# Investor Herd Behavior in the Chinese Stock Market

A study of A/B/H-shares

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## ACKNOWLEDGEMENTS

Dear reader, this master thesis is the final task I needed to fulfill in order to be able to graduate and get my Master of Science degree. It has been the most challenging one. In the beginning I struggled finding a way to organize my thesis. I was in constant doubt whether the decisions I made would turn out to be wise ones. My skepticism and search for confirmation made me spending too much time reading articles. It was not only once that I got lost in the abundance of financial literature. After three months – I meanwhile had made some progress – I decided to do a finance internship at L'Oréal. An opportunity I gladly took. During my internship my thesis doubts started to rise again and afflicted my mood, which made me decide to postpone writing my thesis till after.
In July I concluded to start from scratch again. I now realize I could have made no better decision. My progress increased, my confidence enhanced, and my doubts declined.

Along this bumpy road there were people to support me, and I would like to express my sincere gratitude to you. First of all, I would like to thank my coach Jan Lemmen for your clear and valuable feedback. Your input really helped me to complete my thesis. Furthermore, I would like to thank my parents in particular, my brother, and my close friends. With your help I felt and still feel comfortable after taking some necessary and tough decisions along the way. After all I feel proud and relieved that I have made it to the finish line. It has been one of my biggest challenges in life and I am glad I managed to overcome!

Nick de Jong

## ABSTRACT

This thesis examines the existence and prevalence of herd behavior among investors in the Chinese A-share, B-share, and H-share stock markets. Using a modified testing method, based on the Christie and Huang (1995) and the Chang, Cheng, and Khorana (2000) herding models, I found evidence of market-wide herding toward the market consensus within the Shanghai and Shenzhen B-share market, and the Hong Kong H-share market; markets where foreign and institutional investors play a great role. However, the evidence of herd behavior depends on the chosen time interval. Moreover, in these markets, herding is particularly strong under rising market conditions. No evidence of herding toward the market consensus is found in the A-share market. The findings of the B-share and H-share markets support the behavioral finance framework, whereas the findings of the A-share markets support the traditional finance framework.



**JEL Classification:** G14, G15

**Keywords:** Herding, China, A-share, B-share, H-share, Cross-Sectional Standard Deviation, market return

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# CHAPTER 1 Introduction

Since the 1980s a new research strand in finance has been dominating the field. It has challenged the assumptions of the rational asset pricing framework that investors act rationally and financial markets are efficient. This new research strand, Behavioral Finance, involves the analytical modeling and empirical investigation of several behavioral dimensions regarding investment decision-making. Perhaps the most well-known example in this respect is the one related to phenomena of massive investor psychology, often mentioned with the term "crowd behavior" (Kindleberger C. P., 1978; Galbraith, 1994; Mathiopoulos, 2000; Soros, 2005). Behavioral Finance has been generating a distinct concept to facilitate and systemize the research on investor crowd behavior. As a result, the term "herding" was introduced. In rough terms, herding refers to the alignment of one's behavior to the behavior of others (Bikhchandani, Hirshleifer, & Welch, 1992; Soros, 2005; Gębka & Wohar, 2013).

When a significant number of investors practice herding, they could inflict a certain pressure over prices, that ultimately could lead to the development of trends. These trends have the potential for mispricing (Hirshleifer, 2001) and excess volatility (Koutmos & Saidi, 2001). If herding prevails in a market, then prices have the potential to evolve in large price swings. The above imply that herding has the potential to push prices away from fundamentals (Brunnermeier & Abreu, 2003). Herd behavior is recognized as a source of mispricing and speculative bubbles (Bikhchandani & Sharma, 2001). Historical examples of bubbles are the Dutch Tulip Mania (1634-1637), the 'Roaring 20's (that preceded the 1929 crash), and the Dot-Com bubble (late 1990s).

Another bubble, that quite recently dominated the headlines for weeks, is the Chinese stock market bubble of 2014-2015. In less than a year, the Shanghai Stock Exchange increased with 135%, and the Shenzhen Stock Exchange increased with even 150%. Stocks had become increasingly popular among Chinese retail investors, because they promised much higher rates of return than the low-interest bank savings accounts. Retail investors all dived into the stock market, along with the Chinese Communist Party amplifying the bubble as an opportunity to sell equity stakes in state enterprises having a dangerously high debt ratio. The Communist Party also aims at cleaning up some very untidy balance sheets (Schell, 2016). As a result, the bubble ended up in a severe crash in June 2015.

Since herding is able to cause abrupt price movements, possibly of destabilizing proportions, the concept is of direct interest to regulators and policymakers. It is also of particular interest to the investment community as the presence of herding in the markets could increase risk levels, and could drive prices away from fundamentals (Barberis & Thaler, 2002).

### *1.1 Problem discussion*

The traditional finance framework argues that, following the Efficient Market Hypothesis, prices fully reflect all information at any point in time and investors make choices that are normatively acceptable. Investors are assumed to be of 'rational' nature (Fama, 1970 & 1991). What behavioral finance essentially proposes is that investors have to be viewed as not fully rational. Investors are subject to limitations and biases in both their perception and judgment (Hirshleifer. 2001). People may not completely process all relevant information that they should do in order to make rational decisions. And even if they do, they may reach different decisions as they could perceive information differently, and process it differently.

Evidently, following the behavioral finance strand, markets might not only contain smart money traders, who buy stocks that are undervalued, and sell stocks that are overvalued from their fundamental value, but also noise traders, who base their trading activity on noise rather than market information (De Long, Shleifer, Summers, & Waldmann, 1990). Investors are not only fundamentalists who base their trading activity on macroeconomic and other indicators that have impact on income flows of securities, but are also traders who could buy stocks based on historical data (Hirsheleifer, 2001). Some traders are better informed than others (Grossman & Stiglitz, 1980). Some of these traders do not to react logically to new information. Studies in the field of behavioral finance refer to psychological biases underlying the behavioral explanations of the observed security price. In such a heterogeneous setting, where psychology and less-than-rational investor behavior prevails, herding could underlie the explanation of observed price behavior (Kahneman & Tversky, 1974, 1979; Hirshleifer, 2001; Barberis & Thaler, 2002).

As herding potentially could destabilize asset prices and push prices away from fundamentals and, therefore, is of particular interest to the investment community, policymakers and regulators, the impact of herding on asset prices has become an empirical issue. Since the early 1990s the financial literature has collected lots of research on herding in stock markets. Regarding herd behavior, the empirical evidence is inconclusive for herding toward the market consensus, and for herding in both developed and emerging markets. Some (Lakonishok, Sleifer & Vishny, 1992; Grinblatt & Sheridan, 1989; Gleason, Marthur & Peterson, 2004) have found evidence in favor of herding, while other studies are reporting opposing evidence (Choi & Sias, 2009; Walter & Weber, 2006). Also the question whether herding destabilizes prices remains unanswered (Vasileios, 2006).

### *1.2 Problem statement*

In relation to the Chinese stock market, there have only been few studies regarding the formation of herds among market participants. Tan, Chiang, Mason, and Nelling (2008) and Yao, Ma, and He (2014) find evidence of herd behavior in the Chinese stock market, whereas Demirer and Kutan (2006) and Fu (2010) do not. The recent turmoil in the Chinese stock markets give reasons to believe that noise traders could have destabilized prices and pushed prices away from fundamentals. As such, herd behavior could underlie the explanation of the observed price behavior. The results of empirical herding studies in the Chinese stock markets are inconclusive. Besides, no study has regarded the investigation of herd behavior in the Chinese stock market during the recent turbulent couple of years. To fill this gap in the literature, herd behavior in the Chinese stock market will be examined for the period 2011-2015; a period that has not been examined yet, and includes the years of the stock market turmoil in the Chinese stock market. On the basis of the following research question this thesis investigates whether investors in the Chinese stock markets herd toward the market consensus:

**Research question:** Does herd behavior exist among investors in the Chinese stock market on a total market level?

China forms an interesting sample for research on investors' herd behavior. Unlike in developed stock markets, individual investors are major market participants in Chinese stock markets. These individuals are often speculators. Their investing behavior is one of the major forces that cause large price swings in the markets. Understanding investors' trading behavior in Chinese markets would interestingly help us, and is of major importance for comprehending the Chinese stock markets characteristics (Green, 2003).

Evidence of herd behavior among investors in Chinese stock markets would have implications to asset pricing behavior and market information efficiency. As the Chinese stock market is known for its unique market and demographic features, being a relatively immature market, growing at a stupefying speed, it is an interesting setting for the analysis of herd behavior. Previous studies have found that investors tend to speculate in the stock market when investors have to deal with little investment alternatives and heavy government involvement. This could generate significant volatility (Green, 2003). In such a market, which is hardly transparent, which is dominated by marginally educated retail investors, which contains high government involvement, and is undergoing enormous amounts of reform, comprehending asset pricing behavior and the investment decisions of investors is considered to be relevant and important.

Moreover, multiple types of shares are traded in the Chinese stock market. These shares are generally divided in three categories: A-shares, B-shares, and H-shares. Herd behavior could differ among these distinct share classes. A-shares are shares traded by Chinese companies that trade on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SSZ), and are traded by mainland Chinese investors. These share are denominated in local Chinese currency, the Renminbi (RMB). B-shares are also traded by Chinese companies listed on both exchanges, but denominated in a foreign currency. Shanghai B-shares are traded in US dollars; Shenzhen B-shares are traded in Hong Kong dollars. B-shares are open for both domestic and foreign investment, although they are difficult to access for most Chinese investors, due to currency exchange reasons. Investors outside China are permitted to trade in the B-share market. The A-share markets are dominated by domestic retail investors, while foreign institutional investors play a greater role in the B-share markets. H-shares are also shares issued by Chinese companies, but are listed on the Hong Kong Stock Exchange they are denominated in Hong Kong dollars, and are dominated by institutional investors.

The Shenzhen Stock Exchange is the home of the country's small, new innovative companies. Technology, consumer and healthcare stocks make up almost half the Shenzhen Composite Index, while state-backed banks and industrial mid-large companies dominate the Shanghai Composite Index. In contrast to these China mainland markets, the Hong Kong market is a developed market, which is dominated by institutional investors and is predominantly service-oriented.

### *1.3 Main findings*

The main finding of the thesis is that herd behavior is present in the Chinese stock market, but it depends on the timeframe and the particular market. The test results reveal significant evidence of herd behavior in the B-share market, but not during the whole sample period. Herd behavior is only present in the B-share market when the stock price is rather volatile. The results provide even stronger evidence for herd behavior in the H-share market, during (almost) the whole sample period. These results indicate that investors in the B and H-share markets tend to suppress their own beliefs and investment decisions in favor of the market consensus, and are in line with the behavioral finance framework. In contrast, the results do not provide evidence for herd behavior in the A-share market, during the whole sample period. Returns seem to rather deviate from the market consensus. Gębka and Wohar (2013) argue that this could indicate localized herd behavior, where investors move away from the market consensus. This finding more or less supports the hypothesis of the rational asset pricing models that predict that periods of market stress lead to increased levels of dispersion, whereas herd behavior among investors leads to decreased levels of dispersion.

### *1.4 Thesis outline*

The remainder of the thesis is structured as follows. Chapter 2 provides a review of the most important literature regarding herd behavior. This chapter comprises the theoretical foundation of the thesis and includes the development of the four testable hypotheses, that are considered to be the fundamentals of the empirical study. In the third part the dataset investigated is described and it contains an analysis of the data used. Chapter 4 presents the methodology used to detect herding. Chapter 5 covers the empirical findings of the thesis. These are related to the previous findings in literature. Chapter 6, the final part, contains the conclusion and the discussion of the thesis. Answers will be given on the research question and its related hypotheses.

# CHAPTER 2 Literature review

In the past ten years China has grown to one of the largest economies in the world. Since 2010, it is the largest economy after the US. Its stock market got an impulse after the establishment of the Shanghai Stock Exchange and the Shenzhen Stock Exchange; established on November 26, 1990, and December 1, 1990, respectively. Not only have both stock exchanges been growing in market capitalization, but also in number of listed firms, securities, and number of market participants. Both markets are still relatively immature compared to most European and American stock markets, which are more developed. They still differ from the developed markets with respect to issues related to market segmentation, government regulations, and investor structure (Sutthisit, Wu, & Yu, 2012).

