Africa, UK, and USA. Six of them are developed markets, whereas others are the members of BRICS, a group of potentially growing economies. As most on the list are the world leaders who employ better standards, the finding implies that the returns are awarded for the additional transparency (Eccles et al., 2001). Conversely, China, Greece, Ireland, Italy, Japan, Spain, and UAE are the countries that portfolio returns and the R-squared move in the opposite direction. In other word, the lower corporate transparency, the higher stock returns. Except for Japan, it is important to note that those countries are either emerging markets or financial distress developed countries. Since corporate opacity implies uncertainty (Lee & Chung, 1998), the incremental portfolio return is more likely to be considered as the risk compensation in the weak-rule-of-law countries. For the Augmented Dickey–Fuller test, time-series samples are generally stationary. Even the autocorrelation is not severe, this chapter calculates the standard errors of the estimated coefficients by following Newey & West (1987). The process helps mitigate heteroscedasticity and autocorrelation.

As Ireland has too small number of active listed companies, it is removed from decile portfolio construction. In conclusion, the decile portfolio results suggest the same inferences as the quintile. Portfolios of companies with lower corporate transparency have higher average CASD in all countries. On the other hand, higher 60-day equally weighted portfolio return is mostly shown among high corporate transparency stocks. According to the result, unit root is normally insignificant, whereas serial correlation is minor. However, to mitigate autocorrelation problems, Newey & West (1987)'s standard error is applied in the following regression analysis.

3.4 Methodology

Stock return synchronicity, the coefficient of determination from market model (Dasgupta et al., 2010), is a proxy of corporate transparency in this study. Large coefficient of determination demonstrates that firm information is captured by stock return and market consensus which suggests corporate transparency. This chapter utilizes daily stock return and market return with market model. With 60-day rebalancing period, coefficient of determination for each firm is evaluated throughout the research interval.

$$R_{i,t} = \propto_{i,0} + \beta_{i,1} R_{m,t} + \varepsilon_{i,t} \tag{3.1}$$

where $R_{i,t}$ is a return of stock i during day t which is equal to $100 \times (\ln P_{i,t} - \ln P_{i,t-1})$. $R_{m,t}$ is an equally weighted market return during day t.

The R-squared form equation (3.1) reflects the corporate transparency.

$$Stock\ seturn\ synchronicity = R^2_{i,T} \tag{3.2}$$

where $R^2_{i,T}$ is a R-squared of firm i during period t.

Every 60 days, quintile and decile portfolios are constructed based on stock return synchronicity ranking.

Considering aggregate market herding measure, the six modifications of Chang et al. (2000) are compared by using Akaike's information criterion (AIC), corrected Akaike's information criterion (AICc), Bayesian information criterion (BIC), and Hannan–Quinn information criterion (HQIC). The six models from Chang et al. (2000), Chiang & Zheng (2010), Yao et al. (2014), Bui et al. (2017), and Blasco et al. (2017) are compared. The model that has the lowest average information selection criteria is selected. The results of information selection criteria are shown in Table 3.3. Blasco et al. (2017) has the lowest overall statistics suggesting that the propose model provides the lowest information loss.

$$CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m.t} + \gamma_3 |R_{m.t}| + \gamma_4 R_{m,t}^2 + \varepsilon_t \tag{3.3}$$

where $CSAD_t$ is a cross-sectional absolute deviation of 60-day return during period t. $CSAD_{t-1}$ is a cross-sectional absolute deviation of 60-day return during period t-1. $R_{m,t}$ is an equally weighted 60-day portfolio return during period t.

Because investors are prone to neglect their information and follow observed trade during uncertainty period. With the declining of independent decision, non-linear relationship between portfolio return and stock returns dispersion is expected. Thus, aggregate market herding is analyzed by using a coefficient of non-linear term (Υ_4) from Blasco et al. (2017). The Chow test is used to compare the equality herding coefficients between the lowest and highest corporate transparency portfolios.

For the robustness check, the transformation of R-squared (Vo, 2017) is used as an alternative measure of corporate transparency. The logarithmic substitution is an unbound-continuous version of stock return synchronicity. Additionally, the non-lagged CSAD version of Yao et al. (2014), is utilized for aggregate market herding analysis. The coefficient of non-linear term (Υ_2) from Yao et al. (2014) is the key herding measure for the robustness check.

$$Stock\ price\ synchronicity\ (Vo, 2017) = \log\left(\frac{R_{i,T}^2}{1 - R_{i,T}^2}\right) \tag{3.4}$$

$$CSAD_t = \propto + \gamma_1 \left|R_{m,t}\right| + \gamma_2 \left(R_{m,t} - \overline{R_m}\right)^2 + \varepsilon_t \tag{3.5}$$

Table 3.1 Data description for each equity market.

Note: This table reports research interval, number of observations, target stock exchange, and number of stocks for 19 sample countries.

Country	Period	No. of Obs. (60 Trading Days)	Exchange	No. of maximum stocks
AUS	1/1/1991 to 2/11/2018	121	Australian Securities Exchange	2,524
BRA	1/1/1991 to 2/11/2018	111	Sao Paulo Stock Exchange	337
CAN	1/1/1991 to 2/11/2018	121	Toronto Stock Exchange	1,339
CHN	1/1/1991 to 2/11/2018	113	Shanghai Stock Exchange	1,433
FRA	1/1/1991 to 2/11/2018	121	Euronext Paris	1,221
GER	1/1/1991 to 2/11/2018	119	Frankfurt Stock Exchange	1,203
GRE	1/1/1991 to 2/11/2018	121	Athens Exchange	294
IND	1/1/1991 to 2/11/2018	121	Bombay Stock Exchange	3,671
IRE	1/1/1991 to 2/11/2018	100	Euronext Dublin	49
ITA	1/1/1991 to 2/11/2018	121	Borsa Italiana	455
JAP	1/1/1991 to 2/11/2018	121	Tokyo Stock Exchange	3,312
POR	1/1/1991 to 2/11/2018	114	Euronext Lisbon	75
RUS	6/9/1995 to 2/11/2018	83	Moscow Exchange	337
SAF	1/1/1991 to 2/11/2018	121	Johannesburg Stock Exchange	408
SPA	1/1/1991 to 2/11/2018	121	Bolsa de Madrid and Mercado Continuo Espanol	245
THA	1/1/1991 to 2/11/2018	121	Stock Exchange of Thailand and Market for Alternative Investment	752
UAE	1/1/2004 to 2/11/2018	64	Abu Dhabi Securities Exchange	71
UK	1/1/1991 to 2/11/2018	121	London Stock Exchange	2,226
USA	1/1/1991 to 2/11/2018	121	New York Stock Exchange	2,083

Table 3.2 Descriptive statistics of the 60 days cross-sectional absolute deviations (CSAD) and portfolio returns (R_m).

Note: This table reports descriptive statistics of 60 days cross-sectional absolute deviations (CSAD) and equally weighted portfolio returns (R_m) from R-squared ranking portfolios for 19 countries respectively.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

Country	Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag				
							1	2	3	5	10
AUS											
Portfolio 1	$CSAD$	19.772	5.055	83.298	8.327	-5.385***	0.046	0.017	0.064	-0.037	-0.012
	R_m	-2.615	-66.793	45.507	15.333	-5.273***	0.162	0.009	-0.002	-0.003	0.001
Portfolio 2	$CSAD$	21.953	10.799	52.181	5.231	-4.912***	0.140	0.010	0.024	-0.042	-0.020
	R_m	-4.177	-50.420	36.559	13.513	-4.902***	0.157	0.057	-0.082	-0.011	-0.014
Portfolio 3	$CSAD$	22.579	9.961	58.394	5.671	-4.716***	0.247	0.067	0.044	-0.004	0.061
	R_m	-4.884	-49.937	38.028	12.324	-5.385***	0.175	0.080	-0.038	-0.079	-0.002
Portfolio 4	$CSAD$	21.718	10.147	38.115	4.469	-3.800**	0.220	0.322	0.224	0.160	0.079
	R_m	-6.950	-53.895	19.355	11.264	-5.263***	0.227	0.186	-0.048	-0.105	0.011
Portfolio 5	$CSAD$	22.045	11.128	35.388	4.673	-4.046***	0.245	0.213	0.145	0.177	0.047
	R_m	-7.230	-53.251	20.805	10.805	-5.181***	0.256	0.133	-0.018	-0.067	0.043

Table 3.2 (continued)

Country	Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag 1	2	3	5	10
BRA											
Portfolio 1	$CSAD$	17.489	4.405	80.144	12.356	-4.965***	0.293	0.182	0.171	0.093	0.088
	R_m	6.499	-46.541	248.060	39.597	-7.690***	0.584	0.465	0.335	0.053	0.022
Portfolio 2	$CSAD$	17.841	6.139	50.820	9.198	-4.168***	0.292	0.202	0.303	0.123	0.095
	R_m	8.475	-46.735	186.068	32.623	-7.681***	0.683	0.488	0.336	0.013	-0.029
Portfolio 3	$CSAD$	19.888	3.965	129.252	13.650	-7.704***	0.288	0.324	0.040	0.045	0.049
	R_m	7.108	-27.846	283.112	35.388	-7.880***	0.559	0.418	0.356	0.017	-0.013
Portfolio 4	$CSAD$	19.252	6.408	113.519	14.042	-8.052***	0.489	0.370	0.124	0.021	0.027
	R_m	6.543	-45.151	285.987	36.097	-7.539***	0.536	0.415	0.332	0.012	0.029
Portfolio 5	$CSAD$	17.910	6.598	67.533	9.228	-5.082***	0.299	0.264	0.042	0.029	0.019
	R_m	5.186	-28.950	259.849	30.278	-7.8780***	0.386	0.325	0.383	-0.023	0.029
CAN											
Portfolio 1	$CSAD$	18.323	9.042	58.314	7.855	-4.858***	0.359	0.242	0.275	0.131	0.185
	R_m	-3.124	-51.258	42.799	15.078	-4.836***	0.208	-0.061	-0.037	-0.025	-0.008
Portfolio 2	$CSAD$	18.575	9.174	61.357	7.120	-4.645***	0.296	0.179	0.213	0.077	0.094
	R_m	-1.618	-47.051	32.210	12.322	-4.481***	0.224	-0.036	-0.045	-0.015	-0.097
Portfolio 3	$CSAD$	18.678	11.328	48.032	5.232	-3.727**	0.310	0.206	0.284	0.128	0.051
	R_m	-3.481	-47.943	21.069	10.182	-4.182***	0.226	-0.029	0.009	0.070	0.015
Portfolio 4	$CSAD$	19.609	11.347	54.107	5.561	-3.563**	0.222	0.102	0.084	0.162	0.065
	R_m	-3.420	-53.578	25.642	11.412	-4.347***	0.199	-0.011	-0.003	0.023	-0.059
Portfolio 5	$CSAD$	19.025	11.460	43.889	4.802	-3.502**	0.260	0.166	0.238	0.071	0.028
	R_m	-4.400	-57.370	22.492	9.986	-4.438***	0.225	-0.064	0.080	-0.018	0.016

Table 3.2 (continued)

Country	Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag				
							1	2	3	5	10
CHN											
Portfolio 1	$CSAD$	6.376	2.073	21.757	2.957	-3.428*	0.127	0.033	0.283	-0.060	-0.044
	R_m	-4.536	-41.942	103.425	19.938	-5.028***	-0.052	-0.139	0.075	-0.238	-0.031
Portfolio 2	$CSAD$	8.649	2.921	29.974	3.754	-3.193*	0.262	0.077	0.240	0.058	-0.038
	R_m	-1.534	-40.418	99.880	20.336	-5.102***	0.019	-0.090	0.057	-0.224	-0.038
Portfolio 3	$CSAD$	10.591	3.590	32.528	5.084	-3.361*	0.172	0.001	0.227	-0.004	-0.056
	R_m	0.668	-39.087	88.835	20.222	-5.153***	0.043	-0.086	0.063	-0.247	-0.039
Portfolio 4	$CSAD$	12.891	4.237	40.689	5.915	-3.419*	0.183	0.107	0.189	0.022	-0.044
	R_m	4.185	-34.018	119.720	21.817	-5.284***	0.066	-0.104	0.050	-0.228	-0.043
Portfolio 5	$CSAD$	16.656	5.423	49.374	6.839	-3.131	0.370	0.211	0.304	0.111	-0.025
	R_m	8.303	-33.477	132.526	22.528	-4.765***	0.118	-0.042	0.041	-0.163	-0.043
FRA											
Portfolio 1	$CSAD$	11.144	5.405	58.638	5.680	-3.115	0.389	0.272	0.273	0.209	0.113
	R_m	0.471	-37.772	76.439	14.615	-4.804***	0.065	0.039	-0.035	-0.042	-0.068
Portfolio 2	$CSAD$	12.910	6.735	59.777	5.353	-3.985**	0.277	0.130	0.135	0.040	0.104
	R_m	0.091	-34.667	43.904	11.149	-4.805***	0.165	-0.027	-0.079	-0.015	-0.090
Portfolio 3	$CSAD$	13.865	6.388	55.625	4.997	-3.797**	0.173	-0.028	0.057	0.098	0.004
	R_m	-0.364	-34.728	31.014	9.367	-4.356***	0.174	-0.055	-0.061	0.026	-0.117
Portfolio 4	$CSAD$	14.584	7.895	38.803	4.330	-4.347***	0.186	0.157	0.094	0.117	0.059
	R_m	-1.182	-33.053	21.755	8.007	-4.330***	0.217	0.022	-0.054	0.023	-0.130
Portfolio 5	$CSAD$	14.845	7.000	46.823	4.529	-4.265***	0.245	0.164	0.159	0.127	0.101
	R_m	-1.436	-28.513	26.552	7.656	-4.279***	0.282	-0.010	-0.005	0.009	-0.082

Table 3.2 (continued)

Country	Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag 1	2	3	5	10
GER											
Portfolio 1	$CSAD$	12.618	3.863	70.593	7.939	-2.390	0.402	0.392	0.317	0.381	0.134
	R_m	0.788	-40.742	80.214	16.257	-4.092***	0.205	0.040	-0.027	0.052	-0.157
Portfolio 2	$CSAD$	14.575	4.892	49.598	6.517	-1.898	0.468	0.377	0.458	0.466	0.182
	R_m	-0.942	-37.273	33.834	11.585	-3.745**	0.339	0.070	0.106	0.069	-0.150
Portfolio 3	$CSAD$	14.596	4.899	37.075	4.799	-2.453	0.477	0.420	0.498	0.367	0.223
	R_m	-2.447	-40.138	21.678	10.195	-3.885**	0.381	0.073	0.056	0.065	-0.145
Portfolio 4	$CSAD$	14.560	5.507	25.514	4.381	-2.768	0.627	0.534	0.594	0.460	0.392
	R_m	-2.925	-32.622	15.188	7.888	-4.041***	0.343	0.066	0.099	0.019	-0.111
Portfolio 5	$CSAD$	14.274	4.722	31.510	4.604	-3.101	0.552	0.476	0.448	0.434	0.314
	R_m	-3.405	-37.892	18.558	8.352	-4.226***	0.336	0.036	0.046	0.059	-0.082
GRE											
Portfolio 1	$CSAD$	12.356	3.140	43.995	6.449	-3.397*	0.383	0.132	0.139	0.195	-0.086
	R_m	-3.265	-45.503	59.743	22.678	-4.682***	0.180	0.046	0.001	-0.052	-0.065
Portfolio 2	$CSAD$	14.538	2.353	48.639	7.757	-3.399*	0.354	0.247	0.172	0.208	0.016
	R_m	-1.497	-41.574	79.936	21.247	-4.798***	0.194	0.015	-0.011	-0.037	-0.003
Portfolio 3	$CSAD$	16.337	1.763	57.697	8.045	-3.273*	0.506	0.436	0.303	0.260	0.063
	R_m	-1.411	-40.750	79.077	19.818	-4.216***	0.240	0.126	0.100	0.026	-0.016
Portfolio 4	$CSAD$	17.507	5.077	52.227	7.848	-4.116***	0.400	0.383	0.349	0.053	0.050
	R_m	-0.903	-32.736	95.607	19.060	-4.566***	0.311	0.257	0.198	-0.026	-0.028
Portfolio 5	$CSAD$	20.708	6.006	99.744	14.343	-4.136***	0.359	0.113	0.068	0.016	-0.081
	R_m	2.035	-26.191	162.459	23.313	-4.390***	0.502	0.269	0.107	-0.012	-0.058

Table 3.2 (continued)

Country	Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag				
							1	2	3	5	10
IND											
Portfolio 1	$CSAD$	22.119	7.602	59.572	9.082	-3.814**	0.362	0.189	0.127	0.032	0.207
	R_m	-0.477	-59.800	90.345	23.453	-5.801***	0.048	-0.021	0.051	-0.144	0.162
Portfolio 2	$CSAD$	24.172	9.695	61.658	9.042	-2.966	0.440	0.290	0.221	0.214	0.307
	R_m	-1.780	-54.064	79.304	21.199	-5.240***	0.160	0.097	0.189	-0.044	0.237
Portfolio 3	$CSAD$	25.604	10.562	77.431	10.062	-3.203*	0.347	0.202	0.204	0.147	0.290
	R_m	-1.601	-50.536	82.949	20.636	-4.853***	0.117	0.100	0.253	-0.026	0.261
Portfolio 4	$CSAD$	26.389	11.519	97.030	11.027	-2.688	0.385	0.290	0.259	0.260	0.222
	R_m	-2.292	-41.334	70.055	19.766	-4.063***	0.202	0.165	0.334	0.078	0.296
Portfolio 5	$CSAD$	27.224	14.863	82.258	11.403	-2.465	0.458	0.347	0.367	0.300	0.380
	R_m	-1.834	-34.535	79.604	19.087	-3.580**	0.328	0.259	0.397	0.163	0.371
IRE											
Portfolio 1	$CSAD$	16.345	0.652	104.719	16.281	-3.937**	0.009	-0.061	0.023	0.050	-0.013
	R_m	-7.382	-87.804	206.613	32.134	-5.000***	0.033	-0.089	-0.084	-0.063	-0.048
Portfolio 2	$CSAD$	12.443	0.618	34.403	6.894	-3.377*	0.336	0.153	0.134	0.105	-0.026
	R_m	-2.190	-57.509	38.951	14.988	-3.605**	0.251	0.110	0.048	0.084	-0.063
Portfolio 3	$CSAD$	12.851	0.337	62.341	9.667	-3.532**	0.142	0.183	0.210	0.096	0.082
	R_m	-0.774	-47.892	63.746	15.981	-4.475***	0.061	-0.154	-0.036	-0.061	-0.125
Portfolio 4	$CSAD$	11.768	0.085	43.972	7.463	-2.861	0.001	0.161	0.063	0.098	-0.146
	R_m	-0.894	-47.909	46.131	14.525	-4.548***	0.128	-0.089	0.078	-0.045	-0.009
Portfolio 5	$CSAD$	10.929	0.464	54.309	8.237	-3.958**	0.057	-0.021	-0.114	0.143	0.039
	R_m	0.405	-45.572	55.325	14.825	-4.722***	0.021	0.035	-0.132	-0.085	0.032

Table 3.2 (continued)

Country	Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag 1	2	3	5	10
ITA											
Portfolio 1	$CSAD$	9.414	2.836	55.795	5.390	-4.239***	0.371	0.075	0.068	0.011	0.037
	R_m	-1.259	-37.016	67.079	15.623	-4.276***	0.176	0.001	-0.009	0.015	-0.166
Portfolio 2	$CSAD$	10.870	2.320	63.439	6.504	-4.584***	0.399	0.098	0.074	-0.031	0.001
	R_m	-0.180	-35.699	47.278	13.639	-4.656***	0.228	0.018	-0.027	-0.061	-0.128
Portfolio 3	$CSAD$	11.390	5.735	42.460	5.374	-4.434***	0.100	0.105	0.002	0.069	-0.011
	R_m	-0.227	-30.665	50.888	12.559	-4.366***	0.188	0.059	-0.011	-0.014	-0.106
Portfolio 4	$CSAD$	12.185	4.634	63.341	7.283	-4.371***	0.113	0.094	-0.092	0.073	0.018
	R_m	-0.117	-37.516	61.160	12.461	-4.409***	0.265	-0.029	-0.012	-0.008	-0.018
Portfolio 5	$CSAD$	12.365	5.798	90.807	9.731	-4.877***	0.131	0.001	-0.065	-0.034	-0.026
	R_m	-0.026	-27.643	83.831	12.187	-4.539***	0.211	-0.011	-0.107	0.013	-0.061
JAP											
Portfolio 1	$CSAD$	8.731	4.717	18.193	2.702	-3.818**	0.559	0.364	0.361	0.118	0.107
	R_m	-2.570	-33.918	25.176	12.368	-4.914***	0.124	-0.139	-0.085	-0.033	-0.018
Portfolio 2	$CSAD$	9.998	5.888	18.184	2.600	-3.474**	0.525	0.277	0.315	0.164	0.075
	R_m	-1.277	-30.001	24.684	11.158	-4.779***	0.146	-0.173	-0.065	-0.021	-0.002
Portfolio 3	$CSAD$	11.209	6.616	21.966	2.858	-3.356*	0.448	0.254	0.328	0.160	0.006
	R_m	-0.539	-27.209	27.324	10.994	-4.685***	0.198	-0.166	-0.057	0.001	-0.019
Portfolio 4	$CSAD$	12.331	6.302	23.944	3.055	-4.146***	0.330	0.111	0.222	0.033	-0.097
	R_m	0.289	-25.015	27.998	10.819	-4.552***	0.241	-0.127	0.008	-0.005	-0.031
Portfolio 5	$CSAD$	12.810	6.794	28.181	3.875	-4.599***	0.379	0.173	0.211	0.088	-0.031
	R_m	0.787	-23.179	30.038	10.144	-4.303***	0.364	0.003	0.097	0.100	-0.020

Table 3.2 (continued)

Country	Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag 1	2	3	5	10
POR											
Portfolio 1	$CSAD$	15.902	2.159	157.158	17.483	-5.453***	-0.039	0.040	0.071	-0.019	-0.016
	R_m	-2.113	-44.874	151.785	22.221	-4.561***	0.026	0.011	0.048	0.045	-0.101
Portfolio 2	$CSAD$	13.068	0.263	63.393	9.848	-3.395*	0.047	-0.001	0.032	0.077	0.003
	R_m	0.141	-30.840	57.413	16.696	-3.893**	0.199	0.015	-0.056	0.066	-0.070
Portfolio 3	$CSAD$	12.366	1.142	35.411	5.996	-3.855**	0.278	0.092	0.143	0.128	0.043
	R_m	-3.665	-35.375	24.736	11.771	-4.358***	0.218	0.045	0.029	0.005	-0.059
Portfolio 4	$CSAD$	13.465	1.794	34.979	7.369	-2.908	0.148	0.183	0.263	0.227	-0.023
	R_m	-1.534	-30.977	32.876	11.823	-4.424***	0.196	0.131	-0.027	0.004	-0.040
Portfolio 5	$CSAD$	12.871	2.344	120.300	12.166	-4.474***	0.097	0.047	-0.010	0.063	-0.035
	R_m	0.009	-29.356	115.754	14.824	-4.010**	0.173	0.028	0.089	0.118	0.029
RUS											
Portfolio 1	$CSAD$	12.472	2.184	43.841	7.309	-4.553***	0.209	-0.182	-0.118	-0.028	0.053
	R_m	0.295	-63.868	76.419	19.271	-5.435***	0.147	-0.095	-0.199	-0.133	-0.068
Portfolio 2	$CSAD$	14.794	1.944	48.645	8.143	-4.343***	0.124	0.086	-0.048	-0.100	-0.225
	R_m	3.472	-65.503	92.799	23.948	-5.407***	0.255	0.077	-0.113	-0.095	-0.001
Portfolio 3	$CSAD$	17.331	4.396	51.700	8.959	-4.071**	-0.171	0.284	-0.083	-0.152	-0.130
	R_m	2.479	-65.184	60.733	21.791	-4.453***	0.031	-0.035	-0.006	-0.056	-0.021
Portfolio 4	$CSAD$	18.913	3.515	57.245	9.629	-4.039**	-0.103	0.193	-0.080	-0.068	-0.015
	R_m	0.815	-72.344	92.468	19.879	-3.824**	0.092	0.051	-0.025	0.101	0.125
Portfolio 5	$CSAD$	19.444	5.247	66.458	10.382	-3.042	-0.014	0.217	0.180	0.134	-0.130
	R_m	1.242	-49.222	42.449	15.120	-3.670**	0.070	0.080	0.058	-0.052	0.124

Table 3.2 (continued)

Country	Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag				
							1	2	3	5	10
SAF											
Portfolio 1	$CSAD$	13.652	5.637	64.340	7.406	-5.455***	0.305	0.099	0.057	0.163	0.118
	R_m	0.752	-35.282	58.643	12.056	-4.280***	-0.068	-0.046	-0.047	0.082	-0.004
Portfolio 2	$CSAD$	15.193	6.096	54.129	6.616	-3.863**	0.313	0.090	0.249	0.154	0.150
	R_m	1.547	-34.551	57.720	10.979	-4.462***	0.124	-0.182	0.087	-0.030	0.144
Portfolio 3	$CSAD$	15.811	8.168	29.947	4.435	-3.223*	0.210	0.212	0.226	0.223	0.007
	R_m	-0.604	-28.631	39.441	9.744	-3.453**	0.247	0.203	0.155	0.112	0.071
Portfolio 4	$CSAD$	17.114	8.450	32.674	4.942	-3.824**	0.287	0.271	0.094	0.102	0.161
	R_m	-0.445	-29.293	28.029	9.714	-3.540**	0.280	0.192	0.153	0.114	0.071
Portfolio 5	$CSAD$	16.476	6.965	29.257	4.141	-3.282*	0.399	0.433	0.395	0.257	0.013
	R_m	-1.523	-32.275	22.696	9.257	-3.180*	0.249	0.158	0.218	0.139	0.125
SPA											
Portfolio 1	$CSAD$	8.139	3.312	18.931	3.152	-3.672**	-0.043	0.131	-0.032	0.069	-0.007
	R_m	-0.514	-29.656	35.639	12.820	-4.198***	0.119	-0.046	0.086	-0.018	-0.163
Portfolio 2	$CSAD$	10.961	3.633	32.093	4.493	-4.097***	0.094	0.056	0.078	-0.008	-0.008
	R_m	0.910	-39.332	44.167	13.320	-4.613***	0.149	-0.099	-0.044	-0.014	-0.155
Portfolio 3	$CSAD$	12.065	4.287	43.544	5.301	-4.197***	0.004	0.223	-0.066	-0.045	-0.003
	R_m	0.491	-29.405	51.455	14.077	-4.044***	0.230	0.032	0.030	0.009	-0.055
Portfolio 4	$CSAD$	12.870	4.250	62.620	6.855	-3.947**	0.072	0.075	0.174	0.033	-0.108
	R_m	1.385	-37.987	50.902	13.116	-3.574**	0.317	-0.045	0.079	0.106	-0.078
Portfolio 5	$CSAD$	13.044	3.886	45.281	6.713	-3.895**	0.361	0.113	0.086	0.072	-0.070
	R_m	1.695	-24.691	37.683	11.221	-3.853**	0.342	0.094	0.076	0.070	-0.071

Table 3.2 (continued)