After twenty-six years, the Chinese government and regulators have not been able to control and stabilize that stock market; something they seem to have desperately wanted. The Chinese stock market has been the target of unrelenting intervention by the Chinese government for several years, which seems to make and change rules without regard for their consequences. The purpose of the government's interventions is to try to save and stabilize the market, while at the same time huge risks are taken, that could bring negative results. Several market manipulation techniques have been introduced by the Chinese policymakers in the past years, and all to no avail (Green, 2003).

As this turmoil in Chinese markets has not seem to come to an end, and the government interventions provisionally fail to control and stabilize the stock market, this would suggest that the Chinese stock market is not as efficient as the Chinese regulators would like it to be.

This chapter answers the questions what the characteristics of the Chinese stock markets are; why herd behavior is to be investigated in the Chinese stock market; what theories underlie investor trading behavior, and herd behavior in particular; and this chapter provides an overview of the (most important) empirical findings regarding herd behavior in stock markets in and outside China.

### *2.1 Institutional background*

The three largest and most important stock exchanges in China are the Shanghai Stock Exchange (SSE), the Shenzhen Stock Exchange (SSZ), and the Hong Kong Stock Exchange (HKE). When talking about mainland China, only the SSE and the SSZ are referred to. The Shanghai Stock Exchange and the Shenzhen Stock Exchange are still developing (emerging) markets, whereas the Hong Kong Stock Exchange is a rather mature market. Hong Kong, a former colony of the British Empire, was handed over to China in 1997. Hong Kong is a special administrative region that exists as part of the People's Republic of China. Though, Hong Kong enjoys greater political and social autonomy than mainland China. It has separate administrative and legal systems and a separate currency. Hong Kong has its own stock exchange, the Hong Kong Stock Exchange. More than half of foreign investment into mainland China is done through companies listed in Hong Kong.

The Shanghai and Shenzhen exchanges are both established in 1990 and are self-regulated legal entities under the supervision of the China Securities Regulatory Commission (CSRC). Both markets have shown a rapid expansion ever since their establishment, and both markets trade two classes of shares, A-shares and B-shares. The Hong Kong stock exchange finds its origins in 1891 when China's first formal securities market, the Association of Stockbrokers in Hong Kong, was founded. After a merger with a second market in 1947, the today's Hong Kong Stock Exchange emerged. The shares that are traded on the Hong Kong exchange are H-shares.
The three stock markets differ in their market capitalization. On August 31st, 2015, the market capitalization of the SSE was $4.1 billion, whereas the market capitalization of the SSZ and the HKE were $2.7 billion and $1.8 billion, respectively. The HKE is growing at a less staggering speed than the mainland China stock exchanges, presumably because the Honk Kong market is more mature.

A-shares and B-shares differ in their investor characteristics. A-shares can be purchased and traded by domestic Chinese investors only and are RMB-denominated. B-shares were restricted to foreign investors before February 2001, and have ever since been tradable by both domestic and foreign investors. Nowadays, B-shares are mostly traded by foreign investors. B-shares are US dollar denominated on the SSE and Hong Kong dollar denominated on the SSZ. H-shares are Hong Kong dollar denominated on the HKE. H-shares are shares of companies incorporated in the Chinese mainland that are listed on the HKE or other foreign exchanges. The different characteristics of the A-share, B-share, and H-share investors may result in differences in the level of herding in the respective markets.

There are multiple differences among these stock markets. The A-share markets are dominated by domestic retail investors, while foreign, institutional traders play a greater role in the B-share and H-share markets. Investors in A-share markets are less sophisticated and lack experience in investments. In contrast, the B-share and H-share markets are dominated by foreign and institutional investors who are generally more sophisticated and have more investment know-how. Retail investors tend to perform technical analysis (past price performance), whereas institutional investors tend to perform fundamental analysis (e.g. earnings per share performance) when investing in the stock market. Besides, foreign investors that have access to the B-share market and the H-share market reportedly have better access to financial statements and timely updates on the world economy.

### *2.2 Herding in the Chinese stock market*

The stock market inefficiency, together with the Chinese stock market characteristics, its investor structure, and the ongoing stock market interventions and manipulations of the government are attributes that have great impact on investors' trading behavior and asset pricing. Under certain circumstances investors' trading behavior could be one of the major forces that drive stock price movement in the markets. Particularly when unsophisticated investors dominate the market and collectively invest in certain assets. This so-called crowd-behavior could drive prices away from fundamentals, could destabilize the market, and could even be responsible for bubble like patterns (Galbraith, 1994; Soros, 2005; Kindleberger & Aliber, 2005). The Chinese stock market seems to have the right circumstances that could feed crowd-like behavior and for investor behavior to be a major force that drive large stock market movements.

#### 2.2.1 Market efficiency

China wants to develop a consumption-oriented economy and improve the capital structure of state controlled listed companies. As residents are encouraged to transfer more bank savings to the stock market, the rise of stock prices will increase the wealth of investors. This will help China to upgrade its economic structure and develop a consumption-oriented economy. In addition, the rise in stock prices will lower the cost of capital and improve the capital structure of firms, which will increase debt capacity of firms and reduce the financial risk of the economy. However, if the stock market is not efficient but speculative, it may have adverse implications for these objectives (Green, 2003).

The question is whether China has the right conditions that make it a market-efficient economy. Efficient and stable markets have a good balance in the structure of their buy and sell decisions. This is not the case in China. The Chinese stock market happens to be a very volatile one, since investment decisions lean toward a particular type of decision. Efficient markets could be explained as the result of a good balance of three types of investment strategies, which are fundamental investment, relative value investment, and speculation. Each of these investment strategies contribute to well-functioning market that is able to keep the cost of capital low, manage risk, and allocate capital efficiently (Pettis, 2013).

China does not have a good balance of these investment strategies. Since China lacks credible data, low transaction costs, and the legal ability to short securities, there is no arbitrage trading in the market. There are relatively little value investors in China. Why? Because China lacks, proper and transparent financial statements, decent macro data, and a vivid corporate governance framework, among others. The next subsections in this chapter will treat China's characteristics in more detail. As a result, China has large amounts of speculators playing around in the market, causing extremely volatile markets. Though, one should remark that the trading volume in China is higher than in the US stock markets (e.g. S&P 500), meaning that stock market volatility could be more likely to occur in the Chinese markets.

One of the reasons brought about by experts for the high ratio of speculators is that China is lacking investors with long-term investment horizons, such as financial institutions, pension funds, and insurance companies; investors that focus on cash flows in the far future. They also argue that China lacks sophisticated investors with decent investing and risk management skills, that are useful, and maybe even necessary, for making long-term decisions (Pettis, 2013).

However, China has already a great deal of these large long-term oriented investors. Besides, since its middle-class has been growing, it has a growing investor base in its tens of millions of individual savers. Moreover, there are lots of Chinese students and employees who have trained at big and important universities and financial institutions in developed markets. One may assume that these people understand the do's and don'ts of investmenting.

So why are these financial professionals together with the financial institutions in the country not able to generate a well-balanced market with a decent mix of investment strategies?

The answer lies in what kind of information can be gathered in the Chinese markets and how the discount rates used by investors to value this information are determined. Information can be split into fundamental information and technical information. Fundamental information is useful for long-term decisions, whereas technical information is particularly useful for short-term decisions. The Chinese stock market contains much of the latter and relatively little of the former. Note that individual investors might (still) look for inside information, leading them base their investment decisions on this so-called technical information. In China the vast majority of investors remain unsophisticated retail investors, with little skills and confidence in the quality of data; ingredients that are needed to make fundamental value decisions (Pettis, 2013).

### 2.2.2 Investor structure

China's investor structure is different compared to developed-country equity markets. Compared to developed markets, not institutional investors, but retail investors dominate China's stock markets. They account for around 80% of daily trading volume. Even for emerging markets, this is a high level (Song, 2016).

Following a recent report of FIS group, more than 90 percent of capital accounts are owned by retail investors. Besides, they account for around 80% of daily trading volume. Even for emerging markets, these are high levels. Both could possibly explain the manic price swings in the Chinese stock market, recently (Chemi & Fahey, 2016).

### 2.2.3 Unsophisticated investors

Another stock market feature is the relatively low experience and education among retail investors. About 65% of Chinese investors have not finished high school. Even Chinese farmers are deciding to stop watching their fields in order to employ stock investments. "Even if a stock is irrationally overvalued, it still might be worth purchasing if there is another 'fool' out there willing to pay a higher price" (Swanson, 2015).

Some people would argue that China's stock market is a market that has more in common with a casino than a market that would function as a source for economic growth, due to the unsophisticated nature of the large group of Chinese retail investors. It is their investing behavior that could have huge impact on the stock price.

### 2.2.4 Lack of investment alternatives

China has faced problems concerning its domestic investment opportunities. The middle class has grown larger, meaning that lots of people have money to save. As their wealth increased and saving accounts offered low rates, more and more people liked to invest their money in securities that provide higher returns. For years, the alternative investment choice was the housing market. After all, there was plenty of demand for housing. The construction industry was smiling for years. But as more investors invested in property, the market became saturated.

Demand for real estate declined and prices dropped. As a result, returns were dropping, and many investors moved their money out of property. Their new investment playground appeared to be the stock market (Yan, 2015).

The result is huge capital inflows in the stock market. Investors cannot diversify their investments. Demand dominates supply and prices could disproportionally increase. As an overload of investors invest in the stock market, this could push prices from their fundamental value, and consequently destabilize the market, as described before.

### 2.2.5 Government regulation

Another important feature is the Chinese stock market being highly regulated by the Chinese government. This has been broadly given attention in the news. The government aims at controlling and stabilizing the stock market. Several market manipulation techniques have been introduced by the Chinese policymakers in the past years, and all to no avail (Rutkovsky, 2015).

China's stock market reached an insane peak in June 2015, followed by a severe crash, as the stock price bubble suddenly burst. In response, the Chinese government tried to hold in the freefall by implementing a couple of manipulation techniques. On August 4, 2015, the policymakers decided to crack down on short selling. Other examples are injecting funds into the market via brokerages, altering margin lending rules, and permitting trading suspensions on some stocks. The China Securities Regulatory Commission (CSRC) is the government regulator that controls the stock market. In practice, they endeavor to regulate the stock market in such a way that the stock market is growing at a stupefying speed, at all time. Next to setting up normal regulations, such as accounting standards, listing requirements and information disclosure, they attempt to regulate the stock market through IPO quotas and applying price limits. Besides, the banking sector got highly involved by lending large amount of money to the stock market, which jeopardized the financial sector (Sutthisit, Wu & Yu, 2012).

The government's dominant involvement in the stock market, including its frequent interventions, caused the market to be very volatile. Every time the government announced to manipulate the market by altering rules, the stock markets responded with a large jump or dive (Sutthisit, Wu & Yu, 2012).

### 2.2.6 Conclusion

Investor trading behavior is one of the major forces that drive stock price movement in the markets. Particularly when unsophisticated investors dominate the market. The increased wealth of the Chinese middle class, a lack of financial information (financial statements), a lack of investment alternatives, unsophisticated retail investors dominating the market, and government interventions limiting the lending rules, all together suggest that Chinese investors collectively and speculatively invest in the stock market. Herd behavior may typify this crowd-like behavior; a trading pattern behavioral finance literature has examined, developed and facilitated extensively over the past two decades.

To understand the concepts/origins of herding, the next chapter will be used to describe the underlying theories and summarize the former empirical results.

## *2.3 Finance theories*

Herding theories have their origin in the behavioral finance framework. Therefore, this section will briefly elaborate on the two earlier mentioned main strands of financial literature, in order to see and understand where herding theories have their origin.

As cautiously mentioned in the introduction, in financial literature there are broadly two frameworks that describe and explain financial markets, Traditional Finance framework and Behavioral Finance framework.

### 2.3.1 Traditional Finance theory

The traditional finance framework, which has dominated the field for decades, tries to understand financial markets using models in which agents are 'rational'. The interpretation of rationality is twofold. Firstly, when agents receive information, they update their beliefs correctly. And secondly, based on those correctly updated beliefs, they make choices that are normatively acceptable (Fama, 1970).

This traditional finance framework is rather simple; apparently too simple to be generally confirmed in the data. Much empirical research has pointed out that functioning of the stock market and the trading behavior of investors are not as easily understood in this framework as one would possibly hope for.

In the traditional finance framework asset prices equal their fundamental value, under the condition that agents are rational. The framework has developed the Efficient Market Hypothesis (EMH), that has been tested in plenty of studies. It that states markets are efficient and prices reflect their fundamental value. Following the EMH, an efficient market implies that investors cannot earn excess risk-adjusted average returns (Fama, 1991).

### 2.3.2 Behavioral Finance theory

Behavioral Finance is a relatively new framework that has emerged as the result of the difficulties the Traditional Finance framework has faced. Behavioral finance argues that agents are not rational, but at least are less-than-fully rational. Asset prices could deviate from their fundamentals as a result of the interplay of less-than-fully rational traders in the market (Barberis & Thaler, 2002).

Opponents of this view argue that rational agents will undo any disruptions in the asset price, which is brought about by the presence of irrational investors (Friedman, 1953). Friedman, among others, argues that after a mispricing, which is the result of a deviation from an asset's fundamental value, an attractive opportunity to quickly make money is created. He states that rational investors will immediately grab this opportunity, which is called an arbitrage opportunity. As a result, the mispricing is corrected. Friedman's reason has not survived theoretical scrutiny, because arbitrage opportunities are not always attractive to investors. Since these opportunities can be risky and costly, the mispricing could remain untouched. Fundamental risk, noise trader risk, and implementation costs are generally called reasons for arbitrage opportunities to be not attractive (Barberis & Thaler, 2002).

To better explain asset price behavior, Behavioral Finance has introduced extra-finance concepts, such as biology and psychology, in order to provide new insights into the behavior of asset prices. The use of these extra-finance concepts provides the financial world new approaches to be able to possibly better explain asset price behavior. This extra dimension in financial research, combined with improving databases have offered researchers new possibilities. They now are able to better identify specific patterns of trading behavior that previously existed only in analytical models, but now could also be tested for empirically.

This research aims at studying one such type of trading behavior, namely market-wide herding; herding towards the market consensus. Herding is founded upon investors' interactive imitation. This behavioral pattern has been investigated rather extensively in the finance literature and this will be outlined in the next section.

### *2.4 The concept of herding*

A substantial effort has been devoted to investigate the issue of the herd behavior in financial markets and its measurements. The literature of herd behavior is evolved in different directions, and studies differ in their explanation of what might trigger herd behavior. Theoretically, researchers mostly focus their attention upon origins and causes of herding behavior among financial markets' investors, because it is difficult to specify a definition for herd behavior. Herding behavior in financial markets is broadly understood as the irrational tendency among investors to follow other investors' actions and abandon fundamental information, predictions and beliefs, resulting in investors flocking together. The fear of regret on missing out on a good investment is often a driving force behind herd instincts (Gębka & Wohar, 2013).

#### 2.4.1 Herding theory

The increasing number of studies on herd behavior have given us more insights in the motivations behind herd behavior. Interestingly, before elaborating on the motivations investors have to practice herding, the concept of herding will be briefly treated by contrasting two forms of herding: spurious herding and intentional herding (Devenow & Welch, 1996).

Spurious herding is an efficient outcome of groups that take similar decisions as a result of groups obtaining similar information. Spurious herding is considered to be fundamental-driven, as this type of herding is not the result of investors blindly following each other's decisions, but it is merely a reaction to commonly known public information Bikhchandi and Sharma (2001). This type of herding leads to efficient decision-making. On the other hand, intentional herding is the result of investors having an obvious intend to copy the behavior of their fellow investors. This type of herding does not necessarily lead to efficient investment decisions (Bikhchandani & Sharma, 2001). The next section will elaborate on the underlying motivations of herd behavior.

#### 2.4.2 Motivations behind herding

The underlying herd motivations could be broadly divided in two categories, rational and irrational motivations of herding (Chang et al., 2000).

Following Devonow and Welch (1991), irrational herding implies that investors blindly follow other investors without regard for their own gathered information. Psychological reasons underlie the motivation to practice herd behavior. Investors could blindly follow other investors as a result of feeling safe by following the crowd. Christie and Huang (1995), CH hereafter, add that investors particularly practice herd behavior in times of market stress. They argue that investors' confidence to make good investment decisions decreases during times of market stress, causing them to follow the market consensus. Lux (1995) propose psychology-related motivations as a possible explanation of herd behavior. He argues that unsophisticated investors do not have enough access to fundamental information, implying that investors decide to follow the decisions of more-sophisticated investors.

Bikhchandani and Sharma (2001), on the other hand, argue that investors intentionally follow the decisions of other investors. Investors do this when investment decisions are congruent, but when there is uncertainty about the quality of information. Each investor makes his own assessment of the publicly available information and draws conclusions about the assessments made by other investors, to see whether he decides to follow the actions of others.

#### *2.4.2.1 What do these theories predict in the context of this research?*

The Traditional Finance framework proposes that investors are rational, have access to all information, interpret them normatively, and investors are sophisticated; meaning that financial markets are efficient. Since everyone has the same access to that information, all securities are appropriately priced at any given time. If markets are efficient, it means that prices always reflect all information.

As subsection 2.1 points out, China has been characterized for the past decade by a lack of financial information (financial statements), a lack of investment alternatives, unsophisticated retail investors dominating the market, and government interventions trying to stabilize the highly volatile market. These characteristics contradict the way the traditional finance theory explains the functioning of the markets. The situation in China seems to be more in favor of the behavioral finance strand of the financial literature that argues that trading behavior of less than fully rational investors or noise traders are the major force that drive stock price movements in the market.

As in China non-sophisticated traders do not have access to (all) information about market fundamentals, Lux (1995) and Devonow and Welch (1996) argue that investors in China (could) act based on what they observe in the market. As China is also characterized by a lack of investment alternatives, faces similar investment decisions, and is known for the uncertainty about the quality of public information, Bikhchandani and Sharma (2001) refer to the intentional action of individuals to follow other investors.

As this subsection explains, both rational and irrational motivations could underlie this crowd-like behavior in the Chinese equity markets. Previous studies, generally experimental studies, have identified several explanations of rational and irrational herding by investors. Although theoretical models of herd behavior have not been tested directly, the empirical literature has examined the presence of herding in a particular market, or among particular group of investors.

### 2.3.4 Importance of understanding investors' herding behavior

Investigating herd behavior in financial markets could be of serious importance. Chang, Cheng and Khorana (2000), CKK hereafter, state that herd behavior could have a major influence on asset prices. Herding could lead to asset price bubbles that eventually crash, causing the asset price to make a freefall. This could be the result of noise traders, being part of a herding group. Their behavior could induce large price swings and volatility. Herding could be viewed as a reason for markets to be not efficient, contradicting the rational asset pricing theory (Lao & Singh, 2011). Inefficient markets, as is described in section 2.2.1 could lead to extremely volatile markets.

Experimental studies on herd behavior have shown us to be able to contribute to the understanding of the decision-making process of investors in the market, whether investors' decisions are made from a rational or an irrational angle. As far as I know, experimental and empirical studies on herd behavior are hardly combined. Although combining might not be an easy thing, future research attempting to combine both research methods could deliver new information and possible more extended insights with respect to herd behavior in financial markets.

Evidence of herd behavior in the Chinese stock markets could provide researchers a tool to investigate the underlying reasons or motivations of herd behavior in the market. This could possibly lead to studies that could combine empirical evidence and theoretical evidence of herd behavior in the Chinese market for instance.

### 2.4.4 Herding models

Generally, researchers have either focused their study on the empirical investigation of the presence of herd behavior in the market, or they have focused on the testing of several herding theories by executing experimental studies. The empirical studies do not examine or test a particular model or theory of herd behavior; exceptions are Wermers (1999) and Graham (1999). The approach generally used is a purely statistical one, to see security prices follow the market consensus, irrespective of the motivation for such behavior. Thus, there is lack of a direct link between the theoretical discussion of herd behavior and the empirical specifications used to test for herding. In experimental studies, researchers try to examine the underlying reasons for herd behavior and test particular models by executing experiments on a limited/small group of individuals. So only a limited part of the studies in the herding literature has focused on developing statistical models that are able to empirically test the presence of herd behavior in the market. Carefully, one should distinct empirical studies from experimental studies.

#### *2.4.4.1 Experimental studies*

Various studies use informational cascades in order to model herd behavior. "An informational cascade occurs when it is optimal for an individual, having observed the actions of those ahead of her, to follow the behavior of the preceding individual without regard to her own information. Convergence of behavior can be idiosyncratic and fragile." (Bikhchandani, Hirshleifer & Welch, 1992). At a certain point, agents do not follow their own assessed information, but decide that it is optimal to follow the decisions of others.

Welch (1992) examines the likelihood of cascades and optimal pricing in the market for initial public stock offerings. Most importantly, this paper has provided a dynamic rational explanation for herd behavior that is often mentioned but rarely explained by financial practitioners and academics. Banerjee (1990) (independently) models herd behavior as cascades. They developed a model that is not affected by the incentive problems inherent in principal-agent relationships. Scharfstein & Stein (1990) proposed a model in which managers ignore their own private information and herd on the investment decisions of others. Trueman (1994) demonstrated that individual analysts may herd toward earnings forecasts issued by other analysts. Devenow & Welch (1996) reviewed papers on the economics of rational herding in financial markets.

### *2.4.4.2 Empirical studies*

Next to these experimental studies, several studies empirically examine the presence of herding in financial markets. A number of models are developed to detect herd behavior in both developed and emerging stock markets. In recent literature, CH were the first to develop a model that tests the presence of herd behavior in the market. Their objective was to test for the presence of herd behavior when herds are most likely to form. They state that herd behavior is most likely to occur during periods of market stress, because during these times investors are more likely to ignore their own beliefs or information assessment in favor of the market consensus. CKK responded to the CH model by using the cross-sectional absolute deviation of returns (CSAD) as the measure of return dispersion, and propose a non-linear regression specification for the detection of herd behavior. The CSAD of returns is derived from the Capital Asset Pricing Model (CAPM). Moreover, CKK uses the entire distribution of market return to detect herding, whereas CH only captures herding during periods of extreme market returns.

Hwang and Salmon (2004) develop a new approach to measuring herding based on observing deviations from the equilibrium beliefs expressed in CAPM prices. By conditioning on the observed movements in fundamentals, they are able to separate adjustment to fundamentals news from herding due to market sentiment and hence extract the latent herding component in observed asset returns. Their approach is similar to Christie and Huang's (1995) to the extent that they utilize the information held in the cross-sectional movements of the market. However, they focus on the cross-sectional variability of factor sensitivities rather than returns. Both the CKK and the Hwang and Salmon models rely on the estimation of the CAPM/beta. The CAPM formula is the following equation.

$$E_t(r_{it}) = \beta_{imt}E_t(r_{mt}) \qquad \text{(Eq. 1)}$$

Where $r_{it}$ and $r_{mt}$ are the excess returns on asset *i* and the market at time *t.* respectively, $\beta_{imt}$ the systematic risk measure, and $E_t(\cdot)$ is conditional expectation at time *t.*

$E_t$ and $\beta_{imt}$ are variables based on fundamental information. Emerging markets generally lack financial information and transparency. Therefore, since this study focuses on the Chinese stock markets, the estimation and/or specification of these variables may be questionable. Besides, for the same reason, the mentioned advantage of the ability to separate adjustments to fundamentals news from herding is questionable in an emerging stock market China (still) is. Multiple studies in the recent herding literature have used the CH/CKK model, or extensions of these models, to study the presence of herd behavior in various stock markets around the world, both developed and emerging markets (Demirer & Kutan, 2005; Tan et al., 2007; Chiang et al., 2009; Chiang et al., 2013; etc.).

In this study a generalized form of the CKK model will be used to examine herd behavior within the Chinese stock markets. The model will be a combination of the CH and the CKK model. This combination attempts to eliminate the most important limitations of both models. Chapter 4 will explain in more detail what model is used in this study to examine the presence of herding behavior.

### 2.4.5 Empirical evidence

Many aspects of the Chinese stock markets have been empirically examined from different angles. These studies provide evidence of several types of information transmission patterns. Some studied cases are asset pricing in segmented Chinese markets (Poon & Granger, 2003; Sun & Tong, 2000; Fernald & Rogers, 1998) the return and volatility link (Fleisher & Su, 1998), market efficiency, the price–volume relation (Long et al., 1999) and the significance of global information in Chinese markets (Bailey, 1994; Hu et al., 1997; Huang et al., 2001). Chen et al. (2003) provide a review of the literature. Nevertheless, these studies do not provide evidence of herd formations in the market.