Country	Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag				
							1	2	3	5	10
THA											
Portfolio 1	$CSAD$	13.359	5.933	83.022	9.096	-3.775**	0.162	0.320	0.372	0.181	0.070
	R_m	-3.497	-52.975	156.785	22.888	-5.801***	-0.174	0.086	0.071	-0.002	-0.100
Portfolio 2	$CSAD$	15.800	7.674	100.336	10.274	-3.985**	0.135	0.140	0.223	0.100	0.048
	R_m	-0.475	-45.979	131.949	19.084	-5.628***	-0.022	0.046	-0.002	-0.021	-0.046
Portfolio 3	$CSAD$	16.037	7.983	85.725	9.442	-3.636**	0.271	0.222	0.229	0.142	-0.024
	R_m	0.590	-38.664	85.208	15.249	-4.984***	0.084	0.071	-0.024	0.009	-0.015
Portfolio 4	$CSAD$	15.427	7.875	42.073	6.689	-3.470**	0.322	0.267	0.176	0.153	0.019
	R_m	0.246	-30.555	39.941	12.341	-4.231***	0.231	0.107	0.129	0.045	0.100
Portfolio 5	$CSAD$	14.844	7.805	38.651	5.648	-3.780**	0.256	0.212	0.069	0.070	-0.056
	R_m	-0.106	-31.544	36.468	10.614	-3.679**	0.318	0.227	0.125	0.142	0.071
UAE											
Portfolio 1	$CSAD$	11.147	3.162	30.140	6.147	-4.743***	0.085	0.074	-0.177	-0.142	-0.154
	R_m	-0.678	-42.183	41.498	18.205	-4.354***	0.271	0.124	0.022	-0.272	0.067
Portfolio 2	$CSAD$	11.870	4.363	26.889	5.713	-4.552***	0.240	0.003	-0.103	-0.228	-0.066
	R_m	-0.105	-37.038	33.632	14.147	-4.366***	0.240	0.036	-0.047	-0.249	0.054
Portfolio 3	$CSAD$	12.955	3.991	61.789	8.452	-3.707**	0.037	-0.118	0.046	0.039	-0.106
	R_m	-0.616	-39.418	37.008	13.304	-4.469***	0.396	0.210	0.028	-0.221	-0.014
Portfolio 4	$CSAD$	12.772	3.136	39.078	6.684	-2.953	0.156	0.063	0.253	-0.054	0.127
	R_m	-0.077	-23.832	33.165	10.813	-3.738**	0.222	0.091	0.061	-0.228	0.087
Portfolio 5	$CSAD$	12.462	3.777	34.560	6.220	-3.439*	0.168	-0.090	0.034	-0.091	-0.158
	R_m	0.487	-25.380	23.880	9.297	-3.582**	0.341	0.142	0.241	-0.192	-0.076

Table 3.2 (continued)

Country	Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag				
							1	2	3	5	10
UK											
Portfolio 1	$CSAD$	11.455	5.133	49.218	5.354	-3.202*	0.462	0.295	0.291	0.176	-0.037
	R_m	0.834	-40.246	49.912	12.093	-4.951***	0.081	-0.084	0.044	-0.085	-0.058
Portfolio 2	$CSAD$	14.295	5.857	34.443	4.434	-3.429*	0.502	0.351	0.352	0.207	0.111
	R_m	0.770	-36.841	24.529	9.873	-4.950***	0.145	-0.028	-0.036	-0.013	-0.006
Portfolio 3	$CSAD$	15.359	8.049	29.472	3.605	-3.015	0.523	0.396	0.334	0.361	0.275
	R_m	0.422	-41.056	22.642	9.020	-4.613***	0.251	0.053	-0.044	0.034	-0.015
Portfolio 4	$CSAD$	16.350	8.265	32.221	3.719	-2.787	0.560	0.511	0.453	0.423	0.249
	R_m	-0.349	-38.124	24.945	8.815	-5.397***	0.230	-0.019	-0.117	-0.079	0.001
Portfolio 5	$CSAD$	17.003	9.075	29.164	3.501	-3.487**	0.491	0.361	0.256	0.321	0.142
	R_m	-1.599	-36.196	20.150	8.244	-4.804***	0.321	0.021	-0.057	0.010	-0.023
USA											
Portfolio 1	$CSAD$	8.842	4.675	21.406	2.716	-2.838	0.452	0.420	0.403	0.225	-0.012
	R_m	1.549	-41.327	39.830	10.496	-5.201***	-0.028	-0.070	-0.110	0.005	-0.071
Portfolio 2	$CSAD$	10.437	6.475	29.167	2.974	-3.083	0.463	0.432	0.335	0.164	-0.087
	R_m	2.022	-37.675	39.675	10.009	-5.183***	-0.011	-0.093	-0.100	-0.006	-0.089
Portfolio 3	$CSAD$	11.622	7.437	29.530	3.107	-3.095	0.490	0.444	0.357	0.185	-0.075
	R_m	1.884	-39.214	37.250	9.633	-5.179***	0.039	-0.107	-0.074	-0.013	-0.097
Portfolio 4	$CSAD$	13.027	8.495	32.375	3.312	-3.247*	0.502	0.469	0.404	0.183	-0.105
	R_m	1.408	-42.875	34.423	9.341	-5.126***	0.105	-0.094	-0.091	-0.052	-0.112
Portfolio 5	$CSAD$	14.983	9.438	35.844	3.621	-3.189*	0.471	0.417	0.384	0.171	-0.024
	R_m	0.362	-49.234	34.233	9.538	-5.088***	0.198	-0.134	-0.090	-0.049	-0.065

3.5 Empirical results

3.5.1 Model selection

Table 3.3 shows the information selection criteria results. Six alternatives of aggregate market herding models are compared. Akaike information criterion (AIC), corrected Akaike information criterion (AICc), Bayesian information criterion (BIC), and Hannan–Quinn information criterion (HQIC) are employed for such comparison. AICc is the modification of AIC especially for small sample size. Four techniques above use different penalty on additional parameter to prevent overfitting. Since all of them have both advantages and drawbacks, the best model is chosen by considering the overall value of those criteria. The model with the smallest value resulted from such criteria is the model that has the lowest degree of information lost and, therefore, is selected. Even Table 3.3 only presents the results from the R-squared ranking, still, the transformation of R-squared also provides the similar conclusion. It appears that Blasco et al. (2017) is the best model for the samples in most countries. It also has the lowest average statistics for all criteria. While Chang et al. (2000) and Bui et al. (2017) always produce higher information lost than other models, Chiang & Zheng (2010) and the two models from Yao et al. (2014) are, yet, preferable in some cases. Therefore, Blasco et al. (2017) is chosen for the main examination. The non-lagged CSAD version of Yao et al. (2014) is also used to check for robustness.

3.5.2 Herd behavior and corporate transparency

The regression results from quintile portfolio ranking based on R-squared for 19 countries are shown in Panel A of Table 3.4. As Portfolio 1 has the highest stock return synchronicity, it is the portfolio of companies with highest corporate transparency. Aggregate market herd behavior is detected by Blasco et al. (2017)'s model. Significantly negative coefficients of non-linear term suggest the imitation across trader behavior. Conversely, significantly positive coefficients of non-linear term suggest the anti-herd behavior which is the enhancement of heterogeneous decision-making. The Chow test indicates the difference between the coefficient of non-linear term from the portfolios of companies with lowest and highest corporate transparency. In general, the linear association between CSAD and portfolio return, measured by the coefficient of absolute portfolio return, is positive and statistically significant. The outcomes also support the rational asset pricing theory which suggests that the return dispersion is the increasing function of overall portfolio return. Nevertheless, the negative association is identified in Portfolio 2 of France and Portfolio 1 of South Africa as it violates the rational asset pricing. Christie & Huang (1995) propose that it can be interpreted as a signal of herd behavior.

Since this chapter focuses on the non-linear term, herding is detected in Brazil, China, Germany, Greece, Portugal, Russia, and UAE. Characteristics of these countries include being emerging markets, having unstable economies as well as information restricted environment which help facilitate the herd behavior. In consideration of the anti-herd behavior, represented via significantly positive coefficients of non-linear term, the phenomenon is found in every market except Australia, Canada, China, Greece, India, and Russia. In view of corporate transparency, Portfolio 5 has significantly smaller coefficient of non-linear term than Portfolio 1 in China, Germany, Italy, South Africa, and UK. Since low return synchronicity portfolios often suggest the occurrence of herd behavior, these markets confirm the argument that corporate opacity intensifies the imitation trading. However, the opposite results are exhibited in Brazil, France, Ireland, Portugal, Spain, UAE, and USA. The most probable explanation is that corporate transparency reduces information asymmetry. It builds up an equality of investor information. Consequently, chances of parallel trading decision are higher when investors have equal access to the same information, which causes spurious herding. For these reasons, not only reducing an intentional herd behavior, corporate transparency also increases spurious herding.

In order to reach the clearer conclusion, Panel B of Table 3.4 shows the findings from decile portfolio construction by using R-squared. Aggregate market herding is still identified by the proposed model from Blasco et al. (2017). Portfolio 10 has the lowest stock return synchronicity which suggests the lack of corporate transparency. Since Ireland has too small number of stocks for decile portfolio analysis, only 18 countries are analyzed. Based on the association between CSAD and absolute portfolio return, return variation is generally increasing with overall portfolio return. However, Portfolio 3 of France, Portfolio 3, 8, and 10 of Italy, Portfolio 4 of Portugal, and Portfolio 5 of UAE violate the rational asset pricing theory as return variation and overall portfolio return move in the opposite direction.

The non-linear relationship indicates that herd behavior is found in Brazil, Canada, Greece, India, Russia, Spain, Thailand, and UAE. Among other countries, Canada is the only developed country with economic stability. The outcomes are reinforced by previous literatures indicating that the imitation across trader behavior is driven by market uncertainty exclusively among developing countries (Christie & Huang, 1995; Chang et al., 2000; and Gelos & Wei, 2005). Additionally, retail investors, who are most likely to join the herd, play an important role in emerging markets (Venezia et al., 2011). On the other hand, significantly positive coefficients of non-linear term are found in all countries except Canada and India. In terms of corporate transparency effect, Portfolio 1 has significantly higher coefficient of non-linear term than Portfolio 10 in Canada, Japan, Portugal, South Africa, Thailand, and UK. However, the opposite outcomes are suggested in France, Italy, UAE, and USA. Hence, the results mostly verify the hypothesis that corporate transparency reduces herd behavior. To sum up, the findings are more straightforward for the decile portfolio technique than the quintile portfolio method. Most importantly, the inferences mostly confirm the argument that corporate transparency decreases herd behavior which is also in line with Wang & Huang (2018).

3.5.3 Robustness

The robustness test utilizes non-lagged CSAD model from Yao et al. (2014) as the alternative proxy of corporate transparency. Quintile and decile portfolios are constructed by applying the logarithmic transformation of R-squared (Vo, 2017). As the logarithmic transformation technique does not change the ranking of return synchronicity, descriptive statistics for the 60-day CSAD and equally weighted portfolio return are in accordance with the main methodology presented in Table 3.3 for both quintile and decile portfolios. Thus, the results from decile portfolios are not discussed in this section. In consideration of unit root test, time-series samples are generally stationary. Also, Newey & West (1987)'s standard error is utilized to reduce autocorrelation problem.

Panel A of Table 3.5 specifies the regression results from quintile portfolio construction by using the unbound-continuous stock return synchronicity (Vo, 2017) with aggregate market herding detection model from Yao et al. (2014). Based on Christie & Huang (1995), the violation of rational asset pricing theory is found in all portfolios except Portfolio 1 of Australia, Portfolio 2 and 5 of France, Portfolio 1 and 2 of Greece, Portfolio 2, and 3 of India, Portfolio 1, 2 and 3 of Italy, and Portfolio 1 of Japan. Hence, the robustness method discovers higher level of the negative linear relationship between return dispersion and portfolio return, thus, suggesting the occurrence of herd behavior.

In terms of the coefficient of non-linear term, the deterioration of independent decision-making is detected only in Brazil, China, and UAE, whereas the main methodology identifies herding in seven countries. As the robustness test cannot detect herd behavior in Germany, Greece, Portugal, and Russia, thus, the main methodology is better than this technique in terms of detection power. On the other hand, anti-herding, which is triggered by significantly positive coefficients of non-linear term, is pointed out in all markets except Canada, Russia, and UAE. With regard to the impact of corporate transparency, the Chow test suggests that the portfolio of companies with the lowest corporate transparency has higher degree of herding than the one with most transparent companies in China, Germany, Greece, Italy, Japan, South Africa, Thailand, and UK. Yet, under the same condition, the anti-herding is more pronounced in Australia, France, India, Ireland, Portugal, and Spain. Therefore, the results from quintile construction are still mixed. However, the findings mostly confirm the hypothesis that herd behavior is reduced in portfolios of companies with high corporate transparency.

In view of decile portfolio of the R-squared transformation, Panel B of Table 3.5 indicates the herding results based on the non-lagged CSAD model from Yao et al. (2014). The positive and significant linear relationship between CSAD and portfolio return is discovered in most cases except for some portfolios in Australia, China, France, Greece, India, Italy, Japan, Portugal, and UAE. It confirms the quintile portfolio conclusion that the robustness methodology identifies a larger number of the violation of rational asset pricing theory. The negative linear association suggests the sign of herding.

Focusing on the non-linear term, herd behavior is detected in Brazil and Spain. On the other hand, according to the results from the main methodology eight markets where herding occurs is discovered. Consequently, Panel B of Table 3.5 confirms that the detection power of the previous technique is more improved than this setting. In contrast, anti-herd behavior can be found in all countries. Based on the Chow test, Portfolio 1 has higher coefficient of non-linear term than Portfolio 10 in Canada, China, Germany, Greece, Japan, Portugal, South Africa, Thailand, and UK. Nonetheless, the opposite results are found in Australia, Brazil, France, India, Italy, and UAE. Hence, the outcomes mostly certify that lower corporate transparency leads to the stronger aggregate market herding which confirms the hypothesis.

Table 3.3 Information selection criteria for different models.

Note: This table represents selection information criteria by using Akaike's information criterion (AIC), corrected Akaike's information criterion (AICc), Bayesian information criterion (BIC), and Hannan–Quinn information criterion (HQIC). The numbers are shown in average value of all portfolios. The six models are compared which are $CSAD_t = \propto + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \varepsilon_t$ (Chang et al., 2000: CCK), $CSAD_t = \propto + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 (R_{m,t})^2 + \varepsilon_t$ (Chiang & Zheng, 2010: CZ), $CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m,t} + \gamma_3 |R_{m,t}| + \gamma_4 (R_{m,t})^2 + \varepsilon_t$ (Blasco et al., 2017: BCF), $CSAD_t = \propto + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (Yao et al., 2014: YMH1), $CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 |R_{m,t}| + \gamma_3 (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$ (Yao et al., 2014: YMH2), and $CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 |R_{m,t}| + \gamma_3 (|R_{m,t}| - \overline{R_m})^2 + \varepsilon_t$ (Bui et al., 2017: BNNT),

where $CSAD_t$ is a cross-sectional absolute deviation of 60-day return during period t, $R_{m,t}$ is an equally weighted 60-day portfolio return during period t, and $CSAD_{t-1}$ is a one-day lag of cross-sectional absolute deviation of 60-day return.

The sample interval is from 01/01/1991 to 2/11/2018.

* indicates the best fit model using AIC, AICc, BIC, and HQIC criteria.

Table 3.3 (continued)

AUS	AIC	AICc	BIC	HQIC
CCK	757.091	757.296	768.274	758.497
CZ	700.525	700.869	714.504	703.066
BCF	693.444*	693.966*	710.219*	697.121*
YMH1	740.829	741.034	752.012	742.235
YMH2	737.003	737.348	750.982	739.545
BNNT	753.977	754.322	767.956	756.519
Base Value	760.119	760.152	765.710	759.254
BRA				
CCK	783.714	783.939	794.552	785.012
CZ	779.775	780.153	793.323*	782.172
BCF	778.604*	779.176*	794.861	782.100*
YMH1	782.789	783.013	793.627	784.086
YMH2	781.284	781.661	794.831	783.680
BNNT	782.081	782.458	795.628	784.477
Base Value	860.178	860.214	865.597	859.277
CAN	AIC	AICc	BIC	HQIC
CCK	767.910	768.115	779.093	769.317
CZ	748.725	749.070	762.704	751.267
BCF	738.328*	738.850*	755.103*	742.006*
YMH1	766.630	766.835	777.813	768.036
YMH2	757.640	757.985	771.619	760.182
BNNT	759.446	759.791	773.425	761.988
Base Value	780.222	780.256	785.814	779.358
CHN				
CCK	630.776	630.996	641.685	632.096
CZ	592.286	592.656	605.923	594.713
BCF	572.554*	573.115*	588.919*	576.088*
YMH1	626.240	626.461	637.150	627.561
YMH2	614.437	614.808	628.074	616.864
BNNT	619.107	619.477	632.744	621.534
Base Value	673.210	673.246	678.665	672.317
FRA				
CCK	670.062	670.267	681.245	671.468
CZ	639.707	640.052	653.686	642.249
BCF	629.917*	630.439*	646.692*	633.594*
YMH1	665.918	666.123	677.101	667.324
YMH2	660.899	661.244	674.878	663.441
BNNT	665.383	665.728	679.362	667.925
Base Value	733.566	733.600	739.158	732.702

Table 3.3 (continued)

GER				
CCK	704.458	704.667	715.574	705.844
CZ	683.175	683.526	697.070	685.689
BCF	641.701*	642.232*	658.375*	645.343*
YMH1	704.410	704.619	715.526	705.795
YMH2	671.147	671.498	685.043	673.661
BNNT	672.108	672.459	686.003	674.622
Base Value	746.200	746.235	751.759	745.329
GRE				
CCK	818.995	819.200	830.178	820.401
CZ	782.588	782.933	796.567	785.130
BCF	768.740*	769.261*	785.514*	772.417*
YMH1	813.297	813.502	824.480	814.703
YMH2	801.668	802.013	815.647	804.210
BNNT	806.790	807.134	820.769	809.332
Base Value	865.280	865.314	870.872	864.416
IND	AIC	AICc	BIC	HQIC
CCK	870.431	870.636	881.614	871.837
CZ	816.351	816.696	830.330	818.893
BCF	782.476*	782.998*	799.251*	786.154*
YMH1	862.886	863.091	874.069	864.292
YMH2	844.476	844.821	858.455	847.018
BNNT	853.872	854.217	867.851	856.414
Base Value	905.456	905.490	911.048	904.592
IRE				
CCK	699.911	700.161	710.331	701.074
CZ	699.335	699.756	712.361	701.553
BCF	697.619*	698.258*	713.250	700.891
YMH1	699.798	700.048	710.219*	700.961
YMH2	698.402	698.823	711.428	700.619*
BNNT	698.562	698.983	711.588	700.780
Base Value	731.104	731.145	736.314	730.158
ITA				
CCK	694.405	694.610	705.589	695.812
CZ	660.682	661.027	674.661	663.224
BCF	655.229*	655.751*	672.004*	658.907*
YMH1	692.006	692.211	703.189	693.412
YMH2	686.242	686.587	700.221	688.784
BNNT	688.734	689.079	702.713	691.276
Base Value	806.147	806.180	811.738	805.282

Table 3.3 (continued)

JAP				
CCK	573.838	574.044	585.022	575.245
CZ	542.661	543.005	556.640	545.203
BCF	491.356*	491.877*	508.130*	495.033*
YMH1	570.242	570.447	581.425	571.648
YMH2	522.506	522.851	536.485	525.048
BNNT	530.964	531.309	544.943	533.506
Base Value	611.157	611.191	616.749	610.293
POR				
CCK	764.337	764.557	775.246	765.657
CZ	761.584	761.954	775.221	764.011
BCF	759.622*	760.182*	775.986	763.155*
YMH1	764.002	764.222	774.912*	765.322
YMH2	762.101	762.471	775.738	764.528
BNNT	762.523	762.894	776.160	764.950
Base Value	840.555	840.591	846.010	839.662
RUS	AIC	AICc	BIC	HQIC
CCK	578.867	579.171	588.542	579.782
CZ	572.070*	572.583*	584.164*	573.957*
BCF	572.100	572.879	586.613	574.959
YMH1	579.923	580.226	589.598	580.838
YMH2	579.831	580.344	591.926	581.718
BNNT	578.952	579.464	591.046	580.839
Base Value	599.881	599.930	604.718	598.852
SAF				
CCK	725.679	725.885	736.863	727.086
CZ	724.089	724.434	738.068	726.631
BCF	713.741*	714.263*	730.516*	717.418*
YMH1	726.889	727.094	738.072	728.296
YMH2	718.444	718.789	732.423	720.986
BNNT	716.913	717.258	730.892	719.455
Base Value	752.937	752.971	758.529	752.072
SPA				
CCK	677.290	677.495	688.473	678.697
CZ	672.119	672.464	686.098	674.661
BCF	668.999*	669.521*	685.774*	672.676*
YMH1	680.242	680.447	691.425	681.649
YMH2	677.109	677.454	691.088	679.651
BNNT	673.950	674.295	687.929	676.492
Base Value	740.711	740.744	746.302	739.846

Table 3.3 (continued)

THA				
CCK	753.209	753.414	764.392	754.616
CZ	728.874	729.219	742.853	731.416
BCF	715.164*	715.686*	731.939*	718.841*
YMH1	752.070	752.275	763.253	753.476
YMH2	747.806	748.151	761.785	750.348
BNNT	748.821	749.165	762.800	751.363
Base Value	850.435	850.469	856.027	849.571
UAE				
CCK	410.947	411.347	419.583	411.499
CZ	393.293*	393.971*	404.088*	394.695*
BCF	393.464	394.498	406.417	395.716
YMH1	410.852	411.252	419.488	411.404
YMH2	411.022	411.700	421.817	412.424
BNNT	411.087	411.765	421.882	412.489
Base Value	425.787	425.852	430.105	424.638
UK	AIC	AICc	BIC	HQIC
CCK	661.888	662.093	673.071	663.294
CZ	653.596	653.941	667.575	656.138
BCF	604.784*	605.306*	621.559*	608.462*
YMH1	662.964	663.169	674.147	664.371
YMH2	621.738	622.082	635.717	624.280
BNNT	620.148	620.492	634.127	622.689
Base Value	685.961	685.995	691.553	685.097
USA				
CCK	573.753	573.958	584.937	575.160
CZ	568.196	568.541	582.175	570.738
BCF	537.452*	537.974*	554.227*	541.129*
YMH1	576.662	576.867	587.845	578.068
YMH2	548.783	549.128	562.762	551.325
BNNT	546.064	546.409	560.043	548.606
Base Value	622.610	622.643	628.201	621.745

Table 3.4 Regression results of the 60 days $CSAD_t$ on R-squared ranking portfolios.

Panel A: Regression results of the 60 days CSADt on five R-squared portfolios.

Note: This table reports regression statistics of the five R-squared portfolios by using $CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m,t} + \gamma_3 |R_{m,t}| + \gamma_4 (R_{m,t})^2 + \varepsilon_t$, where $CSAD_t$ is a cross-sectional absolute deviation of 60-day return during period t, $R_{m,t}$ is an equally weighted 60-day portfolio return during period t, and $CSAD_{t-1}$ is a one-day lag of cross-sectional absolute deviation of 60-day return.

The sample interval is from 01/01/1991 to 2/11/2018. The t-statistics are shown in parentheses which is calculated by using Newey & West (1987)'s heteroscedaticity and autocorrelation consistent standard errors. The F values from Chow Test are shown in square brackets.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

	AUS					BRA				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	17.593***	18.680***	16.513***	13.842***	16.812***	8.613***	11.739***	16.686***	11.862***	13.294***
	(7.72)	(12.33)	(11.36)	(7.33)	(8.87)	(4.49)	(6.21)	(8.45)	(10.11)	(7.41)
$CSAD_{t-1}$	-0.046	0.105*	0.215***	0.324***	0.227**	0.216**	0.191*	0.031	0.089	0.057
	(-0.41)	(1.76)	(2.93)	(4.18)	(2.24)	(2.38)	(1.92)	(0.47)	(1.42)	(0.58)
$R_{m,t}$	0.365***	0.294***	0.348***	0.290***	0.239***	0.119**	0.125***	0.078*	0.077*	0.139***
	(4.56)	(7.23)	(6.44)	(5.78)	(3.54)	(2.21)	(4.43)	(1.68)	(1.71)	(3.54)
$\|R_{m,t}\|$	0.291***	0.150	0.210*	0.256***	0.165	0.322***	0.167***	0.053	0.334***	0.272***
	(2.71)	(1.60)	(1.67)	(3.19)	(1.35)	(3.33)	(2.88)	(1.02)	(4.78)	(6.08)
${R_{m,t}}^2$	0.003	0.003	0.004	0.001	0.002	-0.002***	-0.001***	0.001***	0.001	-0.001***
	(0.81)	(1.57)	(1.47)	(0.90)	(1.02)	(-3.40)	(-3.94)	(6.60)	(-1.01)	(-3.34)
$Adj. R^2$	0.590	0.496	0.538	0.318	0.169	0.344	0.239	0.652	0.722	0.560
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[8.186]***				$\gamma_{4,Low} - \gamma_{4,High}$	[0.859]*			

Table 3.4 Panel A (continued)

	CAN					CHN				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	7.582***	12.134***	11.353***	13.509***	12.546***	4.053***	4.677***	6.029***	6.864***	7.475***
	(4.76)	(10.98)	(8.61)	(11.13)	(7.14)	(8.75)	(7.41)	(9.24)	(8.83)	(7.73)
$CSAD_{t-1}$	0.341***	0.254***	0.276***	0.176**	0.229**	0.263***	0.338***	0.263***	0.246***	0.305***
	(5.70)	(4.72)	(4.10)	(2.59)	(2.59)	(4.34)	(9.28)	(6.02)	(4.32)	(4.85)
$R_{m,t}$	0.204***	0.252***	0.156*	0.249***	0.208**	0.110***	0.121***	0.157***	0.154***	0.166***
	(3.68)	(3.80)	(1.97)	(3.43)	(2.39)	(8.20)	(7.14)	(7.67)	(7.98)	(5.22)
$\lvert R_{m,t} \rvert$	0.535***	0.149	0.369***	0.356***	0.398***	0.100***	0.115***	0.146***	0.185***	0.238***
	(2.92)	(1.13)	(2.94)	(2.95)	(2.88)	(3.04)	(2.68)	(2.65)	(3.20)	(3.69)
${R_{m,t}}^2$	-0.005	0.005	-0.002	0.003	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002***
	(-1.18)	(1.33)	(-1.18)	(1.10)	(-0.64)	(-1.54)	(-1.54)	(-0.94)	(-1.51)	(-3.45)
$Adj. R^2$	0.391	0.361	0.220	0.367	0.215	0.606	0.564	0.587	0.622	0.635
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[2.769]*				$\gamma_{4,Low} - \gamma_{4,High}$	[129.509]***			
	FRA					GER				
$Intercept$	7.493***	9.621***	10.702***	10.316***	10.460***	6.870***	6.508***	5.981***	4.675***	4.576***
	(9.80)	(11.86)	(9.85)	(6.40)	(7.00)	(5.82)	(5.23)	(4.20)	(3.53)	(3.60)
$CSAD_{t-1}$	0.132**	0.232***	0.163***	0.208**	0.260***	0.232**	0.342***	0.447***	0.593***	0.481***
	(2.21)	(6.42)	(4.07)	(2.12)	(3.05)	(2.47)	(3.82)	(4.60)	(8.34)	(4.97)
$R_{m,t}$	0.107***	0.174***	0.269***	0.276***	0.214***	0.159***	0.258***	0.239***	0.145***	0.199***
	(4.35)	(4.11)	(3.53)	(4.05)	(3.29)	(3.73)	(4.01)	(4.68)	(3.91)	(4.71)
$\lvert R_{m,t} \rvert$	0.098*	-0.284**	-0.071	0.168	-0.146	0.107	0.332***	0.286**	0.278**	0.577***
	(1.92)	(-2.01)	(-0.31)	(1.45)	(-0.79)	(1.03)	(3.00)	(1.99)	(2.51)	(5.90)
${R_{m,t}}^2$	0.005***	0.021***	0.017	0.009*	0.029***	0.006***	0.004	0.004	0.001	-0.005*
	(6.26)	(3.55)	(1.35)	(1.75)	(2.65)	(3.46)	(0.95)	(0.93)	(-0.04)	(-1.97)
$Adj. R^2$	0.781	0.671	0.516	0.349	0.483	0.719	0.629	0.551	0.498	0.553
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[74.470]***				$\gamma_{4,Low} - \gamma_{4,High}$	[15.081]***			