Regarding the Chinese stock market, only a couple of studies considered and investigated herd behavior among investors. Demirer and Kutan (2006) where the first to study herd behavior in the Chinese stock market. They hypothesize that due to the distinctive characteristics of the Chinese financial markets, such as the weak legal framework, heavy government involvement, and strong state ownership, investors are more likely to speculate in the stock market and follow the market consensus. They examine the daily returns of 375 Chinese stocks listed on the Shanghai and Shenzhen exchanges over the period January 1999 to December 2002, and find that herd formation is not present in the Chinese market. They also observe that equity return dispersions under conditions of declining markets are much lower than dispersions under conditions of rising markets.

Tan, Chiang, Mason, and Nelling (2008) analyze the returns on Chinese A- and B-shares within the two exchanges separately to investigate whether herding behavior exists and whether they exhibit asymmetric effects under different market conditions. Using daily, weekly and monthly data on 44 dual-listed firms on the Shanghai Stock Exchange and 43 firms on the Shenzhen Stock Exchange, Tan et al. (2008) report significant evidence of herding in both A- and B-share markets on the two exchanges, under both rising and falling market conditions. Consistent with the idea that herding is a short-lived phenomenon (Christie & Huang, 1995), they find the herding coefficient to be less significant for weekly and monthly data. They also find that herding among A-share investors in the Shanghai market is more pronounced under conditions of rising markets, high trading volume and high volatility.

Yao, Ma, and He (2014) report significant evidence of herding behavior in the Chinese stock market, in particular in the B-share market. Herding would be more pronounced under conditions of declining markets. Fu and Lin (2010) do not find herding behavior, but demonstrate the existence of asymmetric reaction that investors' tendency toward herding is significantly higher under conditions of declining markets. The study partly supports the turnover effect that low turnover stocks significantly converge to market return than high turnover stocks during extreme market conditions.

The findings of Demirer and Kutan (2006) and Fu (2010) are in favor of the rational asset pricing framework, whereas the findings of Tan, Chiang, Mason, and Nelling (2008) and Yao, Ma, and He (2014) support the behavioral finance framework.

### *2.5 Hypotheses*

As described before, Behavioral Finance argues that agents are not rational, but are less-than-fully rational. Asset prices could deviate from their fundamentals as a result of the interplay of less-than-fully rational traders in the market. In financial literature herding is often used to examine trading behavior of less-than-fully rational investors in stock markets, since crowd-like behavior among these investors could be a major force that drives stock price movement in the market, drives prices away from fundamentals, and could destabilize the market. Due to the in section 2.2.1 described inefficiency of the Chinese stock market, its stock market characteristics and the high government involvement, I expect that herding exist in the Chinese stock market and influences the stock price. This would confirm the behavioral finance framework and contradict the rational asset pricing framework. This leads to the following hypothesis:

**H1**: Herding behavior significantly exists in the Chinese stock market

The Chinese stock market provides an interesting setting for the analysis of investor herd behavior. Since the establishment of the Shanghai Stock Exchange and the Shenzhen Stock Exchange in December 1990, two classes of shares have been issued. The differences between both types of shares are described in section 2.1. The different characteristics of A-share and B-share investors may result in differences in the level of herding in each market.

Another reason why the Chinese stock market provides an interesting setting for the analysis of herd behavior is that China's stock markets are not (roughly) divided in two but three types of shares. Next to the A-shares and B-shares, the stock market is known for its H-shares. H-shares are permitted to be traded by domestic and foreign investors alike and are traded on the Hong Kong stock exchange. Overseas institutional investors, and local institutional investors on a second place, dominate the market. Compared to Shanghai and Shenzhen, Hong Kong is a developed and international market which has attracted investors from all around the world (Zhou et al., 2009)

A couple of studies have examined the difference in herd behavior between the A and the B share markets. Tan et al. (2008) and Chen, Rui & Xu (2003) find evidence for herd behavior in both A and B-share markets. Yao et al. (2014) finds particularly strong evidence for herd behavior in the B-share market.

The majority of previous studies have found no evidence of herding in the developed markets (Christie & Huang 1995; Chang et al., 2000; Henker, Henker & Mitsios, 2006; Wang, 2008) thus the natural expectation may be that investor behavior in the B-share markets should be similar to that in the developed markets. However, as Tan et al. (2008) point out in their study, investors are likely to trade differently in domestic and foreign markets, especially when the foreign market still has the characteristics of an emerging market. This is supported by the evidence from the Korean market (Choe et al., 1999 and Kim and Wei, 1999). Moreover, there is a significant amount of past empirical evidence which suggests that investors in the A-share markets are more informed that those in the B-share markets, and that A-shares adjust to information faster than B-shares (Chakravarty et al., 1998; Chian et al., 2008; Yao, 2014). Therefore, I expect that herding behavior more strongly exists in the B-share market.

**H2:** Herding behavior is more pronounced in the B-share markets than in the A-share market.

As mentioned before, Hong Kong is a more developed market compared to the Shanghai and Shenzhen markets. Generally, the HKE is part of the developed equity markets, whereas the SSE and the SSZ belong to the emerging markets. Herd behavior could differ between both. Multiple studies have examined the differences in herd behavior between developed and developing countries. Examining herding is interesting in an international context since differences in factors such as the relative importance of institutional versus individual investors, the quality and level of information disclosure, the level of sophistication of derivatives markets, etc., can affect investor behavior in these markets.

In their study of international herding behavior, Chang et al. (2000) find significant evidence of herding in South Korea and Taiwan and partial evidence of herding in Japan. However, there is no evidence of herding on the part of market participants in the US and Hong Kong. Chiang et al. (2009) examines herd behavior in 18 countries worldwide. They divided these countries in three groups, advanced stock markets (Hong Kong), Latin-American markets, and Asian markets (China). This study finds significant evidence to support the existence of herding in each national market, except the US and Latin America. Herd behavior in China and Hong Kong exist. This result stands in contrast to the earlier literature that shows no herding in advanced markets (Chang et al. 2000) and in Chinese markets (Demirer & Kutan, 2006).

There are opposing results regarding herd behavior in developed stock markets. However, for a vast number of developed stock markets, these studies do not find evidence of herd behavior. This feeds the tension that herd behavior seems to be less pronounced in developed stock markets. Therefore, I expect herd behavior in the Hong Kong market to be less pronounced compared to the Shanghai and Shenzhen markets.

**H3:** Herd behavior is less pronounced in the Hong Kong market than in both Shanghai and Shenzhen markets.

Many studies have investigated whether the herding behavior documented above varies with market conditions. In this study, I examine potential asymmetries in herding behavior as the different states of the market could influence stock returns. CH note that herding may be more pronounced during market stress.

A vast amount of studies has proven the existence of herding in developed markets as well as emerging markets (see e.g. Lakonishok et al., 1992; Sentana & Wadhwani, 1992; Bohl & Siklos, 2008; Chiang et al., 2010). Among all these evidences, the most influential literature is Sentana and Wadhwani (1992), SW hereafter.

SW is the first to consider the asymmetry of trading behavior in their data. They find that there are more positive feedback-trading behaviors after market declines than those after market rises. This asymmetry in the SW model is explained as the results of margin trading and portfolio insurance. Market declines increase the margin demand of traders and they have to sell more to meet the margin call. For portfolio insurance, traders sell shares to stop losses when market declines, and this may lead to further selling and larger price declines. In the subsequent studies, researchers rarely emphasize the asymmetry of positive feedback trading in their papers (Koutmos, 2014). Since positive feedback trading is a special case of herding (Nofsinger & Sias, 1999) this theory could also apply to the case of herding.

However, Wan, Liu and Yang (2015) propose that the asymmetry of positive feedback trading and herding in Chinese market might be different. The structure of market participants of China is quite different from that of developed markets, and this may lead to a quite different trading pattern.

Comparing with the developed markets, the Chinese market has a quite larger amount of active trading retail investors. So the number of retail investors is quite large and their power is strong enough to impact the market. Due to the capital requirement for the margin trading and short selling bans, which the government has started to implement since the August 4, 2015, these two instruments are unavailable for most of the retail traders. Thus, the margin trading and portfolio insurance strategies (which usually need to short stocks) are generally not used by retail investors, and therefore the amount of these trading is limited in Chinese market. So the explanations for asymmetric positive feedback trading in SW (1992) might not be so valid in Chinese market. On the contrary, the possible herding behavior and price rising trend chasing of retail investors may increase the trading amount when prices rise and at the same time lead to a relatively low trading volume when prices declines. Interestingly, studies that examine herd behavior in the Chinese stock markets vary in their findings. Yao, Ma, and He (2014) and Fu (2010) demonstrate that herding is more pronounced under conditions of declining markets, whereas Tan et al. (2008) find evidence for herd behavior being more pronounced under conditions of rising markets only in the A share market. They all use the CH and the CKK model.

Following the theory of SW, I expect that herd behavior is more pronounced under conditions of rising markets than after declining markets in the Chinese stock market.

**H4**: For all three shares, herd behavior is more pronounced under conditions of rising markets than under declining markets in the Chinese stock markets.

## Chapter 3 Data

The dataset used in this study is obtained from Datastream EUR. The dataset comprises of firm-specific data over the period January 1, 2011 to December 31, 2015. The data include stock prices for firms listed on the Shanghai (SH), Shenzhen (SZ) and Hong Kong (HK) composite index. The SH and the SZ indices both comprises of all A-shares and B-shares. Therefore, a distinction has been made between A-shares, B-shares, and H-shares. A-shares are quoted in Chinese Renminbi, B-shares in US dollars (Shanghai market) or Hong Kong dollars (Shenzhen market), and H-shares in Hong Kong dollars. Since this research focuses on different shares that are denoted in different currencies, all data are acquired in US dollars. Log returns are used to measure the stock performance. The log returns are calculated for the A-shares, B-shares and H-shares:

$$R_t = 100 \times (Log(P_t) - Log(P_{t-1})) \qquad \text{(Eq. 2)}$$

where $R_t$ is the stock market retun at time *t*, $P_t$ is the stock price at time *t*, $P_{t-1}$ is the stock price at time *t-1.*

Since the constituents lists of indices constantly change, chances are that some constituents that are on the list at the time of writing were not on the list at the beginning of the sample period. I have made the decision to only include the companies (constituents) that were on the list at January 1, 2011 and are still on the list on July 1, 2016. This leaves the Shanghai A-share market with 871 of the 1100 constituents (79%), the Shenzhen A-share market with 1147 of the 1746 constituents (66%), and the Hong Kong market with 388 of the 501 constituents currently on the list (77%). Both B-share markets do not lose any constituent. Since they do not lose constituents, one could think of a survival bias affecting the results of the study. The in chapter 2.4.5 mentioned studies that have examined herding behavior in the Chinese markets ignore this potential bias, and so will this study.

Some daily observations are removed due to missing or lacking data. The final dataset comprises of 1227 daily observations for the SHA market, 1214 for the SHB market, 1230 for the SZA market, 1254 for the SZB market, and 1295 for the HK market.

### *3.1 Descriptive statistics*

Table 1 contains summary statistics for cross-sectional standard deviations (CSSD) and equally weighted market portfolio returns ($R_{m,t}$), for five Chinese markets (SHA, SHB, SZA, SZB, HK) over the sample period 01-01-2011 – 31-12-2015. The statistics are based on daily observations.

Appendices 1-5 list the descriptive statistics of the CSSD and the $R_{m,t}$ for each year. As a result, the time dimension of data will be visible. The most important note is that the mean and the standard deviation are much higher in 2015 compared to the first four years of the sample (Appendix 5). Obviously, this is the result of an extremely volatile market in 2015 including the stock market bubble and the following crash.

**Table 1**

Descriptive statistics of cross sectional standard deviation (CSSD) and average market return ($R_{m,t}$)

Period: 1/1/2011 - 31/12/2015

| Market | No. obs. | Variable | Mean | Std. dev. | Skewness | Kurtosis | Jarque-Bera | ADF |
|---|---|---|---|---|---|---|---|---|
| SHA | 1227 | $R_{m,t}$ | 0.016 | 0.785 | -0.899 | 7.146 | (1043.997)*** | (-29.936)*** |
| | | CSSD | 0966 | 0.305 | 1.836 | 10.842 | (3833.626)*** | (-5.029)*** |
| SHB | 1214 | $R_{m,t}$ | 0.022 | 0.762 | -0.899 | 10.330 | (2881.629)*** | (-24.961)*** |
| | | CSSD | 0.710 | 0.270 | 2.489 | 15.944 | (9728.541)*** | (-8.026)*** |
| SZA | 1230 | $R_{m,t}$ | 0.021 | 0.790 | -0.863 | 5.906 | (585.206)*** | (-29.883)*** |
| | | CSSD | 1.019 | 0.354 | 2.628 | 19.912 | (16074.400)*** | (-4.849)*** |
| SZB | 1254 | $R_{m,t}$ | 0.015 | 0.652 | -0.770 | 9.587 | (2390.740)*** | (-24.426)*** |
| | | CSSD | 0.779 | 0.289 | 0.921 | 6.591 | (851.048)*** | (-8.505)*** |
| HK | 1295 | $R_{m,t}$ | 0.002 | 0.576 | -0.072 | 14.099 | (6648.044)*** | (-31.072)*** |
| | | CSSD | 1.121 | 0.401 | 0.679 | 12.468 | (4936.777)*** | (-14.524)*** |

Table 1 lists descriptive statistics of daily mean, standard deviation, skewness and kurtosis of the CSSD and the $R_{m,t}$ over the total sample period for the Shanghai A (SHA), Shanghai B (SHB), Shenzhen A (SZA), Shenzhen B (SZB), and the Hong Kong (HK) markets. In addition, the Jarque-Bera test for normality and the Augmented Dicky-Fuller test for stationary are reported. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels respectively.

The statistics show that the mean of the equally-weighted market returns ($R_{m,t}$) range from 0.015% in the SZB market to 0.022% in the SHB market. Only the HK market shows a negative average mean, which is -0.002. The A-shares have the highest standard deviation. The standard deviation of the Hong Kong market is with 0.576 relatively low. The first order serial correlation coefficients range from 0.145 in the HK market to 0.188 in the SZB market (Appendix 7). The serial correlation is still significant after 20 lags, for all markets. The Augmented Dickey-Fuller tests are significant across all four markets. This means that the null hypothesis of a unit root can be rejected; $R_{m,t}$ is stationary.

Table 1 also reports the cross sectional standard deviation (CSSD) statistics. As described before, all individual stock returns move in perfect line with the market when the CSSD equals zero. The means for the A-shares turn out to be higher than those of the B-shares. HK shows the highest mean (1.12%), and the SHB market has the lowest mean (0.71%). Also the standard deviation for the A-shares is higher than for the B-shares. Again, HK shows the highest standard deviation (0.401).

Skewness is a term that describes asymmetry from the normal distribution in a set of statistical data. When the data are normally distributed, the skewness coefficient is 0 (Arnold & Groeneveld, 1992). The skewness of the $R_{m,t}$ is negative for all markets, meaning that the data points are skewed to the left. This means that large negative returns occur more frequently than large positive returns. The skewness coefficient of the HK market clearly has a smaller negative magnitude than the Shanghai and Shenzhen markets, indicating that larger negative returns occur less frequently in HK market. The CSSD has a positive skewness for all markets, meaning that the data points are skewed to the right.

Kurtosis measures the 'fatness' of the tails of the distribution. The more the kurtosis coefficient deviates from the 'normal level', the more likely extreme future returns will occur. Positive kurtosis means that the distribution has fatter tails than a normal distribution. When data are normally distributed, the coefficient of the kurtosis is around 3 (Fiori & Zenga, 2009). The kurtosis for all markets is significantly larger than 3, meaning excess kurtosis. Excess kurtosis, implying fat tails, indicates that extreme returns occur more frequently.

The Jarque-Bera test is a goodness-of-fit test testing whether sample data have the skewness and kurtosis matching a normal distribution (Jarque & Bera, 1987). The null hypothesis is a joint hypothesis of the skewness and the kurtosis being zero. As explained, samples from a normal distribution have an expected skewness of 0 and an expected kurtosis of 3. Any deviation increases the Jarque-Bera statistic. The critical value of the Jarque-Bera test statistics depends on the number of observations. The higher the number of observations, the higher the critical value. The null hypothesis of a normal distribution is rejected, since the Jarque-Bera statistics for all four markets are significant at the 1% level, for both CSSD and $R_{m,t}$.

Appendix 6 provides QQ-plots of the CSSD and the $R_{m,t}$. These plots display a quantile-quantile plot of the quantiles of the sample data versus the theoretical quantile values from a normal distribution. Interestingly, the data points of both variables, and $R_{m,t}$ in particular, lay more or less on or close to the red linear line. These plots give reasons to believe that, although the data show negative skewness and excess kurtosis, the data show some signs of a normal distribution.

Also for the CSSD series the ADF tests are significant for all four markets at the 1% level. The serial correlation coefficients show a high level of autocorrelation in the CSSD data. The first order coefficients are all above 55%, and after lag 20 the coefficients are still significant. This suggests the use of a lagged variable in the regression equation, in order to improve the power of the model.

For both CSSD and $R_{m,t}$ the White test, a testing method for heteroscedasticity, shows significant results (Appendix 8), indicating that the null hypothesis of homoscedasticity is rejected. Significant results for both serial correlation and heteroscedasticity support the idea of using heteroscedasticity and autocorrelation consistent (HAC) standard errors to compute the regression coefficients (Newey & West, 1987).

# Chapter 4 Methodology

This chapter gives a thorough explanation of the reasoning behind the decision to choose for the CH (1995) and the CKK (2000) models that form the basis of the model used in this thesis to test herd behavior in the Chinese stock market. All variables will be outlined and the formulas used to run the regressions will be highlighted.

### *4.1 Tests for herding*

To test for herding, multivariable regressions will be conducted in order to measure the relationship between the equally-weighted average market return and the return dispersion. Both are calculated based on the stock price. The average market return is calculated by using the Eq. (2). I adopt Christie and Huang's (1995) CSSD measure of return dispersion in the empirical analysis. The cross-sectional standard deviation (CSSD) of returns is:

$$CSSD_t = S_t \frac{\sqrt{\sum_{i=1}^{N}(Ri,t-Rm,t)^2}}{N-1} \qquad \text{(Eq. 3)}$$

where $S_t$ is the return dispersion at time *t*, *N* is the number of firms in the portfolio, $R_{i,t}$ is the observed stock return of firm *i* at time *t*, and $R_{m,t}$ is the cross-sectional average of the *N* returns in the portfolio at time *t*.

CH suggest that the investment decision-making process used by market participants depends on overall market conditions. They contend that during normal periods, rational asset pricing models predict that the dispersion in returns will increase with the absolute value of the market return, since individual investors are trading based on their own private information, which is diverse. However, during periods of extreme market movements, individuals tend to suppress their own beliefs, and their investment decisions are more likely based on the collective actions in the market. Individual stock returns under these conditions should tend to cluster around the overall market return. Thus, they argue that herding will be more prevalent during periods of market stress, which is defined as the occurrence of extreme returns on the market portfolio. They use the following equation in their empirical specification:

$$CSSD_t = S_t = \alpha + \beta^L D^L + \beta^U D^U + \varepsilon \qquad \text{(Eq. 4)}$$

where $S_t$ is the return dispersion at time *t*. $D_t^L$ is a dummy variable at time *t* taking on the value of unity when the market return at time *t* lies in the extreme lower tail of the distribution, and 0 otherwise. Similarly, $D_t^U$ is a dummy variable with a value of unity when the market return at time $t$ lies in the extreme upper tail of the distribution, and 0 otherwise.

This model suggests that if herding occurs, investors will make similar decisions, leading to lower return dispersions. Thus, statistically significant negative values for $\beta^L$ and $\beta^U$ in Eq. (4) would indicate the presence of herding.

One of the challenges associated with the approach described above is that it requires the definition of extreme returns. CH note that this definition is arbitrary, and they use values of one percent and five percent as the cut-off points to identify the upper and lower tails of the return distribution. In practice, investors may differ in their opinion as to what constitutes an extreme return, and the characteristics of the return distribution may change over time. So you need to use multiple extreme returns for your tests, considering it a sort of robustness test. In addition, herding behavior may occur to some extent over the entire return distribution, but become more pronounced during periods of market stress, and the CH method captures herding only during periods of extreme returns.

CKK, propose an alternative measure of return dispersion, which is the cross-sectional absolute deviation (CSAD) of returns, derived from the Capital Asset Pricing Model (CAPM). The herding test of CCK facilitates the detection of herding over the entire distribution of market return with the following specification:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \varepsilon_t \qquad \text{(Eq. 5)}$$

where $R_{m,t}$ is the equal-weighted average stock return. Note that both $|R_{m,t}|$ and $R_{m}{}^{2}{}_{,t}$ terms appear in the right-hand-side of the equation. CCK note that rational asset pricing models imply a linear relation between the dispersion in individual asset returns and the return on the market portfolio. As the absolute value of the market return increases, so should the dispersion in individual asset returns. The reason that CKK includes the absolute value of the market return in the equation is because their mentioned linear relationship between the market value and the return dispersion applies to both increasing and decreasing market values. It is about the change in magnitude of the variables, not the direction. So if the return on the market portfolio changes with a certain ratio, in either direction, the return dispersion changes with the same ratio.

In case $y_2$ is equal to zero, Eq. (5) turns into a linear equation, since the second part of the equation becomes zero. Perfect linearity would suggest that the predictions of rational asset pricing models perfectly hold. To capture herd behavior in the market, a nonlinear equation is demanded.

During periods of relatively large market price movements, investors may react in a more uniform manner, exhibiting herding behavior**.** Investors tend to suppress their own beliefs and individual stock returns tend to cluster around the overall market return. This behavior is likely to increase the correlation among asset returns, and the corresponding dispersion among returns will decrease, or at least increase at a less-than-proportional rate with the market return. The relationship between the aggregate market return and the return dispersion has changed from a linear to a nonlinear relationship.

In times of herding, the relationship between the return dispersion and the average market return becomes nonlinear and negative. Nonlinear refers to the fact that both variables don't change at the same rate. Negative refers to the fact the return dispersion changes at a smaller rate than the market return. As explained, this is/would be the case when herding is present in the market. For this reason, a nonlinear market return ($R_m{}^2{}_{,t}$) is included in test Eq. (5), and a significantly negative coefficient $\gamma_2$ in the empirical test would be consistent with the occurrence of herd behavior.

So, as the market experiences large price swings, market participants tend to suppress their private information and herd around the information emerging from the consensus of all market constituents. Stock returns under these conditions tend to converge, causing the return dispersion to either decrease or increase at a decreasing rate. Thus, if herding exists, CKK expects the coefficient $\gamma_2$ to be negative and statistically significant.

Would $\gamma_2$ be positive, then the stock returns would not tend to converge but diverge from the market consensus. Also in this case there is a nonlinear relationship between the market return and the return dispersion. The difference with a negative $\gamma_2$ is that investors do not follow the market consensus but trade based on their own, private information, which is diverse. Positive values would indicate that the return dispersion increases (at a more-than-proportional rate) during periods of large price changes. This finding would support the rational asset pricing models that predict that periods of market stress induce increased levels of dispersion as individual returns differ in their sensitivity to the market return.

However, literature since CCK (see Gleason et al., 2004; Hwang and Salmon, 2004; Tan et al., 2008; Chiang & Zheng, 2010) raises concerns regarding the CSAD measure's reliance on the correct specification of the single market factor model.

The measure relies on the accuracy of the specification of a single market factor of the CAPM, the estimation of the beta component of the CAPM formula. This single market factor is the time-invariant systematic risk measure of a market portfolio. The accuracy of the beta estimation may be questionable, at least.