Table 3.4 Panel A (continued)

	GRE					IND				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	6.605***	9.570***	9.013***	10.628***	14.994***	12.691***	13.266***	15.732***	15.970***	15.078***
	(8.07)	(10.69)	(8.20)	(11.11)	(13.27)	(5.56)	(7.64)	(8.13)	(6.06)	(9.86)
$CSAD_{t-1}$	0.287***	0.262***	0.349***	0.252**	0.076	0.373***	0.422***	0.335***	0.281**	0.312***
	(6.92)	(5.49)	(4.73)	(2.58)	(1.10)	(3.54)	(4.48)	(3.31)	(2.42)	(5.39)
$R_{m,t}$	0.157***	0.171***	0.188***	0.242***	0.382***	0.270***	0.263***	0.320***	0.329***	0.355***
	(5.67)	(5.16)	(4.30)	(4.79)	(5.88)	(7.02)	(6.36)	(6.73)	(6.51)	(9.33)
$\lvert R_{m,t} \rvert$	0.229*	0.048	0.132	0.295***	0.285*	0.120	0.085	0.146	0.304*	0.324***
	(1.88)	(0.50)	(1.36)	(2.70)	(1.80)	(1.36)	(0.91)	(1.33)	(1.85)	(3.33)
${R_{m,t}}^2$	-0.003	0.002	0.001	-0.004**	-0.001	-0.001	0.001	-0.001	-0.001	0.001
	(-1.10)	(0.94)	(0.02)	(-2.45)	(-0.75)	(-0.90)	(-0.14)	(-0.35)	(-0.36)	(-0.14)
$Adj. R^2$	0.460	0.496	0.576	0.491	0.732	0.612	0.600	0.596	0.602	0.789
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[30.763]***				$\gamma_{4,Low} - \gamma_{4,High}$	[31.167]***			
	IRE					ITA				
$Intercept$	8.766***	5.761***	8.279***	7.623***	9.271***	6.741***	6.936***	8.938***	10.717***	6.915***
	(4.74)	(3.50)	(5.60)	(5.09)	(5.96)	(7.31)	(8.12)	(14.11)	(10.48)	(9.12)
$CSAD_{t-1}$	0.074	0.332***	0.163**	0.049	0.039	0.158**	0.260***	0.075	-0.047	0.096***
	(0.97)	(3.19)	(2.33)	(0.46)	(0.84)	(2.21)	(4.68)	(1.49)	(-0.75)	(3.67)
$R_{m,t}$	0.055	0.032	0.089	0.113*	0.083	0.086***	0.140**	0.140***	0.226***	0.351***
	(0.60)	(0.56)	(1.66)	(1.75)	(1.20)	(2.76)	(2.14)	(5.84)	(4.45)	(4.78)
$\lvert R_{m,t} \rvert$	0.300	0.290*	-0.038	0.270	-0.172	-0.030	-0.094	-0.010	0.050	0.492***
	(1.48)	(1.93)	(-0.27)	(1.34)	(-0.77)	(-0.39)	(-0.90)	(-0.12)	(0.53)	(2.65)
${R_{m,t}}^2$	0.001	-0.003	0.012***	0.004	0.014**	0.007**	0.011***	0.011***	0.011***	0.002
	(0.27)	(-1.26)	(4.68)	(0.61)	(2.55)	(2.35)	(3.32)	(4.58)	(6.81)	(0.81)
$Adj. R^2$	0.306	0.131	0.419	0.252	0.410	0.669	0.574	0.690	0.735	0.856
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[10.247]***				$\gamma_{4,Low} - \gamma_{4,High}$	[37.467]***			

Table 3.4 Panel A (continued)

	JAP					POR				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	3.232***	4.006***	4.888***	7.227***	7.390***	11.971***	9.954***	6.074***	8.913***	7.828***
	(5.19)	(7.08)	(6.34)	(8.77)	(9.40)	(7.33)	(8.45)	(5.96)	(5.40)	(8.64)
$CSAD_{t-1}$	0.556***	0.511***	0.449***	0.301***	0.277***	-0.012	-0.022	0.224***	0.132	0.147***
	(7.26)	(10.50)	(7.60)	(5.34)	(5.00)	(-0.27)	(-0.76)	(3.63)	(1.37)	(6.90)
$R_{m,t}$	0.076***	0.075***	0.097***	0.118***	0.181***	0.144*	0.183**	0.023	0.088**	0.074
	(5.07)	(5.01)	(7.16)	(6.41)	(7.06)	(1.88)	(2.62)	(0.38)	(2.32)	(1.07)
$\lvert R_{m,t} \rvert$	-0.037	0.009	0.075	0.062	0.111	0.156	0.073	0.485***	0.176	0.227**
	(-0.63)	(0.12)	(0.91)	(0.85)	(1.41)	(0.98)	(0.32)	(2.89)	(0.89)	(2.07)
${R_{m,t}}^2$	0.008***	0.007**	0.006	0.007**	0.008**	0.004***	0.009	-0.008*	0.009	0.006***
	(3.43)	(2.26)	(1.63)	(2.43)	(2.56)	(3.35)	(1.50)	(-1.74)	(1.49)	(4.58)
$Adj. R^2$	0.633	0.612	0.645	0.622	0.684	0.697	0.509	0.142	0.217	0.766
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[87.437]***				$\gamma_{4,Low} - \gamma_{4,High}$	[3.514]*			
	RUS					SAF				
$Intercept$	9.201***	11.508***	15.586***	17.095***	16.101***	10.990***	9.211***	11.595***	11.689***	9.345***
	(11.24)	(9.62)	(7.47)	(8.10)	(3.41)	(8.31)	(8.23)	(8.41)	(7.77)	(9.41)
$CSAD_{t-1}$	0.125**	0.073	-0.171	-0.162***	-0.024	0.167**	0.306***	0.191*	0.236***	0.387***
	(2.54)	(1.13)	(-1.49)	(-2.86)	(-0.12)	(2.15)	(3.16)	(1.72)	(3.42)	(6.77)
$R_{m,t}$	0.147***	0.131***	0.098**	0.070	0.135***	0.130**	0.163***	0.065**	0.053	0.028
	(5.88)	(4.38)	(2.24)	(1.60)	(2.75)	(2.03)	(2.67)	(2.46)	(1.61)	(0.51)
$\lvert R_{m,t} \rvert$	0.127	0.030	0.258	0.503**	0.323	-0.218**	0.022	0.183	0.120	0.101
	(1.43)	(0.23)	(1.55)	(2.63)	(1.52)	(-2.04)	(0.15)	(1.52)	(0.66)	(0.75)
${R_{m,t}}^2$	0.001	0.002	0.001	-0.004*	0.001	0.015***	0.008***	0.001	0.006	0.002
	(0.01)	(1.40)	(0.39)	(-1.85)	(0.02)	(4.82)	(3.13)	(-0.13)	(0.88)	(0.29)
$Adj. R^2$	0.231	0.538	0.431	0.145	0.138	0.517	0.415	0.111	0.167	0.194
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[19.006]***				$\gamma_{4,Low} - \gamma_{4,High}$	[19.135]***			

Table 3.4 Panel A (continued)

	SPA					THA				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	5.759***	7.402***	8.367***	9.785***	6.790***	8.355***	9.984***	9.593***	7.923***	7.900***
	(6.16)	(8.60)	(7.66)	(3.75)	(7.97)	(5.54)	(6.76)	(6.03)	(6.20)	(6.02)
$CSAD_{t-1}$	0.042	0.136**	0.109	0.055	0.245***	0.194	0.165*	0.245**	0.300***	0.194**
	(0.53)	(2.08)	(1.47)	(0.40)	(3.32)	(1.55)	(1.72)	(2.26)	(3.02)	(2.11)
$R_{m,t}$	0.011	0.094***	0.100***	0.077***	0.074**	0.246***	0.229***	0.163***	0.158***	0.190***
	(0.55)	(4.02)	(3.34)	(2.69)	(2.14)	(5.59)	(7.13)	(5.29)	(3.65)	(4.04)
$\left\|R_{m,t}\right\|$	0.188**	0.103	0.120	0.034	0.192	0.216***	0.231***	0.097	0.199	0.599***
	(2.07)	(1.37)	(1.19)	(0.18)	(1.62)	(3.05)	(3.29)	(1.65)	(1.14)	(4.78)
${R_{m,t}}^2$	0.001	0.005**	0.005	0.011**	0.011***	0.001	0.001**	0.006***	0.007	-0.005
	(0.42)	(2.12)	(1.53)	(2.11)	(2.98)	(-0.09)	(2.28)	(6.17)	(1.63)	(-1.57)
$Adj.R^2$	0.272	0.408	0.396	0.555	0.621	0.745	0.767	0.670	0.625	0.567
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[84.513]***				$\gamma_{4,Low} - \gamma_{4,High}$	[24.045]***			
	UAE					UK				
$Intercept$	9.743***	4.770***	9.432***	8.635***	9.861***	6.023***	6.146***	6.277***	6.864***	7.865***
	(6.52)	(4.70)	(10.86)	(5.65)	(10.45)	(9.52)	(6.76)	(6.31)	(5.52)	(5.14)
$CSAD_{t-1}$	0.003	0.238***	-0.014	0.049	0.082*	0.359***	0.502***	0.535***	0.541***	0.461***
	(0.04)	(3.72)	(-0.24)	(0.71)	(1.94)	(7.51)	(9.31)	(9.61)	(7.92)	(5.89)
$R_{m,t}$	0.157***	0.191***	0.315***	0.245***	0.280***	0.123**	0.161***	0.093***	0.124***	0.086**
	(6.73)	(5.88)	(3.33)	(2.81)	(4.55)	(2.22)	(3.73)	(2.78)	(4.41)	(2.46)
$\left\|R_{m,t}\right\|$	0.067	0.641***	0.401***	0.468*	-0.103	-0.031	0.022	0.132*	0.054	0.227**
	(0.35)	(4.25)	(3.08)	(1.82)	(-0.41)	(-0.37)	(0.24)	(1.89)	(0.73)	(2.35)
${R_{m,t}}^2$	0.002	-0.012**	0.001	-0.001	0.026**	0.010***	0.008***	0.001	0.005**	0.001
	(0.38)	(-2.42)	(0.06)	(-0.14)	(2.28)	(5.11)	(2.80)	(0.15)	(2.27)	(0.18)
$Adj.R^2$	0.230	0.535	0.478	0.449	0.423	0.729	0.456	0.387	0.467	0.384
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[10.353]***				$\gamma_{4,Low} - \gamma_{4,High}$	[101.942]***			

Table 3.4 Panel A (continued)

	USA				
Portfolio	1	2	3	4	5
$Intercept$	4.548***	5.962***	5.855***	6.816***	8.372***
	(5.43)	(4.71)	(5.53)	(7.51)	(9.40)
$CSAD_{t-1}$	0.383***	0.345***	0.398***	0.398***	0.329***
	(3.46)	(2.70)	(4.03)	(4.30)	(4.17)
$R_{m,t}$	0.051***	0.062***	0.045***	0.062***	0.116***
	(3.77)	(3.74)	(3.38)	(5.21)	(3.72)
$\lvert R_{m,t} \rvert$	0.070	0.003	0.084	0.069*	0.221***
	(1.08)	(0.03)	(1.37)	(1.69)	(2.80)
${R_{m,t}}^2$	0.002	0.007**	0.005**	0.006***	0.003**
	(1.65)	(2.55)	(2.51)	(4.25)	(2.07)
$Adj.R^2$	0.429	0.561	0.528	0.503	0.572
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[164.713]***			

Panel B: Regression results of the 60 days $CSAD_t$ on ten R-squared portfolios.

Note: This table reports regression statistics of the ten R-squared portfolios by using $CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m,t} + \gamma_3 |R_{m,t}| + \gamma_4 (R_{m,t})^2 + \varepsilon_t$, where $CSAD_t$ is a cross-sectional absolute deviation of 60-day return during period t, $R_{m,t}$ is an equally weighted 60-day portfolio return during period t, and $CSAD_{t-1}$ is a one-day lag of cross-sectional absolute deviation of 60-day return.

The sample interval is from 01/01/1991 to 2/11/2018.

The t-statistics are shown in parentheses which is calculated by using Newey & West (1987)'s heteroscedaticity and autocorrelation consistent standard errors. The F values from Chow Test are shown in square brackets.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

	AUS									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	18.019***	15.686***	18.884***	16.876***	17.046***	17.665***	14.666***	16.117***	19.276***	13.457***
	(10.37)	(6.04)	(9.65)	(9.64)	(10.42)	(9.86)	(8.96)	(5.98)	(10.69)	(6.53)
$CSAD_{t-1}$	-0.124***	0.133	0.031	0.150*	0.186**	0.172**	0.282***	0.183*	0.137	0.294***
	(-3.15)	(0.98)	(0.48)	(1.68)	(2.17)	(2.29)	(4.32)	(1.74)	(1.62)	(3.10)
$R_{m,t}$	0.323***	0.283***	0.316***	0.289***	0.368***	0.357***	0.291***	0.318***	0.260***	0.261***
	(5.12)	(5.69)	(9.16)	(5.91)	(8.22)	(6.27)	(7.94)	(6.04)	(4.09)	(3.16)
$\|R_{m,t}\|$	0.138	0.289***	0.247**	0.270**	0.237*	0.096	0.243**	0.362***	0.157	0.347**
	(0.74)	(2.82)	(2.02)	(2.26)	(1.85)	(0.61)	(2.18)	(4.06)	(1.23)	(2.26)
${R_{m,t}}^2$	0.006	-0.001	0.003	0.001	0.004	0.009**	0.002	0.001	0.002	-0.001
	(1.21)	(-0.69)	(1.01)	(0.38)	(1.36)	(2.14)	(1.02)	(-0.03)	(0.83)	(-0.25)
$Adj. R^2$	0.647	0.377	0.512	0.411	0.454	0.539	0.366	0.197	0.162	0.213
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[13.564]***								

Table 3.4 Panel B (continued)

	BRA									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	3.767***	9.773***	11.014***	11.097***	11.999***	12.000***	13.319***	13.287***	12.099***	12.619***
	(2.80)	(10.47)	(4.44)	(6.27)	(6.15)	(5.72)	(8.92)	(9.13)	(6.81)	(8.23)
$CSAD_{t-1}$	0.436***	0.077*	0.095	0.112	0.019	-0.049	0.035	-0.161**	0.145	0.039
	(3.56)	(1.85)	(1.39)	(1.07)	(0.25)	(-0.54)	(0.83)	(-2.13)	(1.31)	(0.84)
$R_{m,t}$	-0.009	0.152***	0.122**	0.164***	0.089	0.170**	0.165*	-0.001	-0.010	0.058
	(-0.19)	(3.18)	(2.28)	(4.31)	(1.59)	(3.18)	(1.94)	(-0.02)	(-0.16)	(0.98)
$\lvert R_{m,t} \rvert$	0.277***	0.165	0.188	0.116	0.516***	0.625***	-0.084	0.517***	0.195	-0.145
	(3.47)	(1.32)	(0.82)	(0.79)	(2.94)	(3.38)	(-0.44)	(3.07)	(0.80)	(-0.43)
${R_{m,t}}^2$	-0.001	0.004**	0.001	0.003	-0.008**	-0.007	0.012***	-0.004	0.001	0.019
	(-0.95)	(2.02)	(0.18)	(1.00)	(-2.34)	(-1.60)	(2.88)	(-0.95)	(-0.03)	(1.46)
$Adj. R^2$	0.306	0.732	0.159	0.383	0.070	0.343	0.631	0.258	0.030	0.434
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[18.306]***								
	CAN									
$Intercept$	9.933***	10.489***	10.416***	13.363***	14.563***	14.334***	12.582***	16.778***	15.568***	12.129***
	(5.01)	(5.71)	(9.81)	(11.82)	(9.19)	(9.96)	(9.22)	(11.27)	(10.05)	(7.64)
$CSAD_{t-1}$	0.252***	0.261***	0.218***	0.134***	0.036	0.143***	0.199***	-0.010	0.037	0.205**
	(3.12)	(3.59)	(4.72)	(2.84)	(0.45)	(3.15)	(2.86)	(-0.11)	(0.47)	(2.61)
$R_{m,t}$	0.210***	0.221***	0.257***	0.277***	0.129***	0.322***	0.289***	0.238***	0.240***	0.297***
	(3.87)	(2.98)	(4.11)	(3.61)	(2.99)	(2.67)	(4.19)	(5.18)	(3.15)	(4.38)
$\lvert R_{m,t} \rvert$	0.266	0.296	0.439***	0.309***	0.443***	0.169	0.315	0.411***	0.397***	0.600***
	(1.10)	(1.65)	(2.68)	(2.65)	(4.67)	(0.90)	(1.66)	(3.98)	(3.15)	(5.92)
${R_{m,t}}^2$	0.001	0.004	-0.001	0.002	-0.004	0.012	0.008	0.001	0.001	-0.003*
	(0.10)	(0.52)	(-0.15)	(0.45)	(-1.34)	(1.52)	(1.24)	(0.33)	(0.43)	(-1.74)
$Adj. R^2$	0.359	0.368	0.461	0.250	0.199	0.315	0.559	0.287	0.155	0.324
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[5.751]***								

Table 3.4 Panel B (continued)

	CHN									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	4.122***	4.936***	5.813***	5.519***	6.124***	6.552***	7.854***	7.055***	8.250***	7.617***
	(6.97)	(6.80)	(5.88)	(7.38)	(6.88)	(9.98)	(9.01)	(8.69)	(6.79)	(11.64)
$CSAD_{t-1}$	0.288***	0.272***	0.234***	0.306***	0.225***	0.245***	0.232***	0.306***	0.220***	0.363***
	(5.29)	(3.43)	(4.09)	(7.59)	(4.21)	(6.08)	(6.43)	(5.57)	(3.35)	(8.72)
$R_{m,t}$	0.085***	0.103***	0.110***	0.103***	0.143***	0.150***	0.131***	0.144***	0.130***	0.144***
	(4.70)	(7.23)	(6.25)	(6.89)	(8.53)	(7.44)	(8.78)	(6.15)	(4.86)	(4.68)
$\lvert R_{m,t} \rvert$	-0.009	0.004	0.032	0.030	0.120***	0.126**	-0.003	0.117	0.187*	0.132*
	(-0.15)	(0.09)	(0.48)	(0.51)	(2.94)	(2.15)	(-0.06)	(1.48)	(1.82)	(1.97)
${R_{m,t}}^2$	0.002	0.002**	0.001	0.001	0.001	0.001	0.003***	0.001	0.001	0.001
	(1.58)	(2.07)	(1.19)	(1.19)	(-0.01)	(-0.12)	(3.78)	(0.20)	(-0.05)	(0.81)
$Adj. R^2$	0.576	0.636	0.487	0.602	0.562	0.544	0.641	0.581	0.556	0.726
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[205.882]***								
	FRA									
$Intercept$	6.791***	7.923***	9.564***	8.954***	11.794***	9.452***	8.878***	11.749***	11.294***	12.413***
	(10.21)	(10.76)	(12.65)	(8.05)	(9.95)	(9.65)	(8.13)	(5.57)	(8.10)	(10.83)
$CSAD_{t-1}$	0.074	0.214***	0.215***	0.259***	0.150***	0.168***	0.269***	0.146	0.229***	0.126**
	(1.23)	(3.99)	(5.54)	(4.99)	(3.16)	(3.93)	(3.64)	(1.31)	(3.19)	(2.14)
$R_{m,t}$	0.077***	0.142***	0.133***	0.198***	0.218***	0.297***	0.236***	0.319***	0.172***	0.215***
	(3.43)	(3.33)	(3.86)	(3.92)	(4.03)	(3.54)	(4.23)	(2.99)	(3.55)	(3.81)
$\lvert R_{m,t} \rvert$	0.155***	-0.051	-0.302***	-0.209	-0.354	0.204	0.196	-0.106	-0.239	-0.205
	(2.87)	(-0.53)	(-3.27)	(-1.03)	(-1.42)	(1.19)	(1.47)	(-0.41)	(-1.29)	(-1.49)
${R_{m,t}}^2$	0.003***	0.011***	0.020***	0.021**	0.026**	0.008	0.006	0.029*	0.029***	0.031***
	(4.85)	(3.38)	(5.67)	(2.26)	(2.27)	(0.98)	(1.38)	(1.72)	(3.50)	(5.69)
$Adj. R^2$	0.808	0.642	0.724	0.569	0.499	0.461	0.393	0.453	0.344	0.737
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[180.773]***								

Table 3.4 Panel B (continued)

	GER									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	4.410***	9.631***	9.023***	6.501***	7.198***	8.626***	7.462***	6.407***	7.048***	5.445***
	(4.91)	(6.70)	(7.20)	(4.66)	(5.02)	(4.28)	(4.81)	(5.02)	(3.77)	(3.67)
$CSAD_{t-1}$	0.285***	0.120	0.185***	0.387***	0.352***	0.335***	0.398***	0.423***	0.295**	0.408***
	(4.15)	(1.29)	(4.04)	(5.88)	(4.81)	(2.78)	(4.78)	(5.26)	(2.35)	(3.60)
$R_{m,t}$	0.148**	0.194***	0.265***	0.233***	0.244***	0.284***	0.156***	0.204***	0.237**	0.255***
	(2.50)	(5.23)	(11.61)	(4.29)	(5.58)	(4.87)	(2.93)	(3.99)	(2.62)	(5.05)
$\lvert R_{m,t} \rvert$	0.273*	-0.048	0.007	0.259*	0.153	0.050	0.235	0.392**	0.559***	0.592***
	(1.89)	(-0.46)	(0.09)	(1.85)	(0.86)	(0.25)	(1.22)	(2.54)	(3.88)	(4.82)
${R_{m,t}}^2$	0.001	0.012***	0.016***	0.005	0.011	0.014	0.002	0.001	-0.002	-0.003
	(0.53)	(6.86)	(6.97)	(1.03)	(1.52)	(1.51)	(0.29)	(0.19)	(-0.30)	(-1.00)
$Adj. R^2$	0.648	0.741	0.700	0.547	0.576	0.501	0.271	0.366	0.396	0.474
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[21.197]***								
	GRE									
$Intercept$	8.682***	9.961***	9.227***	10.346***	8.712***	10.823***	8.481***	16.810***	12.044***	11.658***
	(8.36)	(10.88)	(8.49)	(6.54)	(7.66)	(9.19)	(7.41)	(8.06)	(6.06)	(5.44)
$CSAD_{t-1}$	0.180***	0.140**	0.170***	0.098**	0.242***	0.249***	0.365***	-0.036	0.160**	0.116
	(3.11)	(2.30)	(2.84)	(2.02)	(3.79)	(3.98)	(4.33)	(-0.33)	(2.20)	(1.12)
$R_{m,t}$	0.110***	0.172***	0.189***	0.226***	0.177***	0.203***	0.170***	0.209***	0.302***	0.328***
	(4.35)	(3.29)	(4.76)	(3.15)	(4.29)	(4.54)	(4.42)	(4.71)	(5.82)	(3.88)
$\lvert R_{m,t} \rvert$	-0.001	-0.053	0.241*	0.227	0.244*	0.107	0.170**	0.119	0.376***	0.450***
	(-0.01)	(-0.37)	(1.75)	(1.04)	(1.66)	(1.11)	(1.99)	(0.84)	(3.34)	(2.90)
${R_{m,t}}^2$	0.002	0.005**	-0.003	0.001	0.001	0.001	-0.001	0.002	-0.004***	-0.002
	(0.92)	(2.09)	(-1.53)	(0.02)	(0.10)	(0.83)	(-0.41)	(0.73)	(-2.77)	(-1.62)
$Adj. R^2$	0.436	0.439	0.372	0.441	0.515	0.560	0.465	0.403	0.512	0.641
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[20.776]***								

Table 3.4 Panel B (continued)

	IND									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	13.697***	12.903***	13.487***	14.760***	14.914***	18.114***	21.214***	13.984***	15.492***	15.452***
	(8.21)	(4.69)	(6.83)	(9.97)	(6.78)	(15.15)	(6.79)	(6.16)	(12.28)	(10.37)
$CSAD_{t-1}$	0.270***	0.377***	0.388***	0.351***	0.319***	0.258***	0.127*	0.380***	0.298***	0.266***
	(3.07)	(3.18)	(4.07)	(4.89)	(4.54)	(4.70)	(1.68)	(3.41)	(5.46)	(4.69)
$R_{m,t}$	0.284***	0.276***	0.260***	0.278***	0.331***	0.321***	0.267***	0.306***	0.367***	0.368***
	(9.50)	(5.00)	(6.17)	(6.69)	(5.96)	(6.75)	(6.79)	(6.37)	(8.34)	(8.92)
$\|R_{m,t}\|$	0.153	0.144	0.080	0.148	0.235	0.130	-0.065	0.336**	0.347***	0.390***
	(1.66)	(1.29)	(0.94)	(1.19)	(1.47)	(0.84)	(-0.29)	(2.48)	(3.09)	(4.08)
${R_{m,t}}^2$	-0.002	-0.002	0.001	-0.001	-0.002	0.001	0.007	-0.004*	-0.002	0.001
	(-1.48)	(-0.83)	(0.20)	(-0.51)	(-0.64)	(-0.17)	(1.39)	(-1.90)	(-0.98)	(-0.08)
$Adj. R^2$	0.571	0.540	0.594	0.520	0.592	0.509	0.675	0.564	0.686	0.812
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[42.231]***								
	ITA									
$Intercept$	5.235***	7.054***	10.163***	8.359***	8.169***	9.170***	9.948***	11.127***	7.395***	10.653***
	(5.24)	(8.91)	(8.75)	(4.72)	(9.95)	(12.53)	(13.71)	(13.78)	(6.77)	(10.34)
$CSAD_{t-1}$	0.166*	0.150***	0.118**	0.048	0.072	0.053	-0.052	-0.013	-0.021	0.075
	(1.76)	(3.28)	(2.15)	(0.37)	(1.25)	(1.31)	(-0.97)	(-0.27)	(-0.73)	(1.21)
$R_{m,t}$	0.058***	0.113**	0.132***	0.104***	0.158***	0.150***	0.189***	0.195***	0.384***	0.205***
	(3.61)	(2.23)	(2.72)	(3.02)	(4.46)	(4.07)	(4.80)	(4.32)	(3.53)	(3.41)
$\|R_{m,t}\|$	0.040	-0.050	-0.485***	-0.012	0.081	-0.075	0.025	-0.214***	0.574**	-0.427**
	(0.63)	(-0.44)	(-4.09)	(-0.07)	(0.88)	(-0.70)	(0.27)	(-2.93)	(2.27)	(-2.34)
${R_{m,t}}^2$	0.004**	0.009*	0.022***	0.009**	0.007**	0.014***	0.012***	0.017***	0.001	0.033***
	(2.35)	(1.94)	(5.37)	(2.26)	(2.42)	(5.31)	(3.26)	(7.66)	(0.50)	(5.54)
$Adj. R^2$	0.696	0.506	0.726	0.446	0.514	0.715	0.755	0.736	0.856	0.628
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[83.895]***								

Table 3.4 Panel B (continued)

	JAP									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	3.652***	3.355***	3.915***	4.352***	4.664***	5.405***	7.916***	7.063***	8.151***	7.248***
	(6.03)	(4.81)	(6.80)	(7.35)	(5.54)	(6.89)	(7.73)	(8.51)	(11.91)	(7.85)
$CSAD_{t-1}$	0.511***	0.550***	0.513***	0.480***	0.452***	0.419***	0.239***	0.322***	0.252***	0.251***
	(7.19)	(6.99)	(9.11)	(11.16)	(6.54)	(6.90)	(3.43)	(5.94)	(5.09)	(4.28)
$R_{m,t}$	0.083***	0.072***	0.080***	0.072***	0.093***	0.102***	0.117***	0.119***	0.150***	0.212***
	(5.64)	(4.84)	(4.42)	(5.12)	(6.17)	(6.92)	(6.89)	(5.37)	(6.59)	(7.64)
$\lvert R_{m,t} \rvert$	-0.076	-0.024	0.003	0.023	0.074	0.077	0.012	0.080	-0.005	0.201**
	(-1.19)	(-0.36)	(0.05)	(0.26)	(0.85)	(0.96)	(0.12)	(1.05)	(-0.06)	(2.34)
${R_{m,t}}^2$	0.008***	0.008***	0.007**	0.007*	0.006	0.006*	0.010**	0.006*	0.012***	0.006*
	(3.87)	(2.76)	(2.51)	(1.85)	(1.41)	(1.88)	(2.13)	(1.89)	(3.75)	(1.76)
$Adj.R^2$	0.581	0.626	0.590	0.583	0.628	0.608	0.587	0.618	0.656	0.701
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[104.960]***								
	POR									
$Intercept$	10.591**	6.880***	7.391***	8.610***	6.674***	12.003***	9.012***	12.784***	8.604***	5.044**
	(2.60)	(3.71)	(3.46)	(6.38)	(4.54)	(5.71)	(6.94)	(4.47)	(3.26)	(2.63)
$CSAD_{t-1}$	0.011	0.013	0.149***	0.196**	0.170	-0.215**	-0.102	-0.142**	-0.011	0.140
	(0.14)	(0.46)	(3.62)	(2.59)	(1.61)	(-2.50)	(-1.65)	(-2.54)	(-0.11)	(1.06)
$R_{m,t}$	0.004	0.123	0.159	0.063	-0.004	0.242*	0.028	0.044	0.226***	-0.043
	(0.07)	(1.36)	(1.64)	(0.94)	(-0.09)	(1.67)	(0.50)	(0.49)	(3.97)	(-0.54)
$\lvert R_{m,t} \rvert$	-0.208	0.294	-0.118	-0.476**	0.142	-0.114	0.175	0.232	0.590*	0.520***
	(-0.55)	(1.55)	(-0.30)	(-2.02)	(0.72)	(-0.41)	(0.93)	(0.62)	(1.87)	(3.61)
${R_{m,t}}^2$	0.012*	0.004*	0.016	0.027***	0.006	0.027*	0.008*	0.002	-0.004	-0.002
	(1.74)	(1.98)	(1.52)	(4.53)	(1.04)	(1.95)	(1.69)	(0.20)	(-0.49)	(-0.65)
$Adj.R^2$	0.203	0.711	0.517	0.719	0.174	0.304	0.151	0.022	0.266	0.310
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[0.415]*								

Table 3.4 Panel B (continued)

	RUS									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	8.830***	9.502***	9.743***	10.202***	13.599***	10.556***	8.845***	8.696***	13.770***	11.297***
	(3.58)	(9.13)	(6.13)	(10.80)	(8.95)	(4.10)	(3.41)	(4.14)	(10.39)	(5.21)
$CSAD_{t-1}$	0.061	0.117	0.025	0.179**	0.014	0.189	0.327**	0.306***	0.117**	0.202*
	(0.60)	(1.65)	(0.22)	(2.63)	(0.19)	(1.58)	(2.56)	(2.93)	(2.24)	(1.76)
$R_{m,t}$	0.145***	0.160***	0.231***	0.110***	0.216***	0.144***	0.137***	0.113	0.388***	0.088***
	(3.63)	(5.54)	(2.82)	(4.55)	(3.31)	(3.34)	(4.02)	(1.16)	(4.99)	(3.02)
$\lvert R_{m,t}\rvert$	0.162	0.051	0.338	-0.007	0.079	0.291	0.245*	0.410**	-0.072	0.217
	(0.88)	(0.72)	(1.23)	(-0.12)	(0.42)	(1.36)	(1.92)	(2.47)	(-0.37)	(1.29)
${R_{m,t}}^2$	0.001	0.001	0.001	0.003***	0.003	-0.002	-0.001	-0.004**	0.015***	0.004
	(-0.1)	(1.41)	(0.01)	(3.81)	(0.92)	(-0.49)	(-0.56)	(-2.17)	(3.08)	(1.08)
$Adj. R^2$	0.275	0.283	0.507	0.446	0.301	0.272	0.383	0.263	0.580	0.431
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[27.172]***								
	SAF									
$Intercept$	9.974***	9.531***	10.548***	9.759***	14.124***	12.918***	14.467***	13.645***	12.891***	10.529***
	(11.16)	(8.36)	(6.84)	(6.22)	(8.27)	(9.80)	(8.16)	(8.50)	(6.36)	(5.76)
$CSAD_{t-1}$	0.077*	0.135**	0.127	0.262*	0.040	0.084	0.084	0.136**	0.182**	0.319***
	(1.85)	(2.34)	(1.40)	(1.84)	(0.39)	(1.17)	(0.97)	(2.21)	(2.05)	(3.42)
$R_{m,t}$	0.007	0.042	0.136*	0.209*	0.062	0.045	0.043	0.105**	0.046	0.049
	(0.10)	(0.62)	(1.86)	(1.69)	(1.25)	(0.83)	(0.88)	(2.19)	(1.03)	(0.78)
$\lvert R_{m,t}\rvert$	-0.088	0.269	0.111	0.121	-0.058	0.228	-0.087	-0.001	0.009	-0.046
	(-1.30)	(1.55)	(0.82)	(0.99)	(-0.32)	(1.14)	(-0.35)	(0.01)	(0.04)	(-0.28)
${R_{m,t}}^2$	0.012***	-0.001	0.009***	0.003	0.011	-0.001	0.013*	0.012	0.007	0.011*
	(18.29)	(-0.10)	(3.08)	(1.60)	(1.38)	(-0.10)	(1.67)	(1.32)	(0.65)	(1.76)
$Adj. R^2$	0.795	0.093	0.329	0.224	0.178	0.067	0.077	0.119	0.040	0.170
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[24.559]***								

Table 3.4 Panel B (continued)

	SPA									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	4.718***	7.024***	7.668***	8.723***	7.695***	9.447***	6.766***	10.199***	6.942***	7.333***
	(7.43)	(5.81)	(7.80)	(8.45)	(5.29)	(8.56)	(5.05)	(8.11)	(6.10)	(5.90)
$CSAD_{t-1}$	0.019	0.047	0.043	0.050	0.041	0.071	0.090	0.041	0.162***	0.131*
	(0.31)	(0.61)	(0.54)	(0.70)	(0.53)	(1.20)	(1.02)	(0.75)	(4.39)	(1.83)
$R_{m,t}$	0.001	0.002	0.018	0.107**	0.107***	0.102**	0.063*	0.001	0.135**	0.142***
	(0.02)	(0.05)	(0.51)	(2.28)	(2.65)	(2.30)	(1.80)	(-0.01)	(2.61)	(3.51)
$\lvert R_{m,t}\rvert$	0.279***	-0.088	0.051	-0.057	0.365***	-0.212	0.341**	-0.003	0.106	0.426***
	(4.62)	(-0.57)	(0.40)	(-0.56)	(3.30)	(-1.49)	(2.42)	(-0.03)	(0.45)	(3.45)
${R_{m,t}}^2$	-0.002	0.010**	0.009**	0.010***	-0.004**	0.018***	0.001	0.007***	0.011	0.005
	(-1.27)	(2.31)	(2.25)	(3.45)	(-2.57)	(3.91)	(0.10)	(6.87)	(1.23)	(1.23)
$Adj.R^2$	0.302	0.101	0.288	0.337	0.231	0.487	0.369	0.788	0.448	0.563
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[101.744]***								
	THA									
$Intercept$	9.187***	7.453***	10.648***	9.784***	9.749***	8.868***	7.310***	8.926***	6.858***	9.818***
	(7.96)	(6.82)	(8.15)	(10.48)	(5.95)	(6.93)	(5.31)	(9.16)	(6.91)	(9.72)
$CSAD_{t-1}$	0.131	0.267**	0.101	0.132*	0.275**	0.237***	0.364***	0.136	0.270***	0.084
	(1.30)	(2.41)	(1.44)	(1.68)	(2.06)	(2.90)	(3.13)	(1.52)	(5.07)	(1.04)
$R_{m,t}$	0.213***	0.254***	0.223***	0.244***	0.195***	0.184***	0.179***	0.184***	0.192***	0.198***
	(5.67)	(5.48)	(5.92)	(5.50)	(5.95)	(4.00)	(4.59)	(3.80)	(5.16)	(3.49)
$\lvert R_{m,t}\rvert$	0.124*	0.255***	0.211***	0.320**	0.046	0.174*	0.145	0.456***	0.508***	0.525***
	(1.89)	(4.08)	(3.55)	(2.07)	(0.50)	(1.90)	(0.90)	(4.09)	(4.04)	(2.80)
${R_{m,t}}^2$	0.001*	-0.001*	0.001*	0.001	0.004***	0.007***	0.006	0.001	-0.003	-0.003
	(1.86)	(-1.74)	(1.90)	(0.82)	(5.79)	(3.54)	(1.64)	(-0.17)	(-1.06)	(-0.43)
$Adj.R^2$	0.791	0.635	0.759	0.713	0.645	0.652	0.593	0.582	0.642	0.401
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[31.205]***								

Table 3.4 Panel B (continued)

	UAE									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	6.164***	8.515***	5.443***	5.498***	10.390***	7.554***	7.739***	4.023*	6.713***	12.710***
	(2.96)	(7.81)	(3.49)	(4.30)	(11.63)	(6.38)	(7.81)	(1.88)	(4.82)	(8.55)
$CSAD_{t-1}$	0.001	-0.130*	0.326***	0.051	-0.008	0.208**	0.050	0.035	0.147***	-0.136***
	(0.01)	(-1.69)	(2.83)	(0.68)	(-0.34)	(2.44)	(0.98)	(0.37)	(6.81)	(-2.77)
$R_{m,t}$	0.117***	0.214***	0.120***	0.202**	0.218**	0.151***	0.234***	0.291***	0.239*	0.335***
	(3.09)	(5.74)	(5.45)	(2.49)	(2.48)	(3.88)	(3.15)	(5.09)	(1.80)	(7.38)
$\lvert R_{m,t} \rvert$	0.384	0.294*	0.104	0.860***	-0.305**	0.034	0.359	1.267***	0.086	-0.219
	(1.57)	(1.92)	(0.92)	(3.47)	(-2.01)	(0.28)	(1.40)	(2.85)	(0.25)	(-1.25)
${R_{m,t}}^2$	-0.006	-0.003	0.001	-0.016*	0.021***	0.006**	0.005	-0.029*	0.023***	0.022***
	(-1.12)	(-0.93)	(0.38)	(-1.93)	(6.08)	(2.11)	(0.55)	(-1.73)	(2.74)	(4.84)
$Adj. R^2$	0.094	0.310	0.250	0.357	0.868	0.126	0.333	0.448	0.691	0.680
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[20.545]***								
	UK									
$Intercept$	5.823***	7.739***	6.936***	6.571***	6.113***	7.324***	8.947***	8.097***	7.289***	9.832***
	(12.63)	(8.34)	(6.04)	(6.76)	(5.45)	(6.94)	(6.15)	(5.55)	(7.07)	(5.27)
$CSAD_{t-1}$	0.321***	0.218***	0.424***	0.462***	0.522***	0.476***	0.409***	0.425***	0.492***	0.334***
	(6.72)	(4.78)	(5.35)	(9.36)	(9.42)	(8.60)	(4.96)	(5.07)	(8.04)	(3.55)
$R_{m,t}$	0.120**	0.134**	0.185***	0.140***	0.112***	0.090**	0.105***	0.182***	0.057	0.112**
	(2.56)	(2.25)	(3.74)	(3.88)	(3.21)	(2.61)	(3.09)	(4.34)	(1.65)	(2.14)
$\lvert R_{m,t} \rvert$	-0.043	0.025	-0.013	0.108	0.154	0.116	0.017	0.178	0.218***	0.277*
	(-0.61)	(0.22)	(-0.12)	(0.85)	(1.44)	(1.32)	(0.24)	(1.35)	(3.23)	(1.89)
${R_{m,t}}^2$	0.010***	0.011***	0.011**	0.004	0.001	0.001	0.007***	0.004	-0.001	0.001
	(6.41)	(3.77)	(2.43)	(1.21)	(-0.06)	(0.62)	(3.70)	(1.03)	(-0.74)	(0.13)
$Adj. R^2$	0.721	0.607	0.413	0.415	0.372	0.309	0.311	0.380	0.361	0.277
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[115.351]***								

Ref. code: 25615602320029OJA

Table 3.4 Panel B (continued)

	USA									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	3.875***	5.593***	6.399***	5.704***	5.947***	6.183***	7.688***	6.709***	9.356***	8.916***
	(6.06)	(5.33)	(5.83)	(5.09)	(6.46)	(6.03)	(13.18)	(5.63)	(11.99)	(9.65)
$CSAD_{t-1}$	0.397***	0.328**	0.290**	0.364***	0.375***	0.378***	0.313***	0.377***	0.203***	0.33***
	(4.56)	(2.38)	(2.32)	(3.37)	(3.87)	(4.29)	(5.76)	(3.71)	(2.78)	(6.26)
$R_{m,t}$	0.053***	0.043**	0.069***	0.048***	0.036**	0.053***	0.071***	0.050***	0.119***	0.119***
	(4.89)	(2.36)	(3.29)	(3.47)	(2.53)	(3.59)	(7.03)	(2.93)	(10.89)	(3.59)
$\lvert R_{m,t} \rvert$	0.104**	0.021	-0.013	0.050	0.101	0.073	0.003	0.211***	0.231***	0.198**
	(2.00)	(0.27)	(-0.15)	(0.57)	(1.17)	(1.09)	(0.06)	(3.46)	(4.45)	(2.61)
${R_{m,t}}^2$	0.002	0.005**	0.007***	0.006*	0.004*	0.006***	0.009***	0.002	0.002***	0.004***
	(0.95)	(2.50)	(3.32)	(1.88)	(1.69)	(2.65)	(6.82)	(0.88)	(2.93)	(2.80)
$Adj.R^2$	0.423	0.390	0.540	0.502	0.441	0.536	0.481	0.461	0.440	0.533
Chow Test	$\gamma_{4,Low} - \gamma_{4,High}$	[202.865]***								

Table 3.5 Regression results of the 60 days $CSAD_t$ on logarithmic R-squared ratio portfolios.

Panel A: Regression results of the 60 days $CSAD_t$ on five logarithmic R-squared ratio portfolios.

Note: This table reports regression statistics of the five logarithmic R-squared ratio portfolios by using $CSAD_t = \propto + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$, where $CSAD_t$ is a cross-sectional absolute deviation of 60-day return during period t and $R_{m,t}$ is an equally weighted 60-day portfolio return during period t.

The sample interval is from 01/01/1991 to 2/11/2018.

The t-statistics are shown in parentheses which is calculated by using Newey & West (1987)'s heteroscedaticity and autocorrelation consistent standard errors. The F values from Chow Test are shown in square brackets.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

	AUS					BRA				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	17.638***	22.786***	23.557***	22.266***	22.639***	10.934***	13.843***	16.229***	12.504***	13.340***
	(15.08)	(25.01)	(28.26)	(23.84)	(22.08)	(5.96)	(5.83)	(14.32)	(14.69)	(22.49)
$\lvert R_{m,t} \rvert$	0.064	-0.290***	-0.355***	-0.141**	-0.132**	0.407***	0.294***	0.151***	0.429***	0.391***
	(0.31)	(-2.84)	(-3.23)	(-2.20)	(-2.15)	(4.09)	(5.11)	(3.50)	(5.02)	(7.26)
$(R_{m,t} - \overline{R_m})^2$	0.005	0.013***	0.018**	0.007**	0.006**	-0.001***	-0.001***	0.001***	0.001	-0.001***
	(0.80)	(3.18)	(2.55)	(2.13)	(2.02)	(-3.38)	(-4.00)	(6.45)	(-1.07)	(-3.35)
$Adj. R^2$	0.194	0.182	0.299	0.068	0.036	0.292	0.168	0.648	0.713	0.529
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[8.192]***				$\gamma_{2,Low} - \gamma_{2,High}$	[0.828]*			

Ref. code: 25615602320029OJA

Table 3.5 Panel A (continued)

	CAN					CHN				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	15.732***	17.098***	17.162***	17.932***	17.891***	6.213***	7.975***	9.142***	9.321***	11.107***
	(13.64)	(16.46)	(22.39)	(25.54)	(28.73)	(13.34)	(13.21)	(15.16)	(14.01)	(14.98)
$\lvert R_{m,t} \rvert$	0.102	-0.002	0.166*	0.101	0.120*	-0.036	0.003	0.041	0.261***	0.433***
	(0.58)	(-0.01)	(1.77)	(1.05)	(1.68)	(-1.16)	(0.06)	(0.62)	(3.88)	(6.08)
$(R_{m,t} - \overline{R_m})^2$	0.006	0.010	0.002	0.006	0.002	0.002***	0.002***	0.002**	0.001	-0.003***
	(0.91)	(1.03)	(0.35)	(1.07)	(0.69)	(5.89)	(2.66)	(2.48)	(-0.78)	(-5.14)
$Adj. R^2$	0.162	0.140	0.063	0.171	0.062	0.342	0.239	0.303	0.389	0.462
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[3.300]*				$\gamma_{2,Low} - \gamma_{2,High}$	[124.202]***			
	FRA					GER				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	9.328***	12.841***	13.253***	13.861***	14.851***	9.538***	11.902***	13.403***	13.276***	11.732***
	(19.43)	(15.33)	(12.33)	(21.92)	(20.24)	(10.44)	(11.26)	(13.32)	(12.10)	(11.27)
$\lvert R_{m,t} \rvert$	0.011	-0.372*	-0.177	-0.038	-0.388*	0.087	0.134	-0.007	0.158	0.352***
	(0.22)	(-1.85)	(-0.50)	(-0.22)	(-1.90)	(0.77)	(0.62)	(-0.03)	(1.06)	(2.90)
$(R_{m,t} - \overline{R_m})^2$	0.008***	0.025***	0.021	0.015	0.039***	0.008***	0.012	0.012	0.005	0.002
	(13.51)	(2.62)	(1.04)	(1.11)	(2.74)	(5.38)	(1.19)	(1.02)	(0.62)	(0.24)
$Adj. R^2$	0.715	0.496	0.264	0.127	0.389	0.596	0.329	0.184	0.078	0.220
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[83.464]***				$\gamma_{2,Low} - \gamma_{2,High}$	[17.179]***			

Table 3.5 Panel A (continued)

	GRE					IND				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	12.775***	14.424***	15.316***	14.565***	13.046***	21.741***	24.698***	25.321***	25.194***	24.694***
	(12.12)	(13.19)	(14.17)	(6.26)	(6.72)	(19.37)	(20.06)	(18.03)	(12.58)	(13.80)
$\lvert R_{m,t} \rvert$	-0.240***	-0.208**	-0.122	0.173	0.563***	-0.128	-0.265**	-0.231*	-0.222	-0.105
	(-3.28)	(-2.24)	(-0.99)	(1.03)	(3.13)	(-1.11)	(-2.38)	(-1.88)	(-1.39)	(-0.51)
$(R_{m,t} - \overline{R_m})^2$	0.008***	0.008***	0.007***	0.002	0.001	0.005***	0.008***	0.009***	0.011***	0.011***
	(5.01)	(5.29)	(3.74)	(0.93)	(0.18)	(2.75)	(3.75)	(3.19)	(3.21)	(4.50)
$Adj. R^2$	0.225	0.317	0.336	0.222	0.607	0.122	0.200	0.253	0.386	0.507
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[30.338]***				$\gamma_{2,Low} - \gamma_{2,High}$	[33.393]***			

	IRE					ITA				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	10.865***	9.930***	10.478***	8.664***	9.924***	8.606***	10.237***	10.354***	10.142***	8.165***
	(5.63)	(6.80)	(8.00)	(7.50)	(7.84)	(17.49)	(18.23)	(22.64)	(14.57)	(6.58)
$\lvert R_{m,t} \rvert$	0.212	0.276**	-0.077	0.190	-0.219	-0.138*	-0.263**	-0.167**	-0.036	0.378
	(1.31)	(2.30)	(-0.54)	(0.82)	(-1.13)	(-1.89)	(-2.49)	(-2.09)	(-0.30)	(1.54)
$(R_{m,t} - \overline{R_m})^2$	0.001	-0.003	0.013***	0.005	0.015***	0.010***	0.018***	0.017***	0.015***	0.008***
	(1.20)	(-1.36)	(5.57)	(0.66)	(2.87)	(3.29)	(3.11)	(7.13)	(10.92)	(3.00)
$Adj. R^2$	0.312	0.029	0.398	0.224	0.393	0.632	0.431	0.606	0.629	0.730
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[10.687]***				$\gamma_{2,Low} - \gamma_{2,High}$	[38.488]***			

Table 3.5 Panel A (continued)

	JAP					POR				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	8.279***	9.383***	10.417***	11.322***	10.414***	11.736***	9.745***	9.379***	11.058***	9.854***
	(13.37)	(19.12)	(22.48)	(26.66)	(18.57)	(7.15)	(8.86)	(9.67)	(9.36)	(11.12)
$\lvert R_{m,t} \rvert$	-0.120*	-0.105	-0.105	-0.069	0.225*	0.094	-0.094	0.325**	0.046	0.187
	(-1.88)	(-1.06)	(-0.86)	(-0.68)	(1.76)	(0.64)	(-0.53)	(2.42)	(0.29)	(1.55)
$\left(R_{m,t} - \overline{R_m}\right)^2$	0.011***	0.013***	0.014***	0.014***	0.005	0.006***	0.016***	-0.002	0.014***	0.007***
	(4.02)	(2.93)	(2.70)	(3.45)	(0.91)	(7.12)	(4.48)	(-0.39)	(3.20)	(6.85)
$Adj. R^2$	0.284	0.281	0.334	0.315	0.277	0.690	0.453	0.094	0.209	0.745
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[80.096]***				$\gamma_{2,Low} - \gamma_{2,High}$	[4.285]*			

	RUS					SAF				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	10.728***	11.599***	11.470***	14.108***	14.363***	12.733***	13.222***	14.679***	15.793***	15.576***
	(18.06)	(8.96)	(9.70)	(6.91)	(8.23)	(12.72)	(12.74)	(16.12)	(16.98)	(19.17)
$\lvert R_{m,t} \rvert$	0.109	0.116	0.426***	0.487**	0.533**	-0.184	0.126	0.127	0.062	0.101
	(0.89)	(0.70)	(2.72)	(2.05)	(2.52)	(-1.29)	(0.81)	(1.25)	(0.33)	(0.79)
$\left(R_{m,t} - \overline{R_m}\right)^2$	0.001	0.002	-0.001	-0.004	-0.004	0.017***	0.008**	0.002	0.009	0.002
	(0.43)	(1.30)	(-0.53)	(-1.16)	(-0.78)	(5.52)	(2.35)	(0.96)	(1.29)	(0.42)
$Adj. R^2$	0.066	0.398	0.374	0.130	0.127	0.450	0.279	0.073	0.111	0.038
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[18.344]***				$\gamma_{2,Low} - \gamma_{2,High}$	[18.754]***			

Table 3.5 Panel A (continued)

	SPA					THA				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	6.176***	8.552***	10.014***	10.240***	9.103***	11.054***	11.825***	12.579***	11.387***	10.291***
	(10.06)	(16.01)	(12.96)	(8.64)	(12.48)	(12.65)	(11.78)	(14.95)	(12.42)	(25.68)
$\lvert R_{m,t} \rvert$	0.174*	0.174*	0.048	0.058	0.349***	0.065***	0.232**	0.170	0.330*	0.626***
	(1.79)	(1.85)	(0.42)	(0.26)	(2.76)	(3.48)	(2.48)	(1.54)	(1.91)	(3.75)
$(R_{m,t} - \overline{R_m})^2$	0.001	0.004	0.008*	0.012*	0.009*	0.003***	0.003***	0.008***	0.007	-0.003
	(0.51)	(1.01)	(1.87)	(1.82)	(1.89)	(27.83)	(4.91)	(5.04)	(1.44)	(-0.56)
$Adj. R^2$	0.281	0.302	0.330	0.519	0.532	0.575	0.668	0.590	0.508	0.445
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[82.368]***				$\gamma_{2,Low} - \gamma_{2,High}$	[25.029]***			
	UAE					UK				
Portfolio	1	2	3	4	5	1	2	3	4	5
$Intercept$	10.896***	7.285***	9.710***	9.710***	9.180***	9.744***	12.397***	14.186***	15.351***	15.851***
	(8.47)	(7.68)	(8.27)	(6.75)	(7.84)	(14.86)	(14.40)	(19.57)	(12.10)	(17.29)
$\lvert R_{m,t} \rvert$	-0.153	0.683***	0.154	0.232	0.340	0.008	0.271	0.226**	0.141	0.144
	(-0.70)	(2.75)	(0.55)	(0.75)	(1.04)	(0.09)	(1.62)	(2.02)	(1.51)	(1.27)
$(R_{m,t} - \overline{R_m})^2$	0.007	-0.013*	0.010	0.011	0.010	0.011***	-0.002	-0.004	0.001	0.003
	(1.16)	(-1.81)	(0.87)	(0.95)	(0.72)	(4.24)	(-0.53)	(-1.50)	(0.55)	(0.75)
$Adj. R^2$	0.056	0.239	0.265	0.334	0.239	0.531	0.077	0.037	0.056	0.093
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[9.217]***				$\gamma_{2,Low} - \gamma_{2,High}$	[100.081]***			

Table 3.5 Panel A (continued)

	USA				
Portfolio	1	2	3	4	5
$Intercept$	7.685***	9.125***	10.113***	11.577***	12.888***
	(15.12)	(21.04)	(20.67)	(21.52)	(14.02)
$\lvert R_{m,t}\rvert$	0.131*	0.118**	0.168***	0.169***	0.325**
	(1.93)	(2.49)	(3.73)	(3.24)	(2.27)
$\left(R_{m,t}-\overline{R_m}\right)^2$	0.002	0.004**	0.003**	0.004***	0.001
	(0.81)	(2.34)	(2.49)	(2.86)	(0.01)
$Adj. R^2$	0.235	0.362	0.337	0.304	0.387
Chow Test	$\gamma_{2,Low}-\gamma_{2,High}$	[160.421]***			

Panel B: Regression results of the 60 days $CSAD_t$ on ten logarithmic R-squared ratio portfolios.

Note: This table reports regression statistics of the ten logarithmic R-squared ratio portfolios by using $CSAD_t = \propto + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t} - \overline{R_m})^2 + \varepsilon_t$, where $CSAD_t$ is a cross-sectional absolute deviation of 60-day return during period t and $R_{m,t}$ is an equally weighted 60-day portfolio return during period t.