In this paper I establish a generalized form of the CCK model to examine herding within the Chinese stock market using Christie and Huang's estimation of the CSSD measure, which does not rely on the estimation of CAPM/beta (see Gleason et al., 2003; Hwang & Salmon, 2004; Tan et al., 2008; Chiang & Zheng, 2010). Hence, the CH's CSSD will be used to measure the return dispersion; and the CKK's regression model will be used to see if herding is present in the Shanghai and Shenzhen A and B markets and in the Hong Kong market. This leads to the following equation:

$$CSSD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \varepsilon_t \qquad \text{(Eq. 6)}$$

Where $R_{m,t}$ is the equally-weighted average market return, and $CSSD_t$ is the cross-sectional standard deviation. The regression model used to detect herding aims to statistically capture any clustering in return deviations when there is excessive movement in the market. A significantly negative coefficient $\gamma_2$ from the above regression will indicate the existence of herding behavior. I test this assertion by operating the regression over the entire sample, rather than limiting the study to the extreme tails of the return distribution.

Since a high level of serial correlation is expected to exist in high frequency time series market data, the failure to properly address this issue will result in biased estimates of the parameters. Besides, the data analysis shows that the data in the sample show significant heteroscedasticity and autocorrelation. In addition to using Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors to compute the estimated regression coefficients, I also add a 1-day lag of the dependent variable ($CSSD_t$) as a regressor to the equation to (further) improve the power of the model:

$$CSSD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \gamma_3 CSSD_{t-1} + \varepsilon_t \qquad \text{(Eq. 7)}$$

Where $R_{m,t}$ is the equal-weighted average stock return and $CSSD_t$ is the cross sectional standard deviation. $CSSD_{t-1}$ is the 1-day lagged variable of $CSSD_t$. In line with Yao et al. (2014), Chiang et al. (2013), and Hwang and Salmon (2004), the Ordinary Least Square (OLS) method is employed to conduct the regression analysis.

Existing literature does not treat the issue of a statistically significant positive herding coefficient. In case this coefficient is statistically positive the linearity will be broken in an opposite way compared to situations of market-wide herding as the result of a negative herding coefficient. The dispersion will not decrease but increase at a less-than-proportional rate with the market return, diverging away from the market consensus, also known as localized herding. Hence, the herding model used in this thesis will not only be able to detect market-wide herding, but also localized herding. The type of herding depends on the sign of the herding coefficient $\gamma_2$.

### *4.2 Herding asymmetry*

Previous studies have examined herding behavior under different conditions of the market. They investigate whether market returns in up-markets show significantly different herd behavior compared to market returns in down-markets. Put differently, they examine asymmetric herd behavior in the market returns. CKK (2010), Chiang et al. (2007), and Chiang et al. (2009) found herding to be more pronounced in rising markets. Yao et al. (2014), and Fu and Lin (2010) found herding to be more pronounced in declining markets. To test for herding asymmetry, the regression Eq. (7) needs to be adjusted. The regression will be estimated separately for positive and negative market returns. For these tests, the dataset is divided in two parts, based on the sign of the equally-weighted average market return ($R_{m,t}$).

$$CSSD_t^U = \alpha + \gamma_1^U |R_{m,t}^U| + \gamma_2^U (R_{m,t}^U)^2 + \gamma_3^U CSSD_{t-1}^U + \varepsilon_t \qquad \text{(Eq. 8)}$$

if $R_{m,t} \geq 0$

$$CSSD_t^D = \alpha + \gamma_1^D |R_{m,t}^D| + \gamma_2^D (R_{m,t}^D)^2 + \gamma_3^D CSSD_{t-1}^D + \varepsilon_t \qquad \text{(Eq. 9)}$$

if $R_{m,t} < 0$

$R_{m,t}^U/R_{m,t}^D$ are the equally-weighted average market returns at time *t* when the market rises/falls. $CSSD^U/CSSD^D$ are the corresponding cross-sectional standard deviations at time *t*.

### *4.3 Robustness tests*

In order to evaluate the robustness of the results, regression Eq. (7) is used in different subsamples of the data. Since the Shanghai and Shenzhen markets show different stock price behavior over the sample period compared to the Hong Kong market, different subsamples for the Hong Kong market are selected. With respect to volatility, Chiang et al. (2007), Gleason et al. (2004), and Tan et al. (2008), among others, argue that the tendency to herd may be strongest during periods of high volatility. CKK (2000) and CH (1995) have based their models on the rationale that herding is present during periods of large price movements. As can be seen in Appendix 9, the beginning of 2014 has been the start of large price swings in the Shanghai and Shenzhen market. Before 2014, the stock market showed relatively little volatility. Therefore, the sample period is cut in two periods, 1/1/2011 – 31/12/2013 and 1/1/2014 – 31/12/2015.

The second period will also be subdivided. The reason is that this period is marked by a large peak, followed by a stock market crash in June 2015. The crash could affect the results (Yao, Ma, & He, 2014). Therefore, the period after the start of the crash, on June 12, 2015, will be excluded from the sample. Interestingly, by subdividing the second subsample, the results could be compared in order to see whether excluding the period of the crash would significantly change the regression results.

In addition, for the Hong Kong market an extra subsample analysis will be employed. Since the market remains volatile during the whole sample period, the sample is subdivided into five periods of one (calendar) year. This robustness analysis provides insights into the time series evolution of herding in both markets.

The second robustness test examines the possible effect of the stock market crash in summer 2015 on the herding coefficient. All markets faced a severe crash, the stock price falling by more than 60-70%. This provides an interesting basis for testing whether the recent crisis has any effect on the findings of this study, and whether investors in the Chinese stock market exhibit stronger herd behavior in such period of high volatility. Interestingly, the results of this robustness check could be compared with the results of the regression performed on the subsample 1/1/2014 – 6/11/2015 of the crash to see whether the results are consistent. Besides, the results will be compared with the literature.

To test for the crisis effect, an extra variable is added to the test equation. The added variable is a dummy variable, which takes the value 1, value of unity, for the period 12/6/2015 – 2/10/2015, and 0 otherwise. As can be seen in Appendix 9 during this period the stock market fell dramatically. The stock market crashed, and fell even more, again at the beginning of 2016. However, since the sample period ends at the last trading day of 2015, and the last weeks of 2015 showed an increase in the stock price, 2/10/2015 is chosen to be the last day of unity. Although the Hong Kong market shows a constant volatility during the whole sample period,

Appendix 10 shows that also the Hong Kong market faced a severe crash at that time. Therefore, the value of unity of the dummy variable will be the same for all three markets. The following test equation will be used to conduct the second robustness test:

$$CSSD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \gamma_3 CSSD_{t-1} + \varepsilon_t + \gamma_4 DM_t R^2_{m,t} + \varepsilon_t \qquad \text{(Eq. 10)}$$

Where $R_{m,t}$ is the equal-weighted average stock return and $CSSD_t$ is the cross-sectional standard deviation. $CSSD_{t-1}$ is the 1-day lagged variable of $CSSD_t$, and $DM_t R^2_{m,t}$ is a dummy variable that is used to test for the crisis effect.

A statistically significant $\gamma_4$, both positive and negative, will suggest that the summer 2015 stock market crash did have a significant impact on the herd behavior of investors in the market.

# Chapter 5 Results

The regressions are performed using an Ordinary Least Square estimator with Heteroscedasticity and autocorrelation consistent standard errors (HAC standard errors). This is preferred in order to establish a consistent and asymptotically normal estimator as tests for heteroscedasticity and autocorrelation in the standard errors reveal their presence (Appendix 7 & 8). As mentioned before, a significant negative or positive value of the coefficient $R_m^2{}_{,t}$ will be indicative of herd behavior, be it market-wide herding or localized herding. The relevant findings are presented in this section. References to appendices will support the presented findings as well as comprise the complete analysis.

### *5.1 Regression results*

In Table 2 the regression results for the whole sample period are reported. Panel A shows the results under the CKK model, panel B shows the results under the modified model; both using daily data. All tables and appendices are based on daily data.

**Table 2**

Analysis of herd behavior in Chinese stock markets

Period 1/1/2011 - 31/12/2015

*Panel A: regression results under CKK's model Eq. (6)*

| Market | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| $\alpha$ | 0.839 | 0.572 | 0.873 | 0.621 | 0.950 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.182 | 0.306 | 0.196 | 0.388 | 0.429 |
| | *(0.001)* | *(0.000)* | *(0.001)* | *(0.000)* | *(0.000)* |
| $y_2$ | 0.045 | -0.011 | 0.055 | -0.010 | 0.028 |
| | *(0.028)* | *(0.326)* | *(0.006)* | *(0.657)* | *(0.335)* |
| Adjusted $R^2$ | 0.298 | 0.371 | 0.254 | 0.405 | 0.290 |

*Panel B: regression results under modified model Eq. (7)*

| Market | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| $\alpha$ | 0.387 | 0.333 | 0.486 | 0.375 | 0.712 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.131 | 0.209 | 0.129 | 0.303 | 0.395 |
| | *(0.000)* | *(0.000)* | *(0.004)* | *(0.000)* | *(0.000)* |
| $y_2$ | 0.016 | -0.004 | 0.040 | -0.009 | 0.021 |
| | *(0.228)* | *(0.597)* | *(0.154)* | *(0.560)* | *(0.414)* |
| $y_3$ | 0.514 | 0.394 | 0.426 | 0.360 | 0.226 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |

| Adjusted $R^2$ | 0.508 | 0.497 | 0.410 | 0.514 | 0.337 |
|---|---|---|---|---|---|

Table 2 reports the coefficients and the adjusted $R^2$ of following regression models for the Shanghai A-share (SHA), Shanghai B-share (SHB), Shenzhen A-share (SZA), Shenzhen B-share (SZB), and the Hong Kong H-share (HK) markets:
$CSSD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \varepsilon_t$
$CSSD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \gamma_3 CSSD_{t-1} + \varepsilon_t$
where $R_{m,t}$ is the equal-weighted average portfolio return at time *t*. $CSSD_t$ is the cross sectional standard deviation, and $CSSD_{t-1}$ is the 1-day lag of the dependent variable ($CSSD_t$). The sample period is from 1/1/2011 to 31/12/2015. Numbers in parentheses are the power of the coefficients based on Newey & West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. *(0.01), (0.05),* and *(0.1)* represent statistical significance at the 1%, 5%, and 10% levels respectively.

The herding coefficient of the A-share markets and the Hong Kong market is positive, and the herding coefficient in the B markets is negative. This would indicate herd behavior in the B-share markets. However, the coefficients are not statistically significant. The same conclusions could be drawn from panel B. The coefficient of the lagged variable in panel B has a large magnitude and is statistically significant. Besides, the adjusted $R^2$ has improved across all four markets. Both confirm and justify the lagged variable being included in the model.

The reason that both models give insignificant results could be due to the fact that the market evolved in different ways during the sample period. As explained in Chapter 2, the tendency to herd may be stronger during periods of (relatively) high volatility. The insignificant results may be the result of the relatively peaceful first three years of the market being part of the total sample period.

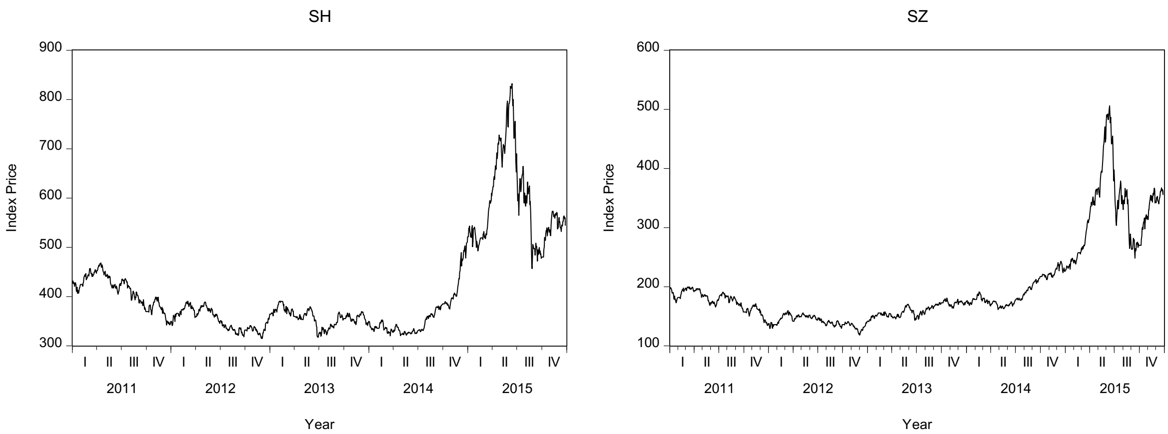


**Figure 1**: plot of the Shanghai (SH) and Shenzhen (SZ) composite price indices.
This composite price index is a capitalization-weighted index. The index tracks the daily performance of all A-shares and B-shares. The number of constituents of both A-shares and B-shares add up to the number of constituents of the composite index.