The sample interval is from 01/01/1991 to 2/11/2018.

The t-statistics are shown in parentheses which is calculated by using Newey and West (1987)'s heteroscedaticity and autocorrelation consistent standard errors. The F values from Chow Test are shown in square brackets.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

	AUS									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	16.828***	19.995***	22.244***	22.012***	23.511***	23.562***	22.404***	21.676***	23.449***	21.360***
	(11.00)	(19.29)	(21.25)	(21.13)	(23.28)	(19.50)	(19.23)	(16.60)	(22.12)	(15.45)
$\|R_{m,t}\|$	-0.134	-0.010	-0.333***	-0.154	-0.343***	-0.434***	-0.191***	-0.097	-0.186**	-0.073
	(-0.50)	(-0.09)	(-3.26)	(-1.18)	(-2.86)	(-4.34)	(-3.27)	(-1.19)	(-2.50)	(-0.94)
$(R_{m,t} - \overline{R_m})^2$	0.001	0.003	0.016***	0.009	0.017**	0.022***	0.011***	0.007	0.008*	0.007**
	(1.56)	(1.03)	(4.44)	(1.62)	(2.17)	(5.14)	(3.47)	(1.57)	(1.90)	(2.24)
$Adj. R^2$	0.446	0.012	0.275	0.117	0.185	0.424	0.147	0.042	0.056	0.035
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[12.302]***								

Table 3.5 Panel B (continued)

	BRA									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	9.658***	11.208***	11.583***	11.422***	11.953***	10.744***	13.968***	10.865***	14.440***	13.482***
	(5.33)	(8.36)	(6.13)	(7.53)	(7.03)	(6.69)	(9.31)	(8.17)	(8.87)	(8.29)
$\lvert R_{m,t} \rvert$	0.319**	0.062	0.307	0.284	0.581***	0.649***	-0.130	0.525**	0.243	-0.240
	(2.11)	(0.33)	(1.26)	(1.45)	(2.90)	(2.67)	(-0.56)	(2.57)	(1.13)	(-0.68)
$\left(R_{m,t} - \overline{R_m}\right)^2$	-0.001	0.007**	-0.001	0.003	-0.009**	-0.007	0.014***	-0.005	-0.003	0.022*
	(-1.05)	(2.54)	(-0.23)	(0.47)	(-2.23)	(-1.10)	(2.63)	(-1.05)	(-0.41)	(1.66)
$Adj.R^2$	0.124	0.683	0.103	0.281	0.081	0.252	0.575	0.248	0.022	0.430
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[17.908]***								
	CAN									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	17.065***	16.134***	15.302***	16.458***	16.044***	18.471***	17.802***	17.882***	17.488***	17.881***
	(8.92)	(14.33)	(17.04)	(14.74)	(26.45)	(14.98)	(20.91)	(19.51)	(24.63)	(24.92)
$\lvert R_{m,t} \rvert$	-0.220	-0.002	0.151	0.156	0.246**	-0.261	-0.060	0.123	0.092	0.148
	(-1.00)	(-0.01)	(0.87)	(0.76)	(2.26)	(-1.42)	(-0.38)	(1.15)	(1.31)	(1.53)
$\left(R_{m,t} - \overline{R_m}\right)^2$	0.012*	0.012	0.009	0.004	-0.001	0.023*	0.017*	0.005	0.004	0.002
	(1.90)	(1.31)	(1.19)	(0.41)	(-0.13)	(1.85)	(1.94)	(0.87)	(1.27)	(0.51)
$Adj.R^2$	0.221	0.245	0.259	0.069	0.121	0.243	0.414	0.146	0.066	0.086
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[6.357]***								

Table 3.5 Panel B (continued)

	CHN									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	6.057***	7.343***	8.458***	8.886***	8.976***	9.725***	10.469***	10.217***	10.184***	11.878***
	(15.62)	(14.86)	(13.15)	(14.47)	(14.79)	(13.74)	(15.41)	(11.99)	(15.56)	(15.10)
$\lvert R_{m,t} \rvert$	-0.114***	-0.137***	-0.131**	-0.119***	-0.035	-0.004	-0.030	0.219**	0.349***	0.378***
	(-4.91)	(-3.91)	(-2.52)	(-2.83)	(-0.61)	(-0.05)	(-0.38)	(2.18)	(3.87)	(6.43)
$\left(R_{m,t} - \overline{R_m}\right)^2$	0.004***	0.005***	0.005***	0.005***	0.004***	0.003***	0.005***	0.001	-0.001	-0.001
	(15.09)	(10.29)	(7.33)	(7.72)	(5.51)	(3.94)	(4.03)	(0.30)	(-0.34)	(-0.96)
$Adj.R^2$	0.463	0.513	0.337	0.403	0.339	0.264	0.357	0.320	0.428	0.465
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[173.501]***								
	FRA									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	7.842***	10.880***	12.505***	12.176***	13.855***	12.459***	13.567***	14.446***	15.012***	14.780***
	(17.40)	(18.83)	(18.11)	(11.11)	(10.74)	(13.72)	(20.56)	(17.27)	(21.04)	(21.28)
$\lvert R_{m,t} \rvert$	0.096**	-0.174*	-0.403***	-0.184	-0.370	-0.023	-0.115	-0.380	-0.390**	-0.409***
	(2.53)	(-1.85)	(-3.54)	(-0.58)	(-1.03)	(-0.08)	(-0.68)	(-1.26)	(-2.61)	(-3.18)
$\left(R_{m,t} - \overline{R_m}\right)^2$	0.004***	0.016***	0.024***	0.021	0.028	0.016	0.017	0.040*	0.035***	0.039***
	(13.44)	(3.90)	(5.41)	(1.31)	(1.52)	(0.91)	(1.56)	(1.76)	(4.42)	(8.38)
$Adj.R^2$	0.781	0.508	0.640	0.315	0.318	0.205	0.155	0.356	0.294	0.699
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[198.968]***								

Table 3.5 Panel B (continued)

	GER									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	7.062***	11.611***	12.383***	12.646***	13.358***	14.626***	13.396***	13.153***	11.787***	12.106***
	(6.66)	(11.53)	(9.86)	(7.87)	(12.58)	(15.06)	(13.13)	(13.13)	(11.94)	(10.85)
$\lvert R_{m,t} \rvert$	0.300**	-0.147	-0.197	0.005	-0.216	-0.284	0.042	0.144	0.230	0.255**
	(2.29)	(-1.05)	(-0.78)	(0.02)	(-1.05)	(-1.29)	(0.28)	(1.11)	(1.19)	(2.24)
$(R_{m,t} - \overline{R_m})^2$	0.003*	0.015***	0.023***	0.015	0.021**	0.023*	0.010	0.008	0.010	0.001
	(1.87)	(6.77)	(2.79)	(1.11)	(2.09)	(1.77)	(1.31)	(1.13)	(0.73)	(0.83)
$Adj. R^2$	0.512	0.640	0.544	0.276	0.377	0.276	0.075	0.119	0.234	0.178
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[24.133]***								
	GRE									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	12.166***	13.425***	13.128***	12.655***	13.961***	15.064***	14.582***	15.989***	13.821***	10.286***
	(15.39)	(10.76)	(10.16)	(6.73)	(9.97)	(14.50)	(6.84)	(8.75)	(9.34)	(4.89)
$\lvert R_{m,t} \rvert$	-0.256***	-0.378***	-0.103	-0.027	-0.039	-0.051	0.006	0.013	0.347**	0.747***
	(-4.30)	(-4.71)	(-0.85)	(-0.14)	(-0.25)	(-0.46)	(0.05)	(0.10)	(2.49)	(3.75)
$(R_{m,t} - \overline{R_m})^2$	0.007***	0.013***	0.004**	0.006*	0.007**	0.006***	0.005***	0.006***	0.001	-0.001
	(6.25)	(6.06)	(2.26)	(1.94)	(2.16)	(3.41)	(3.40)	(2.65)	(0.05)	(-1.56)
$Adj. R^2$	0.353	0.373	0.111	0.337	0.374	0.369	0.268	0.344	0.283	0.554
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[20.796]***								

Table 3.5 Panel B (continued)

	IND									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	20.427***	22.230***	23.526***	25.042***	23.740***	26.566***	25.317***	25.866***	24.873***	24.329***
	(14.30)	(22.81)	(23.41)	(17.28)	(20.09)	(15.19)	(14.15)	(13.03)	(15.10)	(12.21)
$\lvert R_{m,t} \rvert$	-0.091	-0.111	-0.215**	-0.281**	-0.128	-0.346**	-0.337**	-0.210	-0.144	-0.072
	(-0.74)	(-0.90)	(-2.11)	(-2.05)	(-0.73)	(-2.44)	(-2.17)	(-1.23)	(-0.86)	(-0.26)
$(R_{m,t} - \overline{R_m})^2$	0.004***	0.005***	0.007***	0.009***	0.008**	0.010***	0.013***	0.010***	0.012***	0.010***
	(2.69)	(2.93)	(4.19)	(3.09)	(2.18)	(4.00)	(4.12)	(4.55)	(5.29)	(3.39)
$Adj. R^2$	0.080	0.122	0.222	0.179	0.241	0.252	0.613	0.232	0.384	0.571
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[44.526]***								
	ITA									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	6.655***	9.174***	12.037***	9.241***	9.627***	10.344***	9.833***	10.771***	7.517***	11.832***
	(12.93)	(13.83)	(12.66)	(17.18)	(16.52)	(16.14)	(13.01)	(17.55)	(4.30)	(13.26)
$\lvert R_{m,t} \rvert$	-0.009	-0.212	-0.628***	-0.122	-0.136	-0.214*	-0.126	-0.262***	0.388	-0.587***
	(-0.15)	(-1.61)	(-4.85)	(-1.12)	(-1.63)	(-1.81)	(-0.91)	(-2.80)	(1.34)	(-4.29)
$(R_{m,t} - \overline{R_m})^2$	0.006***	0.013**	0.026***	0.013***	0.015***	0.019***	0.017***	0.021***	0.007***	0.040***
	(4.08)	(2.36)	(5.70)	(5.33)	(6.10)	(7.53)	(3.70)	(6.99)	(2.78)	(10.27)
$Adj. R^2$	0.666	0.470	0.682	0.405	0.418	0.649	0.716	0.635	0.784	0.592
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[91.056]***								

Table 3.5 Panel B (continued)

	JAP									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	7.959***	8.646***	9.153***	9.614***	9.961***	10.752***	11.245***	11.378***	11.411***	9.106***
	(13.14)	(14.36)	(16.01)	(19.17)	(20.79)	(25.15)	(28.88)	(23.91)	(23.35)	(13.71)
$\lvert R_{m,t} \rvert$	-0.147**	-0.116*	-0.114	-0.103	-0.076	-0.106	-0.127	-0.030	-0.055	0.557***
	(-2.28)	(-1.69)	(-1.08)	(-1.02)	(-0.60)	(-0.93)	(-1.10)	(-0.28)	(-0.53)	(3.04)
$\left(R_{m,t} - \overline{R_m}\right)^2$	0.011***	0.012***	0.013***	0.013***	0.013**	0.014***	0.017***	0.012***	0.016***	-0.007
	(4.67)	(3.63)	(2.69)	(2.78)	(2.26)	(3.23)	(3.45)	(2.85)	(3.82)	(-0.75)
$Adj. R^2$	0.294	0.278	0.262	0.285	0.324	0.321	0.355	0.284	0.337	0.315
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[91.545]***								
	POR									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	8.579***	7.350***	9.642***	10.654***	7.998***	9.853***	6.998***	11.345***	9.138***	6.615***
	(3.59)	(4.31)	(6.10)	(7.44)	(7.61)	(6.62)	(6.38)	(4.68)	(4.43)	(4.92)
$\lvert R_{m,t} \rvert$	0.085	0.196	-0.274	-0.393***	0.276*	-0.252	0.299*	0.150	0.396	0.526***
	(0.51)	(1.48)	(-1.33)	(-3.65)	(1.86)	(-0.64)	(1.97)	(0.50)	(1.23)	(3.63)
$\left(R_{m,t} - \overline{R_m}\right)^2$	0.006**	0.006***	0.020***	0.025***	0.002	0.030	0.005	0.004	0.003	-0.002
	(2.49)	(5.92)	(2.82)	(10.67)	(0.64)	(1.53)	(1.46)	(0.43)	(0.44)	(-0.49)
$Adj. R^2$	0.211	0.715	0.508	0.689	0.167	0.278	0.164	0.032	0.202	0.306
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[0.499]*								

Table 3.5 Panel B (continued)

	RUS									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	9.813***	12.233***	11.206***	13.026***	13.194***	12.684***	15.020***	14.006***	15.421***	14.214***
	(7.84)	(11.56)	(4.56)	(11.13)	(9.70)	(6.37)	(14.93)	(10.07)	(16.11)	(12.44)
$\lvert R_{m,t}\rvert$	0.098	-0.193	0.127	-0.108	0.141	0.423	0.082	0.332**	-0.088	0.295
	(0.59)	(-1.41)	(0.48)	(-0.78)	(0.76)	(1.56)	(0.95)	(2.26)	(-0.44)	(1.44)
$\left(R_{m,t}-\overline{R_m}\right)^2$	0.001	0.005***	0.004**	0.004***	0.002	-0.003	0.002	-0.003	0.016**	0.003
	(0.34)	(3.14)	(2.10)	(3.57)	(0.47)	(-0.63)	(1.62)	(-1.19)	(2.61)	(0.72)
$Adj. R^2$	0.081	0.169	0.375	0.341	0.099	0.168	0.110	0.065	0.306	0.374
Chow Test	$\gamma_{2,Low}-\gamma_{2,High}$	[26.889]***								
	SAF									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	10.865***	11.207***	11.856***	13.191***	14.815***	14.411***	15.610***	16.339***	16.056***	15.522***
	(12.09)	(12.39)	(13.95)	(15.04)	(16.52)	(16.36)	(10.85)	(13.64)	(15.71)	(15.98)
$\lvert R_{m,t}\rvert$	-0.084	0.271	0.185	0.245**	-0.095	0.162	-0.038	-0.128	-0.040	0.002
	(-1.04)	(1.45)	(1.49)	(2.42)	(-0.52)	(0.95)	(-0.15)	(-0.66)	(-0.19)	(0.01)
$\left(R_{m,t}-\overline{R_m}\right)^2$	0.012***	0.001	0.009***	0.004*	0.013*	0.002	0.012	0.017*	0.008	0.009
	(15.73)	(0.05)	(3.02)	(1.96)	(1.72)	(0.27)	(1.40)	(1.94)	(0.89)	(1.26)
$Adj. R^2$	0.791	0.085	0.280	0.131	0.175	0.070	0.079	0.100	0.017	0.077
Chow Test	$\gamma_{2,Low}-\gamma_{2,High}$	[25.043]***								

Table 3.5 Panel B (continued)

	SPA									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	4.917***	7.377***	7.915***	8.917***	8.211***	10.406***	7.669***	10.491***	8.729***	8.344***
	(11.65)	(7.99)	(15.61)	(10.56)	(8.92)	(9.78)	(9.66)	(13.31)	(8.90)	(10.74)
$\lvert R_{m,t} \rvert$	0.266***	-0.079	0.082	-0.020	0.355***	-0.246	0.355**	0.024	0.080	0.542***
	(4.39)	(-0.52)	(0.73)	(-0.22)	(3.02)	(-1.34)	(2.27)	(0.25)	(0.33)	(3.68)
$(R_{m,t} - \overline{R_m})^2$	-0.002	0.010**	0.008**	0.011***	-0.003**	0.020***	0.001	0.007***	0.013	0.005
	(-1.44)	(2.29)	(2.38)	(3.40)	(-2.28)	(3.26)	(0.10)	(8.24)	(1.35)	(0.99)
$Adj. R^2$	0.313	0.114	0.289	0.286	0.186	0.438	0.348	0.789	0.370	0.504
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[96.094]***								
	THA									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	11.036***	10.849***	11.920***	11.363***	13.344***	12.059***	11.637***	10.645***	10.133***	11.490***
	(13.86)	(8.16)	(13.57)	(7.98)	(6.57)	(16.36)	(10.57)	(14.91)	(15.29)	(11.11)
$\lvert R_{m,t} \rvert$	-0.023	0.140***	0.147*	0.297*	0.101	0.184	0.295*	0.402***	0.584***	0.326
	(-0.68)	(4.07)	(1.80)	(1.89)	(0.64)	(1.22)	(1.69)	(3.82)	(3.39)	(1.62)
$(R_{m,t} - \overline{R_m})^2$	0.003***	0.002***	0.003***	0.004***	0.006***	0.010***	0.007	0.004**	-0.002	-0.007
	(15.74)	(10.60)	(6.05)	(3.30)	(4.54)	(3.48)	(1.26)	(2.08)	(-0.42)	(0.93)
$Adj. R^2$	0.699	0.403	0.666	0.615	0.547	0.551	0.432	0.497	0.484	0.334
Chow Test	$\gamma_{2,Low} - \gamma_{2,High}$	[32.681]***								

Table 3.5 Panel B (continued)

	UAE									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	8.409***	9.332***	9.826***	6.762***	10.132***	10.210***	9.347***	7.269***	8.902***	10.905***
	(6.33)	(9.70)	(7.86)	(6.76)	(9.04)	(10.61)	(9.49)	(5.22)	(7.01)	(9.97)
$\lvert R_{m,t}\rvert$	-0.022	-0.103	-0.123	0.582**	-0.431**	-0.155	0.055	0.221	-0.138	-0.332*
	(-0.13)	(-1.01)	(-1.08)	(2.62)	(-2.20)	(-1.22)	(0.25)	(0.91)	(-0.53)	(-1.69)
$\left(R_{m,t}-\overline{R_m}\right)^2$	0.004	0.007***	0.006**	-0.005	0.027***	0.011**	0.014	0.016**	0.033***	0.033***
	(1.12)	(2.83)	(2.19)	(-0.57)	(9.49)	(2.12)	(1.47)	(2.02)	(5.93)	(7.16)
$Adj. R^2$	0.034	0.108	0.066	0.237	0.811	0.051	0.225	0.348	0.658	0.493
Chow Test	$\gamma_{2,Low}-\gamma_{2,High}$	[19.301]***								
	UK									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	8.573***	10.077***	12.161***	12.133***	13.493***	14.587***	15.211***	15.480***	15.605***	15.979***
	(15.46)	(9.87)	(14.92)	(11.29)	(12.66)	(17.78)	(17.16)	(9.07)	(23.52)	(15.13)
$\lvert R_{m,t}\rvert$	0.010	0.092	0.212	0.373*	0.262	0.205*	0.111	0.080	0.152*	0.092
	(0.14)	(0.64)	(1.52)	(1.86)	(1.62)	(1.67)	(1.06)	(0.56)	(1.73)	(0.67)
$\left(R_{m,t}-\overline{R_m}\right)^2$	0.011***	0.010***	0.001	-0.005	-0.004	-0.004	0.003	0.006	0.001	0.010
	(6.83)	(2.93)	(0.34)	(-0.86)	(-1.11)	(-1.03)	(0.89)	(1.61)	(0.15)	(1.60)
$Adj. R^2$	0.561	0.475	0.090	0.102	0.049	0.022	0.067	0.088	0.066	0.110
Chow Test	$\gamma_{2,Low}-\gamma_{2,High}$	[116.446]***								

Table 3.5 Panel B (continued)

	USA									
Portfolio	1	2	3	4	5	6	7	8	9	10
$Intercept$	6.856***	8.446***	9.015***	9.088***	9.823***	10.349***	11.097***	11.414***	11.986***	13.594***
	(16.06)	(13.83)	(18.12)	(21.73)	(13.55)	(35.49)	(15.80)	(25.35)	(26.69)	(15.46)
$\lvert R_{m,t}\rvert$	0.167**	0.081	0.077	0.171***	0.181**	0.153***	0.139	0.283***	0.327***	0.306**
	(2.47)	(1.20)	(1.53)	(2.84)	(2.17)	(4.21)	(1.57)	(4.67)	(5.27)	(2.08)
$\left(R_{m,t}-\overline{R_m}\right)^2$	0.001	0.004*	0.006***	0.003	0.003	0.004***	0.005**	0.001	-0.001	0.002
	(0.07)	(1.96)	(3.25)	(1.27)	(1.30)	(3.35)	(2.56)	(0.37)	(-1.00)	(0.50)
$Adj. R^2$	0.217	0.250	0.371	0.323	0.286	0.352	0.329	0.304	0.325	0.360
Chow Test	$\gamma_{2,Low}-\gamma_{2,High}$	[199.816]***								

3.6 Conclusion

This chapter explores the association between corporate transparency and aggregate market herd behavior. As stock return synchronicity is used as a proxy of corporate transparency instead of country-specific annually index, this improves Wang & Huang (2018) in many ways. Firstly, the coefficient of determination from market model is more universal. It is extensively accessible and also suitable for the international study. Secondly, when comparing with quintile and decile portfolio constructions applied by this study, Wang & Huang (2018)'s two-portfolio technique cannot provide a complete perspective of corporate transparency effect as the event window regarding implementation of transparency indicator is unclear. Finally, the research interval of Wang & Huang (2018) is too short making an annually country-level index inapplicable. However, decile portfolio's findings mostly suggest the same conclusion as Wang & Huang (2018) which verifies the hypothesis that corporate transparency reduces aggregate market herd behavior. With regard to the in-depth findings, Blasco et al. (2017) is suitable for herding detection based on information selection criteria. Also, the detection power of the R-squared and Blasco et al. (2017) is superior to the Vo (2017)'s return synchronicity and Yao et al. (2014). In consideration of the corporate transparency and its impact on herd behavior, the results show that the decile portfolio technique provides clearer explanations than the quintile portfolio technique. Moreover, it appears that the average return dispersion is negatively correlated with corporate transparency. However, when examining the relationship between portfolio returns and corporate transparency, the findings are mixed.

CHAPTER 4
MEASURING DYNAMIC HERD BEHAVIOR VIA INVESTOR ATTENTION

4.1 Introduction

Without knowing its reason and disregards their own private information, Banerjee (1992) demonstrates that herd behavior can be originated by the way that individuals observe and follows others[5]. Bikhchandani et al. (1992) define this circumstance as an information cascade. In addition, Banerjee (1992) and Bikhchandani et al. (1992) document that herd behavior arisen from an information cascade is sensitive. But information-based herding is a rational[6] choice as well as reputation and job security (Scharfstein & Stein, 1990; Froot et al., 1992; and Brown et al., 2014), and compensation concern (Trueman, 1994 and Maug, & Naik, 2011). Despite the fact that information cascade is a central foundation of a rational herd behavior (Venezia et al., 2011), empirical evidence of information-based herding is limited by a data which is required to represent investor's information[7].

Efficient market hypothesis assumes that investors have unlimited attention to analyze all arriving information, nevertheless attention is a scare cognitive resource (Kahneman, 1973). Investors would allocate their limited attention on information that catches their interests. By using internet search volume index from AOL as a proxy of investor attention, Mondria et al. (2010) support the view that attention affects investors' trading information. As search engine provides search results matching with users' keyword, they propose that search outcomes consistent with user attention.

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[5] In psychology and sociology, herd behavior is driven by natural instinct for example; need for safety, avoid being different form a group, lack of confidence, and a belief in an accuracy of group decision.

[6] Herding is mostly assumed to be an irrational choice. Spyrou (2013) summarizes explanations of irrational herd behavior, such as; psychological factors (Smith et al., 1988), sociological factors (Keynes, 1936), overreaction (Hong & Stein, 1999), and overconfidence (Daniel et al., 1998).

[7] Previous researches about the information cascade are an experimental study. Spyrou (2013) suggests some papers that examine the relationship between information cascade and herd behavior. Without intense information uncertainty, Avery & Zemsky (1998) conclude that herd behavior cannot be driven by information cascade. Cipriani & Guarino (2005) and Drehmann et al. (2005) did not find herding in frictionless market and flexible market price respectively. While, Fernández et al. (2011) found the effects of information uncertainty and individuals' behavioral biases on herd behavior.

Besides, Mondria et al. (2010) note that the need of information is also fulfilled by internet search. Hence, these infer the internet users gain more relevant information from their search.

Additionally, Follows (2005) analyzes the survey of 2,200 American adults. The study signifies that internet users trust the search results. Furthermore, Follows (2005) suggests that more than half of internet user frequently work with search engine. As number of internet users surge from 1.024 billion in 2005 to 3.896 billion in 2018[8], it is implied that more than half of the world population are using internet. Considering number of search frequency, Google search rises from 32.8 million searches per day in 2000 to 3.2 billion searches per day in 2012[9]. Even though Google has never been officially publishing the number since 2012, the figure is expected to be larger than 5.5 billion searches per day in 2018. There are plenty of search engine providers. But Google has been continuously held more than 86% of worldwide market share since 2009[10]. On average, internet users service search engines more than once per day and the number is continuously rising. Hence, the search engine has been one of the most important databases for decades.

Regulators encourage listed companies to share their financial information on internet especially for the stock exchange website. Besides, the corporate official site, trading platforms, database provider systems, and mobile financial applications generally offer firm-specific financial data. The eXtensible Business Reporting Language (XBRL) is one of the key frameworks that streamlines the online financial database. As Sarbanes-Oxley Act of 2002 encourages listed companies to publish corporate governance practice on their official website, Labelle & Trabelsi (2016) conclude that the online disclosure enhances stock liquidity. Alsartawi (2018) submits that the online financial disclosure (OFD) improves firm performance in the Gulf Cooperation Council (GCC). With the open application programming interface (Open API) initiated by the Second Payment Services Directive (PSD2) that will established

[8] Number of worldwide internet users is retrieved from the following link.
https://www.statista.com/statistics/273018/number-of-internet-users-worldwide/
[9] Google search frequency is gathered from this source.
https://searchengineland.com/google-now-handles-2-999-trillion-searches-per-year-250247
[10] The worldwide search engines market share statistic during 2009 to 2019 is from the websites below.
https://www.statista.com/statistics/216573/worldwide-market-share-of-search-engines/
http://gs.statcounter.com/search-engine-market-share/all/worldwide/2009

with European banks in 2019, online financial information will be extremely connected. I propose that the findings motivate enterprises to adopt the internet disclosure.

Furthermore, Radley Yeldar (2012) reports the interesting survey. The paper indicates that investors and analysts attempt to reach for extra-financial information to improve their trading decision. As on-screen PDF is the most preferable format, it implies that internet is the major source of modern financial information which strengthens the creditability of internet. Libby et al. (2002), Daniel et al. (2002), and Hirshleifer et al. (2011) emphasize that information interpretation ability and reaction to arriving information of investors are improved with their attention. To put it another way, the attention brings additional information that energizes investors' decision. Most importantly, these are the recent evidences that reinforce the validity of internet search volume as a representative of investor attention.

As herding is a group behavior, it is driven by a crowd. the possibility of imitating action is related to number of people. On the other hand, information enhances assessment accuracy which affects the independency of investor decision. Hence, herd behavior is likely to be influenced by investor attention. Since aggregate market herding characterizes the combination of declining of independent activities from all investors in each market, this chapter examines the interaction between investor attention and herd behavior in aggregate level. As far as I am concerned, there is only one empirical study that directly verify the connection between investor attention and herd behavior. Peltomäki & Vahamaa (2015) study under very specific scope which is the European banking sector during the European debt crisis. Disregarding time-varying feature of herding, they employ the cross-sectional absolute deviation (CSAD) as a herding measure instead of a coefficient of non-linear term which is the only direct measure of aggregate market herding suggested by Chang et al. (2000).