Figure 1 confirms that the SH and the SZ markets have faced a relatively quiet period between the beginning of 2011 and the beginning of 2014. From that moment onwards, the stock price started to grow gradually. Since halfway 2014 the markets started to grow exponentially, ending up in bubble-like patterns in 2015, eventually leading into a crash in June 2015.

**Table 3**

Analysis of herd behavior in Chinese stock markets

Period: 1/1/2014 - 31/12/2015

*Panel A: regression results under CKK's model Eq. (6)*

| Market | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| $\alpha$ | 0.861 | 0,544 | 0,938 | 0,596 | 0,96 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.395 | 0,475 | 0,363 | 0,509 | 0,443 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_2$ | -0.023 | -0,055 | -0,001 | -0,039 | 0,038 |
| | *(0.373)* | *(0.000)* | *(0.979)* | *(0.014)* | *(0.074)* |
| Adjusted $R^2$ | 0.386 | 0,519 | 0,372 | 0,531 | 0,361 |

*Panel B: regression results under modified model Eq. (7)*

| Market | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| $\alpha$ | 0.396 | 0.263 | 0.486 | 0.364 | 0.770 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.180 | 0.277 | 0.175 | 0.350 | 0.398 |
| | *(0.000)* | *(0.000)* | *0.009* | *(0.000)* | *(0.000)* |
| $y_2$ | -0.005 | -0.027 | 0,016 | -0.019 | 0.036 |
| | *(0.732)* | *(0.007)* | *(0.425)* | *(0.039)* | *(0.070)* |
| $y_3$ | 0.576 | 0.483 | 0.477 | 0.363 | 0.182 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| Adjusted $R^2$ | 0.576 | 0.678 | 0.540 | 0.625 | 0.390 |

Table 3 reports the coefficients and the adjusted $R^2$ of the following regression models for the Shanghai A-share (SHA), Shanghai B-share (SHB), Shenzhen A-share (SZA), Shenzhen B-share (SZB), and the Hong Kong H-share (HK) markets:

$CSSD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2 + \varepsilon_t$

$CSSD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2 + \gamma_3 CSSD_{t-1} + \varepsilon_t$

where $R_{m,t}$ is the equal-weighted average portfolio return at time *t.* $CSSD_t$ is the cross sectional standard deviation, and $CSSD_{t-1}$ is the 1-day lag of the dependent variable ($CSSD_t$). The sample period is from 1/1/2014 to 31/12/2015. Numbers in parentheses are the power of the coefficients based on Newey & West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. *(0.01), (0.05),* and *(0.1)* represent statistical significance at the 1%, 5%, and 10% levels respectively.

Table 3 reports the regression results for the sub-period 01/01/2014 – 31/12/2015. Panel A shows the results under the CKK model, panel B shows the results under the modified model; both using again daily data. The herding coefficient for the B-share markets are again negative, with the Shanghai B-share market having an $y_2$ of -0.055 and the Shenzhen B-share market an $y_2$

of -0.039. Both are now statistically significant at the 1% and 5% level, respectively. Moreover, also the Shanghai A-share and the Shenzhen A-share markets show a negative $y_2$; both statistically insignificant. Only the Hong Kong market shows a positive, statistically significant herding coefficient.

Again, the modified model shows a higher adjusted $R^2$, and the lagged variable has a large magnitude and is statistically significant across all four markets. The effect of the inclusion of a lagged variable is that for both B-share markets the coefficients are slightly decreased, but remain statistically significant at the 1% and 5% level, respectively. By adding the lagged variable into the model, the model controls for the autocorrelative nature of the dispersion variable. The herding coefficient for the Shanghai A-share market remains negative, the herding coefficient of the Shenzhen A-share market has turned positive. Both remain statistically insignificant. These results indicate that the predicted increased level of dispersion, as proposed by the rational finance theory, does not hold in the B-share markets and herding behavior has been present during this period.

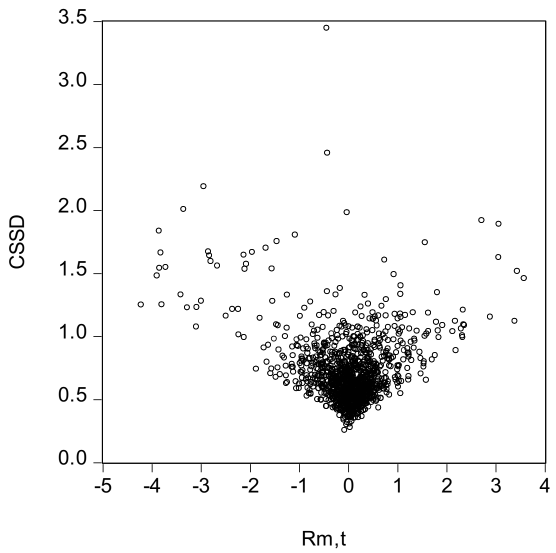


**Figure 2**: scatter plot of the relation between the equally weighted market return ($R_{m,t}$) and the (CSSD).

Figure 2 illustrates the non-linear relationship between the equally-weighted market return ($R_{m,t}$) and the cross-sectional standard deviation (CSSD) in the Shanghai B-share market. In a herd free market, dispersion should grow proportionally with the average market return. In this graph, as the average market return becomes larger in absolute terms, the return dispersions increase, but at a decreasing rate.

Since the modified model has shown to have higher adjusted $R^2$ across all markets and includes a lagged variable that has justified its inclusion in the model (by showing higher statistical significance), the decision has been made to only report and analyze the results of the modified model in the following tables, from now on. When finding statistically significant negative herding coefficients without a lagged variable in the model, this non-linear relationship found could be largely due to serial correlation in the dispersion variable, rather than actual investor herding behavior in the market; especially with highly autocorrelated variables in the model. As shown in Appendix 7, autocorrelation exists across all four markets.

**Table 4**

Analysis of herd behavior in Chinese stock markets

Period 1/1/2014 - 11/6/2015

*Regression results under modified model Eq. (7)*

| Market | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| $\alpha$ | 0.445 | 0.243 | 0.405 | 0.364 | 0.739 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.005 | 0.354 | 0.024 | 0.447 | 0.601 |
| | (0.955) | *(0.000)* | (0.725) | *(0.000)* | *(0.000)* |
| $y_2$ | 0.091 | -0.044 | 0,086 | -0.066 | 0.002 |
| | (0.032) | (0.004) | (0.031) | (0.001) | (0.971) |
| $y_3$ | 0.516 | 0.473 | 0.568 | 0.331 | 0.189 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | (0.008) |
| Adjusted $R^2$ | 0.383 | 0.623 | 0.517 | 0.425 | 0.247 |

Table 4 reports the coefficients and the adjusted $R^2$ of the following regression model for the Shanghai A-share (SHA), Shanghai B-share (SHB), Shenzhen A-share (SZA), Shenzhen B-share (SZB), and the Hong Kong H-share (HK) markets:
$CSSD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2 + \gamma_3 CSSD_{t-1} + \varepsilon_t$
where $R_{m,t}$ is the equal-weighted average portfolio return at time *t.* $CSSD_t$ is the cross sectional standard deviation, and $CSSD_{t-1}$ is the 1-day lag of the dependent variable ($CSSD_t$). The sample period is from 1/1/2014 to 11/6/2015. Numbers in parentheses are the power of the coefficients based on Newey & West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. *(0.01), (0.05),* and *(0.1)* represent statistical significance at the 1%, 5%, and 10% levels respectively.

The results in Table 3 suggest that herd behavior exists in rather volatile markets, at least in the B-share markets. As can be seen in Figure 1, in the period 2011-2013, a relatively stable period (little volatility), the results don't show statistically significant herding coefficients ( $y_2$) for three of the four A/B-share markets. Table 4 reports the regression results for the sub period 01/01/2014 – 11/06/2015. It is the period prior to the stock market crash that started on June 12, 2015. 01/01/2014 is taken as the starting point of the stock market run-up.

The magnitude of the herding coefficients has increased across all four markets. For the B-share markets, the negative $y_2$ has become larger, providing (strong) evidence for herd behavior in these markets. For the A-share markets, the Shanghai market turned positive and statistically significant. The Shenzhen A-share market remains positive, increased in magnitude and turned statistically significant as well. This indicates that in the A-share market the dispersion increases as the magnitude of the market return becomes larger, suggesting that the rationale of the rational asset pricing models could be applied to these markets. The results are statistically significant at the 1% level for the B-share markets, and at the 5% level for the A-share markets. These results would suggest localized herding. Apparently, excluding the stock market crash affects the magnitude of the herding coefficient for all four markets. Later in this chapter, a robustness analysis will be employed in order to see whether the results offer confirmation.

Regarding the Hong Kong market, the highly insignificant, positive herding coefficient does not offer much to say. Obviously, more research needs to be done to explain these insignificant results. As mentioned before, the stock price behavior in the Hong Kong market over the (total) sample period is different. The next subsection will examine more accurately herd behavior in the Hong Kong market.

Comparing Table 3 and Table 4 and, thus, comparing the two respective sample periods, the most important conclusion is that the stock market crash seems to have a (significant) effect on the magnitude of the herding coefficient of all four markets. Later in this chapter, robustness tests will be conducted in order to see what the effect of the crisis is on the results. The results also indicate that the herding coefficient (both positive and negative) is particularly strong when the market rises, since the herding coefficient for all markets has increased with the exclusion of the stock market crash. Also later in this chapter, another robustness test will be conducted in order to see whether herding is stronger in either up-markets or down-markets. Perhaps there is herding asymmetry, perhaps there appears to be no difference.

If the rational asset pricing models would prevail in the market, the regression would have reported perfect linearity. The herding coefficient would have been zero ($\gamma_2$=0). The results in all four markets, as reported in Table 3 and Table 4, suggest that the behavior of investors could not perfectly be explained by the rational asset pricing models. As reported, the herding coefficients in the B-share markets are negative, and the herding coefficients in the A-share market are mainly positive. Moreover, the results also suggest that investors in the A-share market behave differently than investors in the B-share market. The results in the B-share markets indicate that investors may tend to suppress their own beliefs and investment decisions in favor of the market consensus, causing individual stock returns to not deviate far from the overall market return. Both A-share markets, though, indicate that stock return dispersions have increased and deviate (far) from the overall market return. This finding more or less supports the hypothesis of the rational asset pricing models that predict that periods of market stress lead to increased levels of dispersion.

The findings are in line with Yao et al. (2014) who also found that investor herd behavior is particularly strong in the B-share markets. Chiang et al. (2007) also found evidence of herd behavior in the B-share market. However, they also found evidence of herd behavior in the A-share market.

So, strikingly, the rational asset pricing model could be applied to the A-share market, whereas the behavioral finance theories could rather be applied to the B-share markets. This outcome could be the results of both markets having different characteristics that lead to investors behaving in a different way. Chemi & Fahey (2016) and Song (2016) argue that herd behavior particularly exists when unsophisticated retail investors dominate the market. These investors, who mainly base their investment decisions on technical analysis, dominate the A-share market, not the B-share market. However, Zhou (2008) found evidence that herd behavior is more prevalent when people perform fundamental analysis. Fundamental analysis is to be performed by sophisticated, institutional investors. These type of investors dominate the B-share market. This could be a possible explanation for the found empirical evidence herd behavior in the B-share market. Moreover, there is a significant amount of past empirical evidence which suggests that investors in the A-share markets are more transparent and more informed than those in the B-share markets. Moreover, A-shares adjust to information faster than B-shares (see e.g., Chakravarty et al., 1998, Chiang et al., 2008 and Yao, 2014).

### 5.1.1 Hong Kong

Figure 3 shows that the stock price in the Hong Kong market behaves differently as opposed to the Shanghai and the Shenzhen markets. In the Hong Kong market, there has been much more volatility during the sample period. Besides, the Hong Kong market is not characterized by a bubble-like pattern in the first half of 2015, followed by a severe crash. Although, the Hong Kong market also shows a peak around the same time. Where the Shanghai and the Shenzhen market remained relatively stable between the beginning of 2011 and the beginning of 2014, the Hong Kong showed much more volatility.