For an investor attention's proxy, internet search volume index from Google (Google SVI[11]) is used in this chapter. By applying Blasco et al. (2017)'s model

[11] Google SVI is the best proxy of investor attention to date due to a bunch of advantages, Da et al. (2011). Firstly, the users are surely interested in search keyword which means internet search volume index is the direct proxy of investor attention. Secondly, retail investors are the leading users of internet database. Since internet search volume index represents the attention of unsophisticated retail investors who are doubted as the originators of aggregate market herding (Venezia et al., 2011), it matches Google SVI with the study of aggregate market herding. The use of internet search volume index with aggregate market study is suggested by Vozlyublennaia (2014) and Tantaopas et al. (2016) as it represents retail

with 17 equity markets, the coefficient of non-linear term is the main herding indicator (Chang et al., 2000). Because this study analyzes daily coefficient of non-linear term. The time-varying herd behavior is reflected which aligns with literature (Bohl et al., 2013; Sharma et al., 2015; and Ngene et al., 2017). Since investors require time to process arriving information, a deterioration of independent decision may have a positive relationship with a contemporaneous investor attention. In addition, a surging of return volatility, which is a result of imitating behavior, may catch observers' attention. Due to unsolid theoretical setup, the relationship between Google SVI and aggregate market herding is examined by employing vector autoregression (VAR) model.

This is a pioneer study that investigates the relation between investor attention and aggregate market herd behavior. As investor attention links with information that investors access and assess during a trading period, this chapter delivers an insight of aggregate herd behavior and its background regarding the information cascade. It also sheds light on a different perspective of investors' characteristic, which is the investor attention, that influence their behavior. Besides, the drawbacks of Peltomäki & Vahamaa (2015) are solved. All sectors from every continent with lengthen time period are considered. By analyzing the coefficient of non-linear term which is the direct herding measure, daily herd behavior is employed to reflect the dynamic nature of investors behavior.

4.2 Literature review

Fama (1970) proposes a well-known conventional financial theory, called efficient market hypothesis. Depend on an efficiency level, the theory presents that security's price instantaneously and completely captures all incoming information. Under the efficient market, it is impossible to consistently beat the market without

investor attention (Da et al., 2011). Moreover, retail investors mostly trade in broader market index. Thirdly, prior studies show that Google SVI is correlated with other investor attention's proxies, such as; trading volume, news and headlines, advertising expense, extreme returns, price limits. Moreover, Google SVI contains more information that cannot be explained by other attention substitutions. Fourthly, Google SVI is real-time update and publicly accessible. Last but not least, Google is the most renowned search engine. However, it is very importance to note that the selected search keyword must closely represent the target security and acknowledged by most investors.

taking additional risk. This implies that investors are needed to have unlimited attention to response to all arriving information. Even though Lawrence (2013) denotes that investors prefer to invest in high disclosure quality firms. Still, investors have limited attention. They must select the attention-grabbing information in order to allocate their consideration which is a scarce resource (Kahneman, 1973).

Literature suggests the positive influence of investor attention in various perspectives. The experimental study of Libby et al. (2002) proposes that limited attention affects all types of investors in interpreting earnings-related information. Also, Hirshleifer et al. (2011) emphasize that investor's reaction to the accounting information can be improved by investor attention. Daniel et al. (2002) indicate that limited attention and analysis capability lead to investor credulity. Chemmanur & Yan (2011) and Lou (2014) evidence the abnormal stock return during years of advertising growth which is a proxy of investor recognition. But they find a negative return in subsequent year. Bae & Wang (2012) focus on the Wall Street Journal's news coverage. They emphasize that China-name stocks, which had been listed in US stock exchange, gain more investor attention during the 2007 Chinese equity market boom. As other factors are controlled, the flood of investor attention makes them beat non-China-name stocks. As Dow Jones Industrial Average Index's historical high had been used as a representative of high investor attention day, Li & Yu (2012) indicate that market return can be estimated by investor attention. Jin (2014) concludes that stock mispricing of accruals is negatively correlated with number of analysts following.

The negative impacts of the inattention on market efficiency are also discussed. Hirshleifer & Teoh (2003) and Peng (2005) introduce theoretical models assuming that investors have limited attention and time to analyze all information. With those constraints, the models demonstrate that the lack of information affects the price formation. By using different color codes classified by Pink Sheets LLC to separate disclosure levels, Jiang et al. (2016) suggest that the easy to understand technique does not only influence investor behavior. But it also attracts investor attention which enhances the realization of information disclosure. The study also shows a positive relationship between investor attention and liquidity. Since investor attention is lesser on Friday, Dellavigna & Pollet (2009) examine an effect of Friday earnings announcement on stock returns. They show a delay price reaction and lower trading volume on Friday disclosure. Similarly, Louis & Sun (2010) study a Friday merger announcement which supports an inattention effect from Dellavigna & Pollet (2009). Also, Hirshleifer et al. (2009) investigate a lack of attention when information is overwhelming. Evidence emphasizes that stock price under-reaction is positively related to a number of earnings announcements. While under-reaction is reduced with investor attention, Hou et al. (2009) add that the profitability of momentum strategy is linked with investor attention. Besides, Loh (2010) indicates that stock recommendation drift is stronger within low-attention stocks. Li et al. (2011) use portfolios of small market capitalization stocks as a representative of inattention stocks. Evidence indicate that a change of retail investor attention affects a price of neglect stocks more than other stocks. Ehrmann & Jansen (2017) study investor inattention during 2010 and 2014 FIFA World Cups. The trading volume drops in a time that investors' national team was playing.

Some researchers examine the effect of investor attention in other security markets rather than stock exchange. By analyzing investors' reaction to the release of monthly U.S. Leading Economic Index (LEI), Gilbert et al. (2012) state that stock mispricing is due to investor inattention. They also show a treasury futures mispricing, but an influence is less pronounced. Chen et al. (2016) study Chinese stock index futures by using internet search volume index from Baidu. Investor attention is high during an announcement period of consumer price index. The announcement leads to high liquidity, volatility, and short-term price impact. For American Depositary Receipts (ADRs), Eichler (2012) shows the decline of ADRs mispricing due to an increasing of investor attention. Smith (2012) and Goddard et al. (2015) represent a positive relationship between FX market volatility and investor attention, which is measured by Google search volume index. By using advertising expense, Fich et al. (2016) indicate a positive correlation between investor attention and takeover premiums.

Because attention is important and it influences both investors and market as a whole. In order to get insight this feature, academics investigate the stimuli of investor attention. Karlsson et al. (2009) investigate an inattention by using account monitoring frequency. Scandinavian and American investors increasingly pay attention to their portfolios during up-market. Considering investor sentiment, Ali & Garun

(2009) indicate that investor attention on firm information is lower in period of high sentiment, particularly in small stocks. The reason is that retail investors actively trade in that time which intensifies equity mispricing. Barber & Odean (2008) state that individual investors are driven by an eye-catching event such as unexpected news, extreme trading volume, and price shock. Similarly, Li et al. (2017) indicate that retail investors mostly trade based on public information and attention-grabbing event. As noticeable events catch retail investors' consideration which induces them to trade, smart traders make profit by trading against unsophisticated individuals (Seasholes & Wu, 2007). Peng & Xiong (2006) and Peng et al. (2007) signify that investors put more attention on market-wide and industry-wide contents than firm-specific information resulting stock return comovement. Peress (2008) denotes an impact of media coverage on investor attention. As the Wall Street Journal gains more recognition, price reaction following earnings announcement is improved with media coverage. To sum up, there are many circumstances that stimulate investor attention. The understanding does not only open an opportunity to further the study, but it also provides the crucial knowledge for market participants to gain more investor attention.

Because attention is a latent variable, various alternative measures of investor attention have been proposed. Since a penetration of information technology is continuously high around the globe, it has been served for numerous objectives. Therefore, internet databases are enormous and very informative. They are increasingly accepted by financial scholars. The followings exemplify the internet-based investor attention proxy. Rubin & Rubin (2010) use Wikipedia's editing statistics as key measure of investor engagement with firm-specific information. They conclude that internet activity, regarding the company, is a good proxy of how investor is informed about the firm. By using social media activity, Curtis et al. (2014) support a hypothesis that post earnings announcement drift is stronger in low attention firm. Guo et al. (2015) analyze Twitter's statistics. The tweet frequency between retail investors and financial advisors leads to a return volatility. Moreover, they also show an asymmetric investor attention between investment gain and loss. Considering the group of internet search volume, Mondria et al. (2010) employ AOL's internet search query data as an investor attention proxy. They found a two-way positive relationship between investor attention and home bias. While, Zhang et al. (2013) process internet search volume index from

Baidu as a substitution of investor attention in China. They confirm that open source database improves price discovery and market efficiency. Ginsberg et al. (2009) are the first to use Google search volume index (Google SVI) as a representative of attention in general. The paper founds that a volume of influenza-related enquiry is correlated with a number of influenza patients. After that, Da et al. (2011) introduce Google SVI to a financial literature. They propose that it is a direct proxy of retail investor attention. Google SVI does not only correlate with prior proxies. But it also offers incremental information that cannot be described by them. Furthermore, Google SVI predicts two weeks stock price increase and long-term reversal. Bank et al. (2011) support Da et al. (2011). They assert that Google SVI represents a firm recognition from uninformed investors. Bank et al. (2011) and Aouadi et al. (2013) show that Google SVI is positively associated with stock liquidity, market volatility, and trading activity. Ding & Hou (2015) also indicate that stock liquidity improves with Google SVI. While, Fink & Johann (2014) identify a positive relationship between investor attention and volatility. But they do not support a positive impact of Google SVI on liquidity and short-term return. Besides, uninformed traders are the main contributor of trading volume during the high attention days. Also, Andrei & Hasler (2015) show a positive quadratic association between Google SVI and stock return variance. They signify that investor attention is one of the factors that determines a stock price. Vlastakis & Markellos (2012) analyze information demand by using Google SVI. As investors require more information during high uncertainty periods, they show a positive correlation between information demand and market volatility. While, Vozlyublennaia (2014) and Tantaopas et al. (2016) confirm a negative relationship between Google SVI, stock return predictability, and volatility of return. Furthermore, they also indicate that investor attention enhances market efficiency which is supported by Storms et al. (2016). Storms et al. (2016) also state that herd behavior during down-market might be a cause of lower market efficiency when compares to the up-market. Chakrabarty et al. (2016) study an effect of high frequency trading (HFT) during low attention periods. They conclude that inefficiency of market, due to limited investor attention, is reduced by an increasing of HFT.

The study regarding an association between investor attention and herd behavior is limited. Peng & Xiong (2006) and Peng et al. (2007) show that limited attention increases stock price comovement. The reason is that investors allocate their attention more on market-wide and sector-wide factors than firm-specific information. As the comovement reduces stock return dispersion, it implies aggregate market herding. Since investor attention and herd behavior had been acknowledged by the study as the behavioral factors which are assumed to be irrational components, Ma et al. (2017) emphasize that behavioral forces are the main contributors of financial crashes rather than fundamental aspects. The study employs indirect herding measure, which is an analysis of self-exiting effect (Epidemic Type Aftershock Sequence). Again, they do not directly investigate the association between investor attention and herd behavior. By using trading volume, Lötter (2015) suggests that recommendation changes increase investor attention. Additionally, the paper indicates that analysts' recommendation herding should be found within a group of investors who follow the same analyst.

Although, Peltomäki & Vahamaa (2015) is the only paper that explores the association between investor attention and aggregate market herding. By utilizing Google SVI, they show that investor attention reduces herd behavior aligning with the expectation. However, Peltomäki & Vahamaa (2015) have some significant drawbacks. First, they employ cross-sectional absolute deviation (CSAD) instead of the coefficient of absolute market return or the coefficient of non-linear term which is proposed by Christie & Huang (1995) and Chang et al. (2000) respectively. Without the correct aggregate market herding measure, their findings cannot deliver the accurate understanding about the association between return dispersion and market consensus. Second, the CSAD cannot reflect the time-varying nature of herd behavior. Third, the paper selects "euro crisis" as the search keyword to represents national European bank stocks' investor attention regarding the 2010 European debt crisis. As Peltomäki & Vahamaa (2015) do not mention additional Google Trends' enquiry criteria, I summit that the keyword may not be the best representative of their goal. Without specifying the country of search origin, Google Trends gives search volume from the United States by default. Therefore, it does not reflect every groups of national European bank investors. Besides, the system automatically shows the summation of search frequency from all topic of interest rather than focusing on financial category. Hence, the index is noisy due to unrelated searches. Fouth, Peltomäki & Vahamaa (2015) specifically consider only European banking sector during the 2008-2014. Ignoring the short research interval especially for weekly search data, they pool the data of 17 national European bank indices. The different between countries is disregarded.

4.3 Data

This study computes returns by using five-minute industrial index from Thomson Reuters DataScope Select. 17 countries are considered which are Australia (Australian Securities Exchange), Brazil (Bovespa), Canada (Toronto Stock Exchange), China (Shanghai Stock Exchange), France (Euronext Paris), Germany (Deutsche Börse AG), India (Bombay Stock Exchange), Ireland (Euronext Dublin), Italy (Borsa Italiana), Japan (Tokyo Stock Exchange), Portugal (Euronext Lisbon), Russia (Moscow Exchange), South Africa (Johannesburg Stock Exchange), Spain (Bolsa de Madrid and Mercado Continuo Espanol), Thailand (Stock Exchange of Thailand and Market for Alternative Investment), the United Kingdom (London Stock Exchange), and the United States (New York Stock Exchange).

Google Inc., has been providing a search volume index (Google SVI) on the Google Trends' website (https://www.google.com/trends) since 2004. Previous studies denote that Google SVI is a direct proxy of investor attention. Moreover, the index is relative value which is helpful when making comparison across different data sizes. Still, Google SVI depends on search keywords. Pioneering studies suggest stock ticker symbols to be used search keywords (Da et al., 2011; Vlastakis & Markellos, 2012; Drake et al., 2012, and Ding & Hou, 2015). The others recommend company names instead (Bank et al., 2011; Bae & Wang, 2012; Aouadi et al., 2013; Zhang et al., 2013; Vozlyublennaia, 2014; Guo et al., 2015; and Dimpfl & Jank, 2016). As enquirers search over company names for several purposes, it increases the risk of irrelevant search results. While Gao et al. (2016) recommend a use of local languages, this chapter argues that this approach makes results inapplicable for international study as it is quite country-specific information. Therefore, only English search keywords from Google SVI are used as it is regarded as the common trade language. Also, stock exchanges are generally provided English as an optional language. As English alphabets are commonly used to construct security symbols, non-English speaking investors must acknowledge and utilize them. Most importantly, Google Trends already recognizes searches of local users when developing their index. Thus, it can be concluded English search keywords already include domestic investor attention[12]. In summary, careful search keywords selection processes must be taken to develop an accurate internet search volume index. In retrieving indices from Google SVI, this chapter selects search keywords by comparing search results between five alternatives which are stock market full name, stock market short name, market index full name, market index short name, and market index RIC symbol based on Reuters's website recommendation. Focusing on "worldwide enquirer", "finance category", and "web search", the highest average searched English keyword of each stock market suggested by Google is chosen to represent investor attention in that particular market. Such selected keywords are verified the relevancy of search result based on a percentage of accurate outcome shown on a Google's first searched page.

As Google makes available of search volume index on a daily basis only for the search interval under 90 days, the study period of this chapter covers January 1, 2004 to December 31, 2018 for each country by using two-month search interval. However, Google SVI is a relative value of the maximum search frequency for a particular timeframe, not an actual search number. Thus, the index has the maximum value of 100. In reality, actual search frequency of the identical rates from one search interval and another are unequal. Therefore, daily search index with two-month search interval is adjusted for overall trend by matching with monthly search index of the entire timespan (2004-2018). Each daily search volume index is multiplied by a scaled monthly search volume index in the same month.

$$Daily\ SVI = \frac{Daily\ SVI\ Single\ Period\ \times Monthly\ SVI\ Entire\ Period}{100} \tag{4.1}$$

[12] It is important to note that Google does not have the highest market share in the information restricted markets such as China and Russia. In 2018, domestic providers, which are Baidu and Yandex, are the largest search engine controlling 70.26% and 51.08% of market share in China and Russia respectively. Unlike China, Goggle still holds 45.27% of search transaction in Russia. As a result, the Google search volume index in both countries are not the best representative of investor attention. https://alphametic.com/global-search-engine-market-share?fbclid=IwAR1o-r2WyGAkG0xmDmrJoLZDbZXj03bcrEFGsMH-phIjXn2H7DUFbrnLbFc

Table 4.1 represents the data description for each country. As limited by the internet search volume index from Google Trends, the research interval starts from January 1, 2004 to December 31, 2018. Since the availability of five-minute industrial index relies on the Thomson Reuters DataScope Select, it is limited for some market indices. Brazil, France, India, Ireland, Italy, Portugal, Russia, and South Africa are countries that have shorter data period. Portugal has the lowest number of trading days, whereas, Germany has the highest observation. Table 4.1 shows the group of industrial indices for 17 equity markets which are selected based on the completeness of database. Most importantly, the selected industrial index must match the target security exchange as mentioned in the data section. Even the application of the industrial index developed by each stock exchange is more favorable, Thomson Reuters DataScope Select does not provide such index in Brazil, Ireland, Italy, and Russia. Therefore, only for these four markets, Thomson Reuters' industrial index is applied instead. The table also suggests the number of industrial indices, sectors, in each group of indices. Ireland and Japan have the smallest and largest number of sectors respectively. As business types can be classified into sectors and sub-sectors, in order to explore investor behavior to a deeper extent, sub-sectors that can best represent such information and its completeness are taken into account when selecting sectors.

Table 4.2 indicates the selection criteria for the target search keywords. As mentioned earlier, five alternatives are compared. All options are verified their relatedness of search result. If not producing desirable outcomes, it will be replaced by other keywords. Focusing on financial related web search from global users during January 1, 2004 to December 31, 2018, the highest average searched volume keywords are chosen. Also, the most appropriate keywords for the "All categories", which is the unrestricted search scope of interest, are also analyzed. With regard to the relevance of information, the best keywords retrieved from "All categories" and "Finance" topics are mostly identical. Hence, the selected keywords are widely used and recognized. Such keywords are representatives of investor attention in each equity market. The final search keywords are shown in the "Best overall keyword" column. The validity of the "Best overall keyword" is reconfirmed by verifying the relatedness of the search result on first page. All of them deliver the perfect outcomes except for the proxy of German investor attention that has 90% relevant search result.

The chosen keywords are mostly derived from the market index's short form. It is important to note that the "CAC 40" and "FTSE" are selected instead of "Paris Bourse" and "London Stock Exchange" respectively. This has to do with the fact that the search volume of "CAC 40" and "FTSE" has been continuously beating the "Paris Bourse" and "London Stock Exchange" for the last five years. Moreover, the "Paris Bourse" was no longer referred to after the establishment of Euronext Paris in 2000. The average interest overtime for both keywords are almost equal.

Table 4.1 Data description for each equity market.
Note: This table reports research interval, number of observations, group of industrial indices, and number of indices for 17 sample countries.

Country	Period	No. of trading days	Group of indices	No. of indices
AUS	1/1/2004 to 31/12/2018	3,804	S&P/ASX 200	13
BRA	10/9/2009 to 31/12/2018	1,808	Thomson Reuters Brazil	34
CAN	1/1/2004 to 31/12/2018	3,750	S&P/TSX Capped	12
CHN	1/1/2004 to 31/12/2018	3,641	Shanghai Stock Exchange	18
FRA	15/10/2012 to 31/12/2018	1,160	Euronext CAC	10
GER	1/1/2004 to 31/12/2018	3,809	DAX (XETRA)	18
IND	23/10/2006 to 31/12/2018	3,021	S&P BSE	10
IRE	16/6/2009 to 31/12/2018	1,997	Thomson Reuters Ireland	6
ITA	10/9/2009 to 31/12/2018	1,767	Thomson Reuters Italy	28
JAP	1/1/2004 to 31/12/2018	3,676	Nikkei 500 Stock Average	36
POR	15/10/2012 to 31/12/2018	1,158	Euronext PSI	8
RUS	30/8/2010 to 31/12/2018	1,457	Thomson Reuters Russia	19
SAF	1/1/2006 to 31/12/2018	2,971	FTSE/JSE	35
SPA	1/1/2004 to 31/12/2018	3,789	Madrid Stock Exchange IGM	31
THA	1/1/2004 to 31/12/2018	3,641	Thailand Stock Exchange	8
UK	7/12/2004 to 31/12/2018	3,556	FTSE 350 Super Sector	19
USA	30/4/2004 to 31/12/2018	3,726	NYSE Arca Composite	19

Table 4.2 Google's search keyword selection by market.

Note: This table reports five primary search words. The best search keywords have the highest search volume from worldwide enquirers during 2004 to 2019. The best overall search keywords are chosen by computing the highest average score from both all categories and financial search. The relevancy of the selected term is confirmed by verifying the relatedness of search result.

Stock market full name	Stock market short name (Other names)	Market index full name	Market index short name	Market index RIC symbol (Reuters' website recommendation)	Best overall keyword
Australian Securities Exchange	ASX	All Ordinaries	All Ords	AORD	ASX
Sao Paulo Stock Exchange	BM&FBOVESPA	Bovespa Index	Ibovespa	BVSP	Ibovespa
Toronto Stock Exchange	TSX	S&P/TSX Composite Index	TSX Composite	GSPTSE	TSX
Shanghai Stock Exchange	Shanghai Exchange	Shanghai Composite Index	SSE Index	SSEC	Shanghai Exchange
Euronext Paris	Paris Bourse	French stock market index	CAC 40	FCHI	CAC 40
Frankfurt Stock Exchange	Deutsche Börse	German Stock Index	DAX	GDAXI	DAX
Bombay Stock Exchange	BSE	S&P BSE Sensex	SENSEX	BSESN	BSE
Euronext Dublin	Irish Stock Exchange (ISE is irrelevance)	ISEQ Overall Price Index	ISEQ Overall Index	ISEQ	Irish Stock Exchange
Borsa Italiana	Milan Stock Exchange	FTSE MIB Index	FTSE MIB	FTMIB	Borsa Italiana
Tokyo Stock Exchange	Nikkei 225 (ISE/TYO are irrelevance)	Nikkei Stock Average 225	Nikkei	N225	Nikkei
Euronext Lisbon	Bolsa de Lisboa	PSI All Shares Gross Return Index	PSI General	BVLG	Bolsa de Lisboa
Moscow Exchange	MICEX-RTS	MOEX Russia Index	RTS Index	MICEX	RTS Index
Johannesburg Stock Exchange	JSE	FTSE/JSE All Share Index	JSE All Share	JALSH	JSE
Bolsa de Madrid	Madrid Stock Exchange	Madrid General Index	IBEX 35	SMSI	IBEX 35
Stock Exchange of Thailand	Thailand Stock Market	SET Composite Index	SET Index	SET50	SET Index
London Stock Exchange	UK Stock Market	Financial Times Stock Exchange 100 Index	FTSE 100	FTSE	FTSE
New York Stock Exchange	NYSE	New York Stock Exchange Composite Index	NYSE Composite Index	NYSE Index	NYSE

Five-minute industrial indices are used to evaluate daily coefficient of non-linear term from Blasco et al. (2017). Abnormal daily search volume is constructed by analyzing target keywords from Google Trends. Descriptive statistics for daily coefficient of non-linear term and abnormal Google search volume index are shown in Table 4.3. Australia has the smallest average abnormal search volume, while Ireland shows the highest value. In addition, the highest abnormal daily search index is identified in China, whereas the lowest is shown in UK. In view of a standard deviation of the abnormal search statistics, Portugal and India have the largest and smallest dispersion of investor attention respectively. The largest search engine in China is Baidu while a majority of Russians use Yandex.

However, market shares of Yandex and Google are almost the same in Russia. Also, as Google is restricted in China, Baidu holds more than 70% of search transaction in the country. Hence, Google search volume represents the attention of foreign investors better than Chinese investors. On the other hand, Thailand has the smallest daily average herding coefficient, while South Africa has the largest. This signals the chance of intraday herd behavior in those markets. In view of maximum and minimum daily coefficient of non-linear term, Spain has the highest maximum value, whereas Australia has the supreme minimum herding indicator.

Since significantly negative coefficient of non-linear term signifies the imitation across trader behavior, the findings suggest the occurrence of extreme intraday herd behavior and anti-herding in Australia and Spain respectively. Ireland has the lowest standard deviation of the coefficient of non-linear term, while the highest dispersion of herding measure is found in Canada. This is the indication of high degree of time-varying herd behavior. With reference to Augmented Dickey–Fuller test, unit root is insignificant. Thus, all time-series are stationary.

Table 4.3 Descriptive statistics of the daily coefficient of non-linear term and abnormal daily Google search volume index.

Note: This table reports descriptive statistics of daily coefficient of non-linear term $(CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m,t} + \gamma_3 |R_{m,t}| + \gamma_4 (R_{m,t})^2 + \varepsilon_t$, where $CSAD_t$ is a cross-sectional absolute deviation of returns at time t, $R_{m,t}$ is an equally weighted portfolio return at time t, and $CSAD_{t-1}$ is a one-period lag of cross-sectional absolute deviation of returns at time t. Five minute industrial indices are used to measure the variables.) and abnormal daily Google search volume index $(ASVI_t = log\,GSVI_t - log[median(GSVI_{t-1}, \dots, GSVI_{t-8})])$ for 17 sample countries. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

Country	Variable	Average	Min	Max	S.D.	ADF
AUS	$\gamma_{4,t}$	-0.289	-78.649	48.239	3.623	-14.684***
	$ASVI_t$	0.019	-0.695	1.000	0.157	-14.166***
BRA	$\gamma_{4,t}$	0.012	-4.298	5.430	0.712	-9.946***
	$ASVI_t$	0.082	-1.014	0.939	0.207	-12.273***
CAN	$\gamma_{4,t}$	0.983	-28.957	44.385	4.783	-13.080***
	$ASVI_t$	0.052	-0.778	0.832	0.136	-15.673***
CHN	$\gamma_{4,t}$	-0.178	-6.582	10.668	0.725	-8.140***
	$ASVI_t$	0.072	-0.654	2.004	0.229	-13.235***
FRA	$\gamma_{4,t}$	0.855	-33.373	21.963	2.821	-8.926***
	$ASVI_t$	0.071	-0.896	0.733	0.224	-10.218***
GER	$\gamma_{4,t}$	0.962	-32.166	37.862	2.403	-12.649***
	$ASVI_t$	0.052	-0.950	1.000	0.172	-15.355***
IND	$\gamma_{4,t}$	-0.032	-14.148	13.735	1.333	-10.499***
	$ASVI_t$	0.044	-0.713	0.602	0.102	-14.594***
IRE	$\gamma_{4,t}$	-0.058	-3.630	3.164	0.538	-9.262***
	$ASVI_t$	0.111	-0.394	0.969	0.206	-11.424***
ITA	$\gamma_{4,t}$	0.098	-4.629	5.167	0.553	-10.885***
	$ASVI_t$	0.058	-0.853	0.951	0.211	-12.827***
JAP	$\gamma_{4,t}$	0.972	-22.559	28.679	2.410	-12.795***
	$ASVI_t$	0.067	-0.740	1.139	0.226	-15.744***
POR	$\gamma_{4,t}$	0.516	-7.392	13.138	2.131	-9.276***
	$ASVI_t$	0.093	-0.740	1.034	0.239	-10.447***
RUS	$\gamma_{4,t}$	0.068	-6.306	9.711	0.770	-10.080***
	$ASVI_t$	0.064	-0.477	1.254	0.174	-8.119***
SAF	$\gamma_{4,t}$	1.639	-15.190	26.575	3.345	-10.953***
	$ASVI_t$	0.068	-0.900	0.954	0.201	-13.241***
SPA	$\gamma_{4,t}$	0.803	-69.014	59.939	2.877	-14.127***
	$ASVI_t$	0.045	-0.948	1.155	0.150	-14.280***
THA	$\gamma_{4,t}$	-1.348	-19.759	9.894	2.095	-8.275***
	$ASVI_t$	0.053	-0.551	1.046	0.163	-12.891***
UK	$\gamma_{4,t}$	1.522	-14.427	37.511	3.450	-10.229***
	$ASVI_t$	0.058	-1.267	1.347	0.175	-14.693***
USA	$\gamma_{4,t}$	-0.018	-11.965	20.325	1.861	-12.371***
	$ASVI_t$	0.026	-0.913	1.523	0.167	-13.457***

4.4 Methodology

Chang et al. (2000) and Christie & Huang (1995) both rely on rational asset pricing model. Though, Chang et al. (2000) argue Christie & Huang (1995) by asserting that rational asset pricing model predicts positive and linear relationship between equity return dispersion and overall market return. If aggregate market herding exists, then negative and significant non-linear relationship should be found. The reason is that the return dispersion should increase with decreasing rate when investors follow overall market consensus.

Consequently, Chang et al. (2000) extend Christie & Huang (1995) by introducing a non-linear parameter to aggregate market herding analysis. The direct herding measure from Chang et al. (2000)'s model is the coefficient of non-linear term. In order to enhance power of the model, Yao et al. (2014) and Blasco et al. (2017) extend Chang et al. (2000) by introducing one-day lag of dependent variable to the equation.

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{4.2}$$

$$CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m,t} + \gamma_3\left|R_{m,t}\right| + \gamma_4\left(R_{m,t}\right)^2 + \varepsilon_t \tag{4.3}$$

where $CSAD_t$ is a cross-sectional absolute deviation of returns during period t. $CSAD_{t-1}$ is a one-period lag of cross-sectional absolute deviation of returns during period t. $R_{i,t}$ is a stock return from firm i during period t which is equal to $100 \times \left(\ln P_{i,t} - \ln P_{i,t-1}\right)$. $R_{m,t}$ is an equally weighted market return during period t. N is a number of industrial indices.

Not only herd behavior is asymmetric and severe under extreme market movement (Christie & Huang, 1995), it also changes over time (Bohl et al., 2013; Sharma et al., 2015; and Ngene et al., 2017). As a result, the static model causes a misleading inference. In order to capture the dynamic characteristic, this chapter estimates aggregate market herding by computing daily coefficient of non-linear term (γ_4) of Blasco et al. (2017) from five-minute industrial indices.

Due to the debatable foundation regarding the interaction between investor attention and aggregate market herding, the relation is examined by using bivariate vector autoregression (VAR) analysis in each country.

$$\gamma_{4,t} = C_1 + \pi_{1,1}^{1}\gamma_{4,t-1} + \cdots + \pi_{1,1}^{p}\gamma_{4,t-p} + \pi_{1,2}^{1}ASVI_{t-1} + \cdots + \pi_{1,2}^{p}ASVI_{t-p} + \varepsilon_t \tag{4.4}$$

$$ASVI_t = C_2 + \pi_{2,1}^{1}\gamma_{4,t-1} + \cdots + \pi_{2,1}^{p}\gamma_{4,t-p} + \pi_{2,2}^{1}ASVI_{t-1} + \cdots + \pi_{2,2}^{p}ASVI_{t-p} + \varepsilon_t \tag{4.5}$$

$$ASVI_t = \log GSVI_t - \log[median(GSVI_{t-1}, \ldots, GSVI_{t-8})] \tag{4.6}$$

where $\gamma_{4,t}$ is a coefficient of non-linear term from Blasco et al. (2017) at day t. $ASVI_t$ is the abnormal Google search volume index during the prior eight days of day t (Da et al., 2011). $GSVI_t$ is the Google search volume index during day t. p is the optimal lag length determined by Akaike information criteria (AIC).

For the robustness check, this chapter employs the unadjusted Google search volume index instead of the abnormal Google search volume index. Furthermore, the lower frequency industrial indices, which are 10-minute and 15-minute data, are used to measure daily coefficient of non-linear term.

$$\gamma_{4,t} = C_1 + \pi_{1,1}^{1}\gamma_{4,t-1} + \cdots + \pi_{1,1}^{p}\gamma_{4,t-p} + \pi_{1,2}^{1}GSVI_{t-1} + \cdots + \pi_{1,2}^{p}GSVI_{t-p} + \varepsilon_t \tag{4.7}$$

$$GSVI_t = C_2 + \pi_{2,1}^{1}\gamma_{4,t-1} + \cdots + \pi_{2,1}^{p}\gamma_{4,t-p} + \pi_{2,2}^{1}GSVI_{t-1} + \cdots + \pi_{2,2}^{p}GSVI_{t-p} + \varepsilon_t \tag{4.8}$$

4.5 Empirical results

4.5.1 Granger causality

In order to analyze forecasting ability of proposing variables, Table 4.4 shows Granger causality analysis for abnormal daily Google search volume index and daily coefficient of non-linear term from Blasco et al. (2017). In general, Table 4.4 suggests the predictive capability in Australia, Portugal, Spain, and Thailand. Even three of them are developed markets, Portugal and Spain are categorized as the PIIGS nations, a group of economically unstable eurozone nations. The study results can be separated into two groups. First, the hypothesis that daily coefficient of non-linear term does not Granger cause daily abnormal Google search volume index is rejected in Australia, Portugal, and Spain. In other words, the relationship between return dispersion and market return Granger causes internet search frequency. It can be concluded that changes in herd behavior in previous period can be used to estimate the future development of investor attention. Secondly, the null hypothesis that daily Google search volume index does not Granger cause daily coefficient of non-linear term is rejected in Australia, Spain, and Thailand. In this regard, internet search frequency Granger causes the herding coefficient. Hence, the lagged variables of investor attention are useful for predicting potential herd behavior. Additionally, the findings from Australia and Spain confirm the mutual relationship between herd behavior and investor attention. However, VAR coefficient matrix in other countries are diagonal. Therefore, the lag of independent variables keep it from offering significant information to determine the dependent variable in those markets. Interestingly, the findings contradict to Peltomäki & Vahamaa (2015). By combining weekly data of 17 European national bank stock indices developed by FTSE, they suggest one-way relationship. It can be inferred that internet search index Granger causes herding coefficient. On the other hand, Peltomäki & Vahamaa (2015) implicitly examine herd behavior at a continent level rather than a country level. They also study exclusively the European banking sector by comparing EMU (Economic and Monetary Union of the European Union) to non-EMU banking stock indices. Peltomäki & Vahamaa (2015) utilize CSAD instead of coefficient of non-linear term which is a direct proxy of herd behavior. However, herding is quite the analysis of the interaction between return dispersion and market return especially during the period of extreme market movements. Consequently, CSAD does not represent the rational asset pricing theory which is the foundation of aggregate market herding (Christie & Huang, 1995 and Chang et al., 2000). These may yield conflicting inference.

4.5.2 Bivariate VAR model

In order to examine overall influence of abnormal daily Google search volume index on coefficient of non-linear term in 17 equity markets, bivariate vector autoregressive is studied. The results presented in Table 4.5 capture the dependent relationship between change in investor attention and aggregate market herding. Based on Akaike Information Criteria, the highest optimal lag length is four-trading days. The previous-period change in abnormal search volume positively influences the current coefficient of non-linear term particularly in emerging markets which are China and Thailand. The opposite results are identified in Australia and UK which are developed nations. Thus, it may be assumed that abnormal investor attention reduces herd behavior especially in developing countries. Yet, such developing markets face more problems arise from information asymmetry due to lesser degree of investor protection, lack of information accessibility, and more participation of unsophisticated retail investor. Consequently, the enhancement of investor attention empowers individuals and reduces information uncertainty resulting in more independent decision-making and dispersed trading. Still, the study shows that the herd behavior is reduced after the period of high attention in advanced economies. Explanations for such a case can be made based on two perspectives. Firstly, growth in investor attention strengthens investors' trading information, improves decision-making and, therefore, minimizes information uncertainty (Mondria et al., 2010; Libby et al., 2002; Daniel et al., 2002; and Hirshleifer et al., 2011). However, while information asymmetry becomes lower, a possibility of similar judgement also increases resulting in spurious herding. Secondly, it could be psychological factors that drive irrational herd behavior. The deindividuation theory (Le Bon, 1895) suggests a positive influence of attention on herd behavior. As people are affected by social discrimination, they tend to conform to a group behavior during high attention circumstances. In addition, Leonard et al. (2012) characterize a decision versus compromise model. The study shows that cooperation movement is growing with an amount of crowd which links to the investor attention. On the other hand, the lagged changes in daily coefficient of non-linear term have a positive impact on current abnormal search volume index in Australia and USA. However, the negative influence is identified on Brazil, Germany, Ireland, Italy, Portugal, Russia, Spain, and Thailand. Hence, the outcomes mostly confirm that herd behavior intensifies investor attention. Moreover, since aggregate market herding is a market-wide content, it drives return volatility which catches investor attention (Barber & Odean, 2008; Li et al., 2017; Peng & Xiong, 2006; and Peng et al., 2007).

Table 4.4 Granger causality.

Note: This table shows the Granger causality test's result for the relationship between abnormal Google SVI and coefficient of non-linear term. *, **, and *** denote the 10%, 5%, and 1% significance levels, respectively.

Null hypothesis	Chi-square	*p*-value
AUS		
Herding coefficient does not Granger cause ASVI	44.186***	0.001
ASVI does not Granger cause herding coefficient	71.324***	0.001
BRA		
Herding coefficient does not Granger cause ASVI	4.408	0.221
ASVI does not Granger cause herding coefficient	1.033	0.793
CAN		
Herding coefficient does not Granger cause ASVI	2.212	0.697
ASVI does not Granger cause herding coefficient	5.044	0.283
CHN		
Herding coefficient does not Granger cause ASVI	2.471	0.650
ASVI does not Granger cause herding coefficient	4.992	0.288
FRA		
Herding coefficient does not Granger cause ASVI	0.946	0.623
ASVI does not Granger cause herding coefficient	1.422	0.491
GER		
Herding coefficient does not Granger cause ASVI	5.796	0.215
ASVI does not Granger cause herding coefficient	6.303	0.178
IND		
Herding coefficient does not Granger cause ASVI	2.413	0.491
ASVI does not Granger cause herding coefficient	1.505	0.681
IRE		
Herding coefficient does not Granger cause ASVI	4.142	0.387
ASVI does not Granger cause herding coefficient	1.464	0.833

Table 4.4 (continued)

Null hypothesis	Chi-square	p-value
ITA		
Herding coefficient does not Granger cause ASVI	5.484	0.140
ASVI does not Granger cause herding coefficient	0.706	0.872
JAP		
Herding coefficient does not Granger cause ASVI	2.374	0.667
ASVI does not Granger cause herding coefficient	2.741	0.602
POR		
Herding coefficient does not Granger cause ASVI	6.271**	0.043
ASVI does not Granger cause herding coefficient	0.946	0.623
RUS		
Herding coefficient does not Granger cause ASVI	5.133	0.162
ASVI does not Granger cause herding coefficient	0.141	0.986
SAF		
Herding coefficient does not Granger cause ASVI	2.810	0.590
ASVI does not Granger cause herding coefficient	3.292	0.510
SPA		
Herding coefficient does not Granger cause ASVI	12.974**	0.011
ASVI does not Granger cause herding coefficient	11.167**	0.025
THA		
Herding coefficient does not Granger cause ASVI	7.120	0.130
ASVI does not Granger cause herding coefficient	19.887***	0.001
UK		
Herding coefficient does not Granger cause ASVI	6.611	0.158
ASVI does not Granger cause herding coefficient	3.409	0.492
USA		
Herding coefficient does not Granger cause ASVI	5.774	0.217
ASVI does not Granger cause herding coefficient	2.554	0.635

4.5.3 Robustness

To check for robustness, the abnormal Google search volume index is replaced by the unadjusted Google search volume index as an investor attention proxy. In order to estimate the daily coefficient of non-linear term, the lower frequency intraday data is used instead of the five-minute industrial index. Table 4.6 shows the descriptive statistics of daily coefficient of non-linear term and the Google search volume index. India and Russia have the highest and lowest average Google search volume index respectively. Since Google Trends provides relative value of maximum search volume instead of actual search frequency, the value of such index always ranges from 0 to 100. As herding coefficient are exclusively derived from data on trading days, the non-trading days are removed from the time-series of investor attention proxy, consequently, the top and bottom search indices of some countries deviate from the expectation. The smallest dispersion of search statistic is detected in Russia. Also, investor attention appears to be volatile in Spain as it has the largest standard deviation of search index. Based on Augmented Dickey–Fuller test, the samples are stationary. With regard to the herding measure, the inferences are the same as in Table 4.3.

Table 4.5 VAR estimations.

Note: This table shows the VAR estimations of the relationship between the abnormal Google search volume index (*ASVI_t*) and daily coefficient of non-linear term (γ_4), which is $CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m,t} + \gamma_3 |R_{m,t}| + \gamma_4 (R_{m,t})^2 + \varepsilon_t$, where $CSAD_t$ is a cross-sectional absolute deviation of returns at time *t*, $R_{m,t}$ is an equally weighted portfolio return at time *t*, and $CSAD_{t-1}$ is a one-period lag of cross-sectional absolute deviation of returns at time *t*. Five minute industrial indices are used to measure the variables.) for 17 sample countries. The optimal lag lengths for each country are computed by using the minimum consenting AIC. Standard errors are shown in parentheses. *, **, and *** denote the 10%, 5%, and 1% significance levels, respectively.

Variable	AUS		BRA		CAN		CHN	
	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$
$ASVI_{t-1}$	-0.774***	-0.507	-0.654***	0.042	-0.649***	1.658	-0.731***	-0.021
	(0.03)	(0.51)	(0.05)	(0.14)	(0.04)	(1.07)	(0.04)	(0.06)
$ASVI_{t-2}$	-0.528***	-0.446	-0.428***	-0.104	-0.390***	0.725	-0.584***	0.040
	(0.03)	(0.61)	(0.06)	(0.16)	(0.05)	(1.22)	(0.05)	(0.07)
$ASVI_{t-3}$	-0.328***	-2.153***	-0.216***	-0.097	-0.291***	-1.013	-0.368***	0.088
	(0.03)	(0.59)	(0.05)	(0.15)	(0.05)	(1.21)	(0.05)	(0.07)
$ASVI_{t-4}$	-0.187***	-3.285***			-0.081**	0.368	-0.140***	0.115**
	(0.02)	(0.41)			(0.04)	(1.05)	(0.04)	(0.06)
$\gamma_{4,t-1}$	0.011***	-0.774***	-0.024	-0.876***	0.001	-0.782***	-0.030	-0.839***
	(0.01)	(0.03)	(0.02)	(0.05)	(0.01)	(0.04)	(0.02)	(0.03)
$\gamma_{4,t-2}$	0.006***	-0.489***	-0.049**	-0.529***	-0.001	-0.563***	-0.037	-0.709***
	(0.01)	(0.04)	(0.02)	(0.06)	(0.01)	(0.05)	(0.03)	(0.04)
$\gamma_{4,t-3}$	0.004**	-0.276***	-0.027	-0.270***	-0.001	-0.437***	-0.020	-0.360***
	(0.01)	(0.03)	(0.02)	(0.05)	(0.01)	(0.05)	(0.03)	(0.04)
$\gamma_{4,t-4}$	0.002	-0.059***			-0.001	-0.184***	-0.016	-0.232***
	(0.01)	(0.02)			(0.01)	(0.04)	(0.02)	(0.03)

Table 4.5 (continued)

Variable	FRA		GER		IND		IRE	
	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$
$ASVI_{t-1}$	-0.630***	0.393	-0.705***	-0.434	-0.505***	-0.576	-0.769***	-0.099
	(0.05)	(0.62)	(0.04)	(0.37)	(0.04)	(0.49)	(0.06)	(0.24)
$ASVI_{t-2}$	-0.289***	0.712	-0.449***	0.280	-0.181***	-0.390	-0.581***	-0.187
	(0.05)	(0.60)	(0.05)	(0.45)	(0.04)	(0.52)	(0.07)	(0.28)
$ASVI_{t-3}$			-0.253***	0.221	-0.046	-0.028	-0.382***	-0.057
			(0.05)	(0.45)	(0.03)	(0.42)	(0.07)	(0.28)
$ASVI_{t-4}$			-0.104***	0.603			-0.214***	-0.233
			(0.04)	(0.38)			(0.06)	(0.24)
$\gamma_{4,t-1}$	-0.001	-0.660***	-0.002	-0.818***	-0.002	-0.781***	-0.011	-0.723***
	(0.01)	(0.05)	(0.01)	(0.04)	(0.01)	(0.04)	(0.02)	(0.06)
$\gamma_{4,t-2}$	0.003	-0.272***	0.002	-0.568***	0.001	-0.490***	-0.021	-0.562***
	(0.01)	(0.05)	(0.01)	(0.05)	(0.01)	(0.04)	(0.02)	(0.08)
$\gamma_{4,t-3}$			-0.003	-0.374***	0.003	-0.239***	-0.033*	-0.314***
			(0.01)	(0.05)	(0.01)	(0.04)	(0.02)	(0.08)
$\gamma_{4,t-4}$			-0.006*	-0.213***			-0.033*	-0.198***
			(0.01)	(0.04)			(0.02)	(0.07)

Variable	ITA		JAP		POR		RUS	
	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$
$ASVI_{t-1}$	-0.609***	-0.047	-0.709***	-0.110	-0.542***	0.224	-0.575***	0.006
	(0.06)	(0.11)	(0.04)	(0.34)	(0.05)	(0.42)	(0.05)	(0.31)
$ASVI_{t-2}$	-0.414***	0.017	-0.486***	-0.179	-0.291***	-0.222	-0.417***	-0.121
	(0.06)	(0.12)	(0.05)	(0.41)	(0.05)	(0.42)	(0.07)	(0.39)
$ASVI_{t-3}$	-0.117**	-0.051	-0.296***	0.203			-0.383***	-0.027
	(0.05)	(0.10)	(0.05)	(0.41)			(0.05)	(0.29)
$ASVI_{t-4}$			-0.174***	-0.237				
			(0.04)	(0.34)				
$\gamma_{4,t-1}$	-0.007	-0.544***	-0.003	-0.764***	-0.011**	-0.696***	-0.002	-1.047***
	(0.03)	(0.05)	(0.01)	(0.04)	(0.01)	(0.05)	(0.01)	(0.07)
$\gamma_{4,t-2}$	-0.025	-0.471***	-0.002	-0.524***	-0.002	-0.376***	-0.034*	-0.478***
	(0.03)	(0.05)	(0.01)	(0.05)	(0.01)	(0.05)	(0.02)	(0.11)
$\gamma_{4,t-3}$	-0.052**	-0.218***	0.005	-0.409***			-0.007	-0.162
	(0.02)	(0.04)	(0.01)	(0.05)			(0.02)	(0.10)
$\gamma_{4,t-4}$			0.001	-0.243***				
			(0.01)	(0.04)				

Table 4.5 (continued)

Variable	SAF		SPA		THA		UK	
	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$
$ASVI_{t-1}$	-0.704***	-0.684	-0.665***	0.564	-0.873***	2.977***	-0.616***	-0.241
	(0.05)	(0.50)	(0.04)	(0.54)	(0.04)	(1.09)	(0.04)	(0.61)
$ASVI_{t-2}$	-0.544***	-0.350	-0.394***	1.002	-0.782***	4.353***	-0.389***	-0.989
	(0.06)	(0.59)	(0.05)	(0.64)	(0.05)	(1.37)	(0.05)	(0.68)
$ASVI_{t-3}$	-0.350***	0.249	-0.261***	0.966	-0.471***	0.703	-0.273***	-1.133*
	(0.06)	(0.60)	(0.05)	(0.64)	(0.05)	(1.34)	(0.05)	(0.69)
$ASVI_{t-4}$	-0.206***	-0.062	-0.161***	-0.846	-0.292***	2.271*	-0.163***	-0.362
	(0.05)	(0.50)	(0.04)	(0.54)	(0.05)	(1.19)	(0.04)	(0.60)
$\gamma_{4,t-1}$	0.002	-0.757***	-0.006**	-0.680***	-0.001	-0.734***	-0.001	-0.725***
	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)
$\gamma_{4,t-2}$	-0.004	-0.530***	-0.002	-0.502***	-0.003	-0.492***	0.005	-0.674***
	(0.01)	(0.05)	(0.01)	(0.04)	(0.01)	(0.05)	(0.01)	(0.05)
$\gamma_{4,t-3}$	0.002	-0.333***	-0.004	-0.316***	-0.005**	-0.290***	0.002	-0.416***
	(0.01)	(0.05)	(0.01)	(0.04)	(0.01)	(0.05)	(0.01)	(0.05)
$\gamma_{4,t-4}$	0.001	-0.102**	-0.006**	-0.172***	-0.002	-0.185***	-0.004	-0.145***
	(0.01)	(0.04)	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)	(0.05)

Variable	USA	
	$ASVI_t$	$\gamma_{4,t}$
$ASVI_{t-1}$	-0.554***	0.292
	(0.04)	(0.28)
$ASVI_{t-2}$	-0.347***	0.476
	(0.05)	(0.32)
$ASVI_{t-3}$	-0.228***	0.387
	(0.05)	(0.32)
$ASVI_{t-4}$	-0.132***	0.233
	(0.04)	(0.28)
$\gamma_{4,t-1}$	0.008*	-0.769***
	(0.01)	(0.03)
$\gamma_{4,t-2}$	0.005	-0.578***
	(0.01)	(0.04)
$\gamma_{4,t-3}$	-0.001	-0.368***
	(0.01)	(0.04)
$\gamma_{4,t-4}$	0.003	-0.180***
	(0.01)	(0.03)

Table 4.6 Descriptive statistics of the daily coefficient of non-linear term and daily Google search volume index.

Note: This table reports descriptive statistics of daily coefficient of non-linear term ($CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m,t} + \gamma_3 |R_{m,t}| + \gamma_4 (R_{m,t})^2 + \varepsilon_t$, where $CSAD_t$ is a cross-sectional absolute deviation of returns at time t, $R_{m,t}$ is an equally weighted portfolio return at time t, and $CSAD_{t-1}$ is a one-period lag of cross-sectional absolute deviation of returns at time t. Five minute industrial indices are used to measure the variables.) and daily Google search volume index ($GSVI_t$) for 17 sample countries. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% respectively.

Country	Variable	Average	Min	Max	S.D.	ADF
AUS	$\gamma_{4,t}$	-0.288	-78.649	48.239	3.626	-14.693***
	$GSVI_t$	23.672	0.000	100.000	12.311	-5.357***
BRA	$\gamma_{4,t}$	0.012	-4.298	5.430	0.712	-9.946***
	$GSVI_t$	7.447	0.000	100.000	9.028	-6.187***
CAN	$\gamma_{4,t}$	0.980	-28.957	44.385	4.783	-13.141***
	$GSVI_t$	19.379	0.000	100.000	9.431	-5.124***
CHN	$\gamma_{4,t}$	-0.178	-6.582	10.668	0.725	-8.145***
	$GSVI_t$	6.797	0.000	100.000	7.990	-7.793***
FRA	$\gamma_{4,t}$	0.855	-33.373	21.963	2.821	-8.926***
	$GSVI_t$	9.493	0.000	35.000	5.357	-5.217***
GER	$\gamma_{4,t}$	0.961	-32.166	37.862	2.403	-12.656***
	$GSVI_t$	17.717	0.000	100.000	11.293	-7.012***
IND	$\gamma_{4,t}$	-0.032	-14.148	13.735	1.333	-10.499***
	$GSVI_t$	34.989	4.080	100.000	13.587	-5.269***
IRE	$\gamma_{4,t}$	-0.058	-3.630	3.164	0.538	-9.262***
	$GSVI_t$	5.471	0.000	51.000	6.399	-6.765***
ITA	$\gamma_{4,t}$	0.098	-4.629	5.167	0.553	-10.885***
	$GSVI_t$	25.460	0.000	97.000	13.773	-5.858***
JAP	$\gamma_{4,t}$	0.971	-22.559	28.679	2.409	-12.794***
	$GSVI_t$	8.278	0.000	100.000	7.583	-8.010***
POR	$\gamma_{4,t}$	0.516	-7.392	13.138	2.131	-9.276***
	$GSVI_t$	18.419	0.000	88.000	11.306	-4.132***
RUS	$\gamma_{4,t}$	0.068	-6.306	9.711	0.770	-10.080***
	$GSVI_t$	2.499	0.000	41.000	3.657	-6.007***

Table 4.6 (continued)

Country	Variable	Average	Min	Max	S.D.	ADF
SAF	$\gamma_{4,t}$	1.639	-15.190	26.575	3.345	-10.953***
	$GSVI_t$	21.427	0.000	100.000	14.318	-5.011***
SPA	$\gamma_{4,t}$	0.802	-69.014	59.939	2.876	-14.149***
	$GSVI_t$	25.833	0.000	100.000	17.686	-6.577***
THA	$\gamma_{4,t}$	-1.347	-19.759	9.894	2.094	-8.278***
	$GSVI_t$	7.945	0.000	100.000	12.662	-6.934***
UK	$\gamma_{4,t}$	1.522	-14.427	37.511	3.450	-10.229***
	$GSVI_t$	11.984	0.000	100.000	8.249	-7.040***
USA	$\gamma_{4,t}$	-0.018	-11.965	20.325	1.861	-12.371***
	$GSVI_t$	12.205	0.000	100.000	9.950	-7.222***

Based on Granger causality test, Table 4.7 represents the estimating power of variables. In consideration of the unadjusted Google search volume index, Panel A of Table 4.7 indicates the forecasting capability of five countries which are Australia, Portugal, Russia, Spain, and Thailand. Comparing to the main methodology, abnormal Google search volume index, the alternative technique also identifies the same markets except Russia. The herding coefficient significantly Granger causes Google search volume index in four countries which are Australia, Portugal, Russia, and Thailand. On the other hand, the results from Australia and Spain strongly reject the null hypothesis that daily Google search volume index does not Granger cause daily coefficient of non-linear term. Additionally, Granger causality test confirms the mutual relationship between herd behavior and investor attention in Australia. Although the inference of Granger causality test from the raw Google search volume index verifies the main methodology, Panel B of Table 4.7 provides different results. The herding coefficient from 10-minute industrial indices suggest that the variation of herd behavior is helpful for predicting changes in investor attention in Ireland, Russia, and Spain. Alternatively, the transformation of investor attention can explain potential herd behavior in Australia and Spain. Even not being presented on this paper, the results from 15-minute industrial indices also confirm the predicting power of herding coefficient on investor attention proxy in Canada, Ireland, Spain, and Thailand. Yet, opposite results in Australia, China, Spain, and Thailand are also provided.

Table 4.7 Granger causality (Robustness).

Panel A: Granger causality (Google search volume index).

Note: This table shows the Granger causality test's result for the relationship between Google SVI-coefficient of non-linear term. *, **, and *** denote the 10%, 5%, and 1% significance levels, respectively.

Null hypothesis	Chi-square	*p*-value
AUS		
Herding coefficient does not Granger cause SVI	28.096***	0.001
SVI does not Granger cause herding coefficient	74.036***	0.001
BRA		
Herding coefficient does not Granger cause SVI	2.554	0.466
SVI does not Granger cause herding coefficient	1.062	0.786
CAN		
Herding coefficient does not Granger cause SVI	2.771	0.597
SVI does not Granger cause herding coefficient	2.634	0.621
CHN		
Herding coefficient does not Granger cause SVI	0.194	0.996
SVI does not Granger cause herding coefficient	0.894	0.925
FRA		
Herding coefficient does not Granger cause SVI	1.325	0.515
SVI does not Granger cause herding coefficient	0.938	0.626
GER		
Herding coefficient does not Granger cause SVI	4.502	0.342
SVI does not Granger cause herding coefficient	7.223	0.125
IND		
Herding coefficient does not Granger cause SVI	0.899	0.826
SVI does not Granger cause herding coefficient	1.179	0.758
IRE		
Herding coefficient does not Granger cause SVI	0.200	0.995
SVI does not Granger cause herding coefficient	2.841	0.585

Table 4.7 Panel A (continued)

Null hypothesis	Chi-square	p-value
ITA		
Herding coefficient does not Granger cause SVI	4.197	0.241
SVI does not Granger cause herding coefficient	0.322	0.956
JAP		
Herding coefficient does not Granger cause SVI	3.375	0.497
SVI does not Granger cause herding coefficient	1.930	0.749
POR		
Herding coefficient does not Granger cause SVI	5.113*	0.078
SVI does not Granger cause herding coefficient	0.899	0.638
RUS		
Herding coefficient does not Granger cause SVI	17.990***	0.001
SVI does not Granger cause herding coefficient	4.266	0.371
SAF		
Herding coefficient does not Granger cause SVI	4.124	0.389
SVI does not Granger cause herding coefficient	1.915	0.751
SPA		
Herding coefficient does not Granger cause SVI	5.622	0.229
SVI does not Granger cause herding coefficient	26.065***	0.001
THA		
Herding coefficient does not Granger cause SVI	11.302**	0.023
SVI does not Granger cause herding coefficient	3.264	0.515
UK		
Herding coefficient does not Granger cause SVI	2.140	0.710
SVI does not Granger cause herding coefficient	6.133	0.189
USA		
Herding coefficient does not Granger cause SVI	1.562	0.816
SVI does not Granger cause herding coefficient	5.166	0.271

Panel B: Granger causality (Abnormal Google search volume index with 10-minute industrial index data).

Note: This table shows the Granger causality test's result for the relationship between abnormal Google SVI-coefficient of non-linear term. *, **, and *** denote the 10%, 5%, and 1% significance levels, respectively.

Null hypothesis	Chi-square	*p*-value
AUS		
Herding coefficient does not Granger cause ASVI	6.363	0.174
ASVI does not Granger cause herding coefficient	17.695***	0.001
BRA		
Herding coefficient does not Granger cause ASVI	1.233	0.873
ASVI does not Granger cause herding coefficient	1.002	0.909
CAN		
Herding coefficient does not Granger cause ASVI	0.936	0.919
ASVI does not Granger cause herding coefficient	1.808	0.771
CHN		
Herding coefficient does not Granger cause ASVI	4.461	0.347
ASVI does not Granger cause herding coefficient	1.251	0.870
FRA		
Herding coefficient does not Granger cause ASVI	0.078	0.962
ASVI does not Granger cause herding coefficient	0.481	0.786
GER		
Herding coefficient does not Granger cause ASVI	3.157	0.532
ASVI does not Granger cause herding coefficient	6.679	0.154
IND		
Herding coefficient does not Granger cause ASVI	0.184	0.912
ASVI does not Granger cause herding coefficient	0.509	0.775
IRE		
Herding coefficient does not Granger cause ASVI	18.604***	0.001
ASVI does not Granger cause herding coefficient	5.494	0.240

Table 4.7 Panel B (continued)

Null hypothesis	Chi-square	p-value
ITA		
Herding coefficient does not Granger cause ASVI	4.308	0.230
ASVI does not Granger cause herding coefficient	1.963	0.580
JAP		
Herding coefficient does not Granger cause ASVI	3.272	0.513
ASVI does not Granger cause herding coefficient	3.969	0.410
POR		
Herding coefficient does not Granger cause ASVI	2.498	0.287
ASVI does not Granger cause herding coefficient	2.634	0.268
RUS		
Herding coefficient does not Granger cause ASVI	30.236***	0.001
ASVI does not Granger cause herding coefficient	4.789	0.310
SAF		
Herding coefficient does not Granger cause ASVI	0.284	0.991
ASVI does not Granger cause herding coefficient	0.309	0.989
SPA		
Herding coefficient does not Granger cause ASVI	16.923***	0.002
ASVI does not Granger cause herding coefficient	11.476**	0.022
THA		
Herding coefficient does not Granger cause ASVI	5.506	0.239
ASVI does not Granger cause herding coefficient	4.696	0.320
UK		
Herding coefficient does not Granger cause ASVI	1.170	0.883
ASVI does not Granger cause herding coefficient	0.551	0.968
USA		
Herding coefficient does not Granger cause ASVI	6.048	0.196
ASVI does not Granger cause herding coefficient	4.258	0.372

The results from bivariate vector autoregressive analysis for the alternative techniques are shown in Table 4.8. Although the influence of lagged Google SVI on current herding coefficient are insignificant in most countries, Panel A of Table 4.8 suggests that the lagged change in unadjusted search value has a significantly positive influence on current herding coefficient in USA. In contrast, Australia, Germany, Spain, and UK confirm rather negative effect. In conclusion, the results mostly imply that herd behavior is stronger after the period of high investor attention which contradicts the main hypothesis. Alternatively, past-period change in herding coefficient positively influence the current Google search volume in Australia and Italy. The negative effect is detected in Portugal, Russia, and Spain. Therefore, the findings confirm the main conclusion that investor attention is increasing with herd behavior. Panel B of Table 4.8 represents the VAR estimations from the alternative herding coefficient measured from 10-minute industrial indices. Previous-period investor attention significantly lowers herd behavior in Australia and Germany, while it increases traders engaging in imitating behavior in Ireland and Spain. All of these countries are developed market, except Ireland and Spain who are PIIGS nations. Thus, the results are quite inconclusive. In terms of the impact of past coefficient of non-linear term on current abnormal search statistic, herding encourages investor attention in Ireland, Italy, Russia, Spain, and Thailand, while Australia and USA suggest the opposite. As a result, the main inference is confirmed. In relation to the 15-minute industrial indices' outcome, the increase in previous-day abnormal investor attention minimized present herd behavior in Australia, China, and Spain. Still, the reverse indication is found in Thailand. Therefore, the main hypothesis is mostly confirmed by the 15-minute industrial indices' conclusion. In view of the effect of past herding coefficient on current abnormal search index, even investor attention is higher after the occurrence of herd behavior in Canada, China, Ireland, Russia, and Spain, the opposite is also identified in Australia and Thailand. Hence, the main methodology is mostly confirmed. However, this dataset has smaller number of observations which affects the validity of inferences.

Table 4.8 VAR estimations (Robustness).

Panel A: VAR estimations (Google search volume index).

Note: This table shows the VAR estimations of the relationship between the Google search volume index ($GSVI_t$) and daily coefficient of non-linear term ($CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m,t} + \gamma_3 |R_{m,t}| + \gamma_4 (R_{m,t})^2 + \varepsilon_t$, where $CSAD_t$ is a cross-sectional absolute deviation of returns at time t, $R_{m,t}$ is an equally weighted portfolio return at time t, and $CSAD_{t-1}$ is a one-day lag of cross-sectional absolute deviation of returns at time t. Five minute industrial indices are used to measure the variables.) for 17 sample countries. The optimal lag lengths for each country are computed by using the minimum consenting AIC. Standard errors are shown in parentheses. *, **, and *** denote the 10%, 5%, and 1% significance levels, respectively.

Variable	AUS		BRA		CAN		CHN	
	$GSVI_t$	$\gamma_{4,t}$	$GSVI_t$	$\gamma_{4,t}$	$GSVI_t$	$\gamma_{4,t}$	$GSVI_t$	$\gamma_{4,t}$
$GSVI_{t-1}$	-0.687***	-0.020*	-0.731***	0.003	-0.718***	0.035	-0.715***	-0.001
	(0.03)	(0.01)	(0.06)	(0.01)	(0.04)	(0.03)	(0.04)	(0.01)
$GSVI_{t-2}$	-0.476***	-0.028**	-0.296***	-0.002	-0.453***	0.018	-0.594***	-0.001
	(0.03)	(0.01)	(0.07)	(0.01)	(0.05)	(0.04)	(0.05)	(0.01)
$GSVI_{t-3}$	-0.328***	-0.056***	-0.134**	0.003	-0.345***	-0.024	-0.321***	-0.001
	(0.03)	(0.01)	(0.06)	(0.01)	(0.05)	(0.04)	(0.05)	(0.01)
$GSVI_{t-4}$	-0.222***	-0.075***			-0.104***	-0.003	-0.078**	0.001
	(0.02)	(0.01)			(0.04)	(0.03)	(0.04)	(0.01)
$\gamma_{4,t-1}$	0.421***	-0.782***	-0.436	-0.875***	0.062	-0.781***	0.048	-0.838***
	(0.08)	(0.03)	(0.53)	(0.05)	(0.05)	(0.04)	(0.98)	(0.04)
$\gamma_{4,t-2}$	0.276***	-0.503***	-1.108	-0.534***	-0.007	-0.564***	0.335	-0.706***
	(0.10)	(0.04)	(0.70)	(0.06)	(0.06)	(0.05)	(1.20)	(0.04)
$\gamma_{4,t-3}$	0.211**	-0.277***	-0.517	-0.272***	-0.023	-0.438***	0.486	-0.361***
	(0.09)	(0.03)	(0.58)	(0.05)	(0.06)	(0.05)	(1.24)	(0.04)
$\gamma_{4,t-4}$	0.075	-0.060***			0.004	-0.187***	0.265	-0.228***
	(0.05)	(0.02)			(0.05)	(0.04)	(0.95)	(0.03)

Table 4.8 Panel A (continued)

Variable	FRA		GER		IND		IRE	
	$GSVI_t$	$\gamma_{4,t}$	$GSVI_t$	$\gamma_{4,t}$	$GSVI_t$	$\gamma_{4,t}$	$GSVI_t$	$\gamma_{4,t}$
$GSVI_{t-1}$	-0.703***	0.008	-0.607***	-0.046**	-0.548***	-0.008	-0.743***	-0.011
	(0.05)	(0.03)	(0.04)	(0.02)	(0.04)	(0.01)	(0.07)	(0.01)
$GSVI_{t-2}$	-0.309***	0.032	-0.418***	-0.018	-0.232***	-0.007	-0.453***	-0.009
	(0.05)	(0.03)	(0.04)	(0.02)	(0.04)	(0.01)	(0.08)	(0.01)
$GSVI_{t-3}$			-0.230***	-0.011	-0.091**	-0.002	-0.297***	-0.007
			(0.04)	(0.02)	(0.04)	(0.01)	(0.08)	(0.01)
$GSVI_{t-4}$			-0.086**	0.016			-0.098	-0.006
			(0.04)	(0.02)			(0.06)	(0.01)
$\gamma_{4,t-1}$	-0.014	-0.660***	-0.025	-0.818***	-0.010	-0.782***	0.099	-0.726***
	(0.07)	(0.05)	(0.07)	(0.04)	(0.19)	(0.04)	(0.56)	(0.06)
$\gamma_{4,t-2}$	0.068	-0.272***	0.055	-0.566***	-0.027	-0.490***	0.224	-0.563***
	(0.07)	(0.05)	(0.08)	(0.05)	(0.21)	(0.04)	(0.70)	(0.08)
$\gamma_{4,t-3}$			-0.063	-0.373***	0.127	-0.239***	-0.014	-0.306***
			(0.08)	(0.05)	(0.19)	(0.04)	(0.70)	(0.08)
$\gamma_{4,t-4}$			-0.042	-0.215***			-0.010	-0.196***
			(0.07)	(0.04)			(0.62)	(0.07)

Variable	ITA		JAP		POR		RUS	
	$GSVI_t$	$\gamma_{4,t}$	$GSVI_t$	$\gamma_{4,t}$	$GSVI_t$	$\gamma_{4,t}$	$GSVI_t$	$\gamma_{4,t}$
$GSVI_{t-1}$	-0.765***	-0.001	-0.778***	-0.007	-0.598***	0.011	-0.724***	-0.014
	(0.05)	(0.01)	(0.04)	(0.01)	(0.05)	(0.01)	(0.15)	(0.01)
$GSVI_{t-2}$	-0.490***	0.001	-0.555***	-0.001	-0.320***	0.003	-0.288*	-0.014
	(0.06)	(0.01)	(0.05)	(0.01)	(0.05)	(0.01)	(0.16)	(0.01)
$GSVI_{t-3}$	-0.301***	-0.001	-0.251***	0.008			-0.248	-0.003
	(0.05)	(0.01)	(0.05)	(0.01)			(0.17)	(0.01)
$GSVI_{t-4}$			-0.135***	-0.003			-0.236	-0.011
			(0.04)	(0.01)			(0.16)	(0.01)
$\gamma_{4,t-1}$	2.295*	-0.545***	0.001	-0.766***	-0.297*	-0.696***	0.439	-1.005***
	(1.20)	(0.05)	(0.13)	(0.04)	(0.17)	(0.05)	(0.38)	(0.03)
$\gamma_{4,t-2}$	1.164	-0.472***	-0.018	-0.524***	0.052	-0.374***	-4.850**	-0.830***
	(1.24)	(0.05)	(0.15)	(0.05)	(0.18)	(0.05)	(2.19)	(0.16)
$\gamma_{4,t-3}$	-0.181	-0.221***	0.200	-0.407***			-7.161***	-0.505***
	(1.01)	(0.04)	(0.15)	(0.05)			(1.95)	(0.14)
$\gamma_{4,t-4}$			0.082	-0.244***			-4.393**	-0.140
			(0.13)	(0.04)			(2.14)	(0.16)

Table 4.8 Panel A (continued)

Variable	SAF		SPA		THA		UK	
	$GSVI_t$	$\gamma_{4,t}$	$GSVI_t$	$\gamma_{4,t}$	$GSVI_t$	$\gamma_{4,t}$	$GSVI_t$	$\gamma_{4,t}$
$GSVI_{t-1}$	-0.738***	-0.004	-0.579***	0.014	-0.793***	0.022	-0.568***	-0.036
	(0.05)	(0.01)	(0.04)	(0.02)	(0.05)	(0.02)	(0.04)	(0.03)
$GSVI_{t-2}$	-0.604***	-0.004	-0.342***	-0.033	-0.622***	0.024	-0.376***	-0.085**
	(0.06)	(0.01)	(0.05)	(0.03)	(0.06)	(0.02)	(0.04)	(0.04)
$GSVI_{t-3}$	-0.409***	0.010	-0.169***	0.021	-0.423***	0.002	-0.224***	-0.058
	(0.06)	(0.01)	(0.05)	(0.03)	(0.06)	(0.02)	(0.04)	(0.04)
$GSVI_{t-4}$	-0.245***	0.002	-0.125***	-0.086***	-0.266***	0.004	-0.146***	0.001
	(0.05)	(0.01)	(0.04)	(0.03)	(0.05)	(0.02)	(0.04)	(0.03)
$\gamma_{4,t-1}$	0.001	-0.760***	-0.041	-0.661***	0.138	-0.759***	0.014	-0.727***
	(0.20)	(0.04)	(0.06)	(0.04)	(0.12)	(0.04)	(0.05)	(0.04)
$\gamma_{4,t-2}$	-0.373	-0.534***	-0.008	-0.497***	0.081	-0.520***	0.032	-0.674***
	(0.24)	(0.05)	(0.06)	(0.04)	(0.15)	(0.05)	(0.06)	(0.05)
$\gamma_{4,t-3}$	-0.170	-0.333***	-0.065	-0.312***	-0.236	-0.298***	0.034	-0.415***
	(0.24)	(0.05)	(0.06)	(0.04)	(0.15)	(0.05)	(0.06)	(0.05)
$\gamma_{4,t-4}$	-0.053	-0.105**	-0.098**	-0.167***	-0.002	-0.189***	-0.037	-0.144***
	(0.19)	(0.04)	(0.05)	(0.03)	(0.12)	(0.04)	(0.05)	(0.05)

Variable	USA	
	$GSVI_t$	$\gamma_{4,t}$
$GSVI_{t-1}$	-0.681***	0.018*
	(0.04)	(0.01)
$GSVI_{t-2}$	-0.480***	0.027**
	(0.04)	(0.01)
$GSVI_{t-3}$	-0.233***	0.019
	(0.04)	(0.01)
$GSVI_{t-4}$	-0.051	0.013
	(0.03)	(0.01)
$\gamma_{4,t-1}$	0.072	-0.771***
	(0.10)	(0.03)
$\gamma_{4,t-2}$	0.125	-0.581***
	(0.12)	(0.04)
$\gamma_{4,t-3}$	0.028	-0.372***
	(0.12)	(0.04)
$\gamma_{4,t-4}$	0.040	-0.182***
	(0.09)	(0.03)

Panel B: VAR estimations (Abnormal Google search volume index with 10-minute industrial index data).

Note: This table shows the VAR estimations of the relationship between the abnormal Google search volume index ($ASVI_t$) and daily coefficient of non-linear term ($CSAD_t = \propto + \gamma_1 CSAD_{t-1} + \gamma_2 R_{m,t} + \gamma_3 |R_{m,t}| + \gamma_4 (R_{m,t})^2 + \varepsilon_t$, where $CSAD_t$ is a cross-sectional absolute deviation of returns at time t, $R_{m,t}$ is an equally weighted portfolio return at time t, and $CSAD_{t-1}$ is a one-period lag of cross-sectional absolute deviation of returns at time t. 10-minute industrial indices are used to measure the variables.) for 17 sample countries. The optimal lag lengths for each country are computed by using the minimum consenting AIC. Standard errors are shown in parentheses. *, **, and *** denote the 10%, 5%, and 1% significance levels, respectively.

Variable	AUS		BRA		CAN		CHN	
	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$
$ASVI_{t-1}$	-0.790***	-1.980	-0.730***	0.101	-0.650***	1.210	-0.731***	0.013
	(0.03)	(1.37)	(0.12)	(0.13)	(0.04)	(1.11)	(0.04)	(0.06)
$ASVI_{t-2}$	-0.542***	-1.390	-0.481***	0.157	-0.391***	0.480	-0.577***	0.068
	(0.03)	(1.68)	(0.16)	(0.17)	(0.05)	(1.27)	(0.05)	(0.07)
$ASVI_{t-3}$	-0.330***	-2.122	-0.530***	0.131	-0.296***	-0.315	-0.363***	0.064
	(0.03)	(1.63)	(0.18)	(0.19)	(0.05)	(1.26)	(0.05)	(0.07)
$ASVI_{t-4}$	-0.198***	-4.336***	-0.286*	0.051	-0.082**	0.402	-0.138***	0.027
	(0.02)	(1.13)	(0.16)	(0.18)	(0.04)	(1.08)	(0.04)	(0.06)
$\gamma_{4,t-1}$	0.001**	-0.784***	-0.018	-0.893***	0.001	-0.872***	0.021	-0.501***
	(0.01)	(0.03)	(0.06)	(0.07)	(0.01)	(0.04)	(0.02)	(0.04)
$\gamma_{4,t-2}$	0.001	-0.532***	-0.019	-0.466***	0.001	-0.611***	0.013	-0.477***
	(0.01)	(0.03)	(0.12)	(0.13)	(0.01)	(0.05)	(0.02)	(0.04)
$\gamma_{4,t-3}$	0.001	-0.288***	0.048	-0.303***	0.001	-0.440***	-0.001	-0.293***
	(0.01)	(0.03)	(0.08)	(0.09)	(0.01)	(0.05)	(0.02)	(0.04)
$\gamma_{4,t-4}$	0.001	-0.042***	-0.012	-0.188**	-0.001	-0.184***	-0.024	-0.186***
	(0.01)	(0.02)	(0.08)	(0.08)	(0.01)	(0.04)	(0.02)	(0.03)

Table 4.8 Panel B (continued)

Variable	FRA		GER		IND		IRE	
	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$
$ASVI_{t-1}$	-0.628***	0.344	-0.705***	-1.003**	-0.481***	-0.348	-0.767***	0.532**
	(0.05)	(0.61)	(0.04)	(0.47)	(0.03)	(0.50)	(0.06)	(0.24)
$ASVI_{t-2}$	-0.288***	0.365	-0.450***	-0.361	-0.134***	-0.062	-0.570***	0.400
	(0.05)	(0.60)	(0.05)	(0.57)	(0.03)	(0.46)	(0.07)	(0.29)
$ASVI_{t-3}$			-0.254***	-0.758			-0.359***	0.420
			(0.05)	(0.57)			(0.07)	(0.28)
$ASVI_{t-4}$			-0.105***	-0.478			-0.217***	0.249
			(0.04)	(0.49)			(0.06)	(0.24)
$\gamma_{4,t-1}$	-0.001	-0.845***	0.001	-0.809***	-0.001	-0.685***	-0.0122	-0.627***
	(0.01)	(0.05)	(0.01)	(0.04)	(0.01)	(0.03)	(0.02)	(0.06)
$\gamma_{4,t-2}$	0.001	-0.297***	0.002	-0.553***	-0.001	-0.343***	-0.018	-0.438***
	(0.01)	(0.05)	(0.01)	(0.05)	(0.01)	(0.03)	(0.02)	(0.07)
$\gamma_{4,t-3}$			-0.002	-0.365***			-0.039**	-0.294***
			(0.01)	(0.05)			(0.02)	(0.07)
$\gamma_{4,t-4}$			0.001	-0.198***			-0.067***	-0.214***
			(0.01)	(0.04)			(0.02)	(0.06)

Variable	ITA		JAP		POR		RUS	
	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$
$ASVI_{t-1}$	-0.613***	-0.049	-0.710***	0.607	-0.535***	0.656	-1.058***	-0.648
	(0.06)	(0.10)	(0.04)	(0.43)	(0.05)	(0.40)	(0.19)	(0.96)
$ASVI_{t-2}$	-0.406***	-0.158	-0.485***	0.0289	-0.295***	0.263	-0.505*	0.759
	(0.06)	(0.11)	(0.05)	(0.51)	(0.05)	(0.41)	(0.27)	(1.35)
$ASVI_{t-3}$	-0.111**	-0.073	-0.298***	-0.079			-0.197	2.181
	(0.06)	(0.10)	(0.05)	(0.52)			(0.28)	(1.39)
$ASVI_{t-4}$			-0.179***	-0.418			0.100	1.216
			(0.04)	(0.43)			(0.37)	(1.82)
$\gamma_{4,t-1}$	-0.021	-0.704***	-0.003	-0.793***	-0.006	-0.590***	-0.078**	-0.939***
	(0.03)	(0.05)	(0.01)	(0.04)	(0.01)	(0.05)	(0.04)	(0.18)
$\gamma_{4,t-2}$	-0.032	-0.626***	0.001	-0.621***	0.001	-0.350***	-0.249***	-1.046***
	(0.03)	(0.05)	(0.01)	(0.05)	(0.01)	(0.04)	(0.05)	(0.24)
$\gamma_{4,t-3}$	-0.043**	-0.259***	0.002	-0.437***			-0.223***	-0.759**
	(0.02)	(0.04)	(0.01)	(0.05)			(0.07)	(0.32)
$\gamma_{4,t-4}$			-0.002	-0.239***			-0.146**	-0.540
			(0.01)	(0.04)			(0.07)	(0.36)

Table 4.8 Panel B (continued)

Variable	SAF		SPA		THA		UK	
	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$	$ASVI_t$	$\gamma_{4,t}$
$ASVI_{t-1}$	-0.708***	0.0340	-0.662***	0.584	-0.867***	0.938	-0.621***	0.156
	(0.05)	(0.55)	(0.04)	(0.48)	(0.04)	(1.23)	(0.04)	(0.57)
$ASVI_{t-2}$	-0.548***	0.085	-0.377***	1.047*	-0.765***	0.784	-0.400***	-0.150
	(0.06)	(0.65)	(0.05)	(0.57)	(0.06)	(1.57)	(0.05)	(0.64)
$ASVI_{t-3}$	-0.347***	0.197	-0.267***	1.099*	-0.464***	-0.643	-0.272***	-0.365
	(0.06)	(0.65)	(0.05)	(0.57)	(0.05)	(1.52)	(0.05)	(0.64)
$ASVI_{t-4}$	-0.207***	0.298	-0.165***	-0.553	-0.290***	-1.806	-0.165***	-0.167
	(0.05)	(0.55)	(0.04)	(0.48)	(0.05)	(1.35)	(0.04)	(0.56)
$\gamma_{4,t-1}$	0.002	-0.753***	-0.007**	-0.780***	-0.001	-0.844***	0.001	-0.836***
	(0.01)	(0.05)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)
$\gamma_{4,t-2}$	0.002	-0.465***	-0.001	-0.573***	-0.002	-0.599***	0.001	-0.602***
	(0.01)	(0.06)	(0.01)	(0.04)	(0.01)	(0.05)	(0.01)	(0.05)
$\gamma_{4,t-3}$	0.002	-0.396***	-0.005	-0.375***	-0.003	-0.336***	0.003	-0.439***
	(0.01)	(0.06)	(0.01)	(0.04)	(0.01)	(0.05)	(0.01)	(0.05)
$\gamma_{4,t-4}$	0.001	-0.239***	-0.008***	-0.187***	-0.003**	-0.147***	-0.001	-0.190***
	(0.01)	(0.05)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)

Variable	USA	
	$ASVI_t$	$\gamma_{4,t}$
$ASVI_{t-1}$	-0.560***	0.303
	(0.06)	(0.45)
$ASVI_{t-2}$	-0.366***	0.421
	(0.07)	(0.51)
$ASVI_{t-3}$	-0.180***	0.005
	(0.07)	(0.51)
$ASVI_{t-4}$	-0.114**	0.657
	(0.06)	(0.43)
$\gamma_{4,t-1}$	0.010**	-0.815***
	(0.01)	(0.04)
$\gamma_{4,t-2}$	0.004	-0.691***
	(0.01)	(0.04)
$\gamma_{4,t-3}$	0.007	-0.471***
	(0.01)	(0.05)
$\gamma_{4,t-4}$	0.005	-0.297***
	(0.01)	(0.04)

4.6 Conclusion

Kahneman (1973) proposes that investors are overwhelmed by information while attention is a scarce cognitive resource. Therefore, they must allocate their attention selectively. Almost all studies suggest that investor attention enhances market efficiency (Hirshleifer & Teoh, 2003; Vozlyublennaia, 2014; and Tantaopas et al. 2016). Also, investor attention strengthens both trading information and decision-making processes (Mondria et al., 2010; Libby et al., 2002; and Hirshleifer et al., 2011). Consequently, according to previous literatures, limited attention is not only paid on typical information, but also on information useful for investment decision making. Thus, the nonuniform trading behavior is expected to be enhanced by investor attention. This chapter examines the interaction between investor attention and aggregate herd behavior by improving Peltomäki & Vahamaa (2015). In order to capture the time-varying properties, five-minute industrial indices are used for evaluating daily herd behavior. Additionally, this study utilizes daily Google search volume index as it is the best proxy of investor attention as specified by previous literatures. New keyword selection method is also developed in order to obtain more accurate results. However, the findings are mixed. Herd behavior is also increasing with previous-period abnormal investor attention suggesting the spurious herding and psychological stimulus. On the other hand, investor attention is mostly promoted after the presence of herd behavior as the imitation of traders intensifies return volatility which will attract individuals' attention eventually.

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