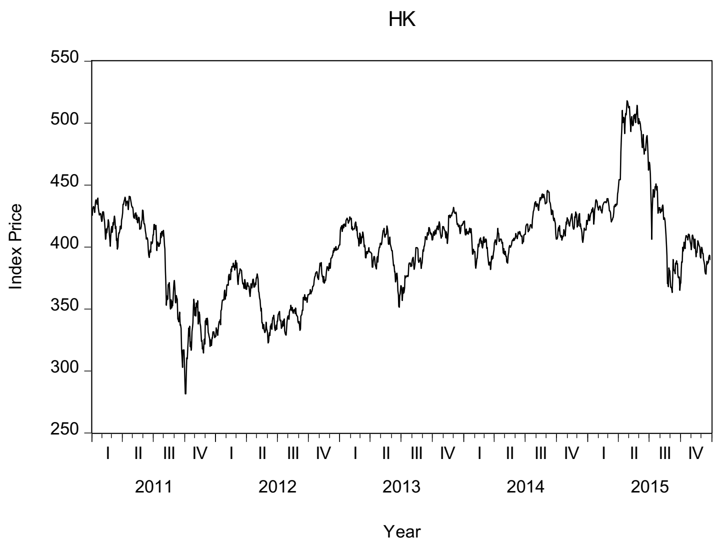


**Figure 3**: plot of the Hong Kong (HK) composite price indices.

Due to the different stock price behavior of the Hong Kong market, the regressions are run again using different subsamples, each for every year, in order to see whether statistically significant results show up.

**Table 5**
Analysis of herd behavior in Hong Kong stock markets
Period 1/1/2011 - 31/12/2015

*Regression results under modified model Eq. (7)*

| Year | 2011 | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|---|
| $\alpha$ | 0.609 | 0.585 | 0.634 | 0.688 | 0.728 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.560 | 0.823 | 1.038 | 1.498 | 0.345 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_2$ | -0.072 | -0.406 | -0.551 | -1.246 | 0.047 |
| | *(0.104)* | *(0.030)* | *(0.000)* | *(0.002)* | *(0.014)* |
| $y_3$ | 0.235 | 0.299 | 0.227 | 0.135 | 0.224 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.011)* | *(0.000)* |
| Adjusted $R^2$ | 0.450 | 0.228 | 0.239 | 0.146 | 0.550 |

Table 5 reports the coefficients and the adjusted $R^2$ of the following regression model for the Hong Kong H-share (HK) market: $CSSD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2 + \gamma_3 CSSD_{t-1} + \varepsilon_t$
where $R_{m,t}$ is the equal-weighted average portfolio return at time *t*. $CSSD_t$ is the cross sectional standard deviation, and $CSSD_{t-1}$ is the 1-day lag of the dependent variable ($CSSD_t$). The sample period is from 1/1/2011 to 31/12/2015. Numbers in parentheses are the power of the coefficients based on Newey & West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. *(0.01), (0.05),* and *(0.1)* represent statistical significance at the 1%, 5%, and 10% levels respectively.

Table 5 shows the regression results for the Hong Kong market for all five years of the total sample period, as explained before under the modified model. Compared to the results in Table 2 – Table 4, the regression coefficients are negative for the first four years and are statistically significant for all years, except for 2011. The herding coefficients are (way) larger in magnitude than the herding coefficients of both B-share markets. These results provide strong evidence that herd behavior exists in the Hong Kong market.

These results are in line with Chiang and Zheng (2009), who find evidence for herd behavior in the Hong Kong market. However, the results contradict the findings of CKK (2010) who do not find evidence of herd behavior in the Hong Kong market. Not only the B-share market but also the Hong Kong market is dominated by institutional investors, who generally are more sophisticated than retail investors. The evidence of herd behavior in the H-share market also suggest that herd behavior is more prevalent when people perform fundamental analysis as opposed to technical analysis (Zhou, 2008).

Another striking result of Table 5 is that the herding coefficient in 2015 is statistically significant, but positive, indicating that during this year the return dispersion increases as the magnitude of the returns increases. Appendix 11 shows that the negative herding coefficient of the years 2011-2014 remains negative until the beginning of April 2015, and turns into a statistically significant, positive herding coefficient right afterwards until the end of the year.

Comparing Figure 1 with Figure 3, a striking difference is the period before the stock market crash in all markets. The Shanghai and the Shenzhen markets are characterized by a more or less ongoing increase of the stock price; a gradual increase in 2014 converting into an exponential increase, leading into the crash in June 2015. The Hong Kong market is constantly volatile over time, in both directions, and show a sudden peak starting in March/April 2015.

"During this period, at around the first week of April, cash flooded into the Hong Kong market. After China allowed mutual funds to buy shares using a new trading link, the stock market has burst into life. Besides, investors are focusing on stimulus efforts from Beijing. The enthusiasm stems from signs China is taking steps to bolster its sluggish economy with plans to better connect the economy with the rest of the world; with more roads, railways, ports and other projects. All this has started to change the market's psychology as well as expectations of China's economy." (Hunter, 2015). As a result, these number of outliers in quite a short time could have affected the results. Appendix 12 shows that the herding coefficient has changed into a significantly negative value for the year 2015 after controlling for outliers.

### *5.2 Herding asymmetry*

This section provides the results of an extension of regression Eq. (7). This equation will be adjusted in order to investigate herding asymmetry in the Shanghai, Shenzhen and Hong Kong markets. Only the subsamples that showed significant $y_2$ coefficients (Table 3 & 4) will be analyzed. For the Shanghai and Shenzhen markets, as shown, there are no statistically significant results over the full sample and over the subsample 2011-2013 (Table 2 & Appendix 13). Therefore, only the (two) subsamples 2014-2015 are examined. For the Hong Kong market, as shown, the subsample 2011 does not show statistically significant results. Therefore, herding asymmetry is tested for the years 2012-2015. The results are reported in Table 6.

#### 5.2.1 Shanghai and Shenzhen

Table 6 reports that in both up- and down-markets, herding coefficients are only negative in the B-share markets. The results are statistically significant, meaning that herding is present under both market conditions. This is in line with the results in Table 4. The herding coefficients for the B-share markets are slightly higher in the up-market. The coefficients of the A-share markets are positive under both market conditions, and also show higher herding coefficients in the up-market. Note that the herding coefficients are only statistically significant in the up-market. These results indicate that, although the A-share markets show statistically significant results in the up-market, the coefficients of the total subsample (Table 2) are statistically insignificant.

**Table 6**
Analysis of herd behavior in rising in declining Chinese stock markets
Period 1/1/2014 - 31/12/2015

*Panel A: regression results when market rises ($R_{m,t}$ > 0), Eq. (8)*

| Market | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| $\alpha$ | 0.422 | 0.243 | 0,372 | 0.337 | 0.801 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.006 | 0.286 | -0.137 | 0.365 | 0.479 |
| | *(0.939)* | *(0.000)* | *(0.062)* | *(0.000)* | *(0.000)* |
| $y_2$ | 0.041 | -0.040 | 0.111 | -0.039 | 0.048 |
| | *(0.095)* | *(0.022)* | *(0.002)* | *(0.027)* | *(0.039)* |

| | | | | | |
|---|---|---|---|---|---|
| $y_3$ | 0.563 | 0.506 | 0.677 | 0.385 | 0.133 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.025)* |
| Adjusted $R^2$ | 0.427 | 0.654 | 0.577 | 0.562 | 0.475 |

*Panel B: regression results when market declines ($R_{m,t}$ < 0), Eq. (9)*

| Market | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| $\alpha$ | 0.624 | 0.301 | 0.689 | 0.439 | 0.809 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.822 | 0.357 | 0.870 | 0.471 | 0.370 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_2$ | 0.007 | -0.038 | -0.009 | -0.035 | 0.018 |
| | *(0.736)* | *(0.010)* | *(0.736)* | *(0.079)* | *(0.565)* |
| $y_3$ | 0.160 | 0.407 | 0.153 | 0.243 | 0.156 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| Adjusted $R^2$ | 0.944 | 0.680 | 0.892 | 0.646 | 0.277 |

Table 6 reports the coefficients and the adjusted $R^2$ of the following regression model for the Shanghai A-share (SHA), Shanghai B-share (SHB), Shenzhen A-share (SZA), Shenzhen B-share (SZB), and the Hong Kong H-share (HK) markets; one for a rising market, and one for a declining market:
$CSSD_t^U = \alpha + \gamma_1^U |R_{m,t}^U| + \gamma_2^U (R_{m,t}^U)^2 + \gamma_3^U CSSD_{t-1}^U + \varepsilon_t$
$CSSD_t^D = \alpha + \gamma_1^D |R_{m,t}^D| + \gamma_2^D (R_{m,t}^D)^2 + \gamma_3^D CSSD_{t-1}^D + \varepsilon_t$
where $R_{m,t}^U (R_{m,t}^D)$ is the equal-weighted average portfolio return during period $t$ when the market is up (down). $CSSD_t^U (CSSD_t^D)$ is the cross sectional standard deviation, and $CSSD_{t-1}^U (CSSD_{t-1}^D)$ is the 1-day lag of the dependent variable ($CSSD_t$) when the market is up (down). The sample period is from 1/1/2014 to 31/12/2015. Numbers in parentheses are the power of the coefficients based on Newey & West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. *(0.01), (0.05),* and *(0.1)* represent statistical significance at the 1%, 5%, and 10% levels respectively.

Table 7 reports the results of the subsample that excludes the period after the beginning of stock market crash. Interestingly, the slightly larger coefficients of the down-market in the B-share markets, as shown in table 6, have increased. The discrepancy between the up-market and the down-market has grown bigger. The herding coefficient of the Shanghai B-share market in the up-market is -0.052, compared to -0.017 in the down-market. The herding coefficient of the Shenzhen B-share market in the up-market is -0.065, compared to -0.041 in the down-market; whereas the differences in Table 6 are 0.002 and 0.004, in absolute terms, respectively. Moreover, these herding coefficients in the down-market are not statistically significant anymore. These results seem to confirm the presumption that emerged after the analysis of Table 4 that (in the Shanghai and Shenzhen markets) herd behavior is particularly pronounced in the up-markets.

In the A-share markets, the herding coefficients also remain positive and more pronounced in the up-market, showing a larger magnitude compared to the results in Table 5. The coefficients in the down-market have a lower magnitude, and are even negative in the Shanghai A-share market; both statistically insignificant. So in both A-share and B-share markets, the herding coefficient is more pronounced in the up-market.

**Table 7**
Analysis of herd behavior in rising in declining Chinese stock markets
Period 1/1/2014 - 11/6/2015

*Panel A: regression results when market rises ($R_{m,t} \geq 0$), Eq.(8)*

| Market | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| $\alpha$ | 0.448 | 0.222 | 0.204 | 0.317 | 0.714 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.044 | 0.357 | -0.076 | 0.423 | 0.822 |
| | *(0.705)* | *(0.000)* | *(0.153)* | *(0.000)* | *(0.000)* |
| $y_2$ | 0.183 | -0.052 | 0.144 | -0.065 | -0.046 |
| | *(0.015)* | *(0.009)* | *(0.016)* | *(0.003)* | *(0.399)* |
| $y_3$ | 0.517 | 0.495 | 0.815 | 0.384 | 0.163 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| Adjusted $R^2$ | 0.274 | 0.656 | 0.685 | 0.518 | 0.388 |

*Panel B: regression results when market declines ($R_{m,t} < 0$), Eq. (9)*

| Market | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| a | 0.653 | 0.324 | 0.653 | 0.426 | 0.772 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.567 | 0.384 | 0.567 | 0.433 | 1.116 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_2$ | -0.001 | -0.017 | 0.062 | -0.041 | -0.713 |
| | *(0.991)* | *(0.668)* | *(0.069)* | *(0.765)* | *(0.039)* |
| $y_3$ | 0.012 | 0.350 | 0.207 | 0.265 | 0.129 |
| | *(0.000)* | *(0.000)* | *(0.012)* | *(0.000)* | *(0.000)* |
| Adjusted $R^2$ | 0.826 | 0.536 | 0.826 | 0.334 | 0.109 |

Table 7 reports the coefficients and the adjusted $R^2$ of the following regression model for the Shanghai A-share (SHA), Shanghai B-share (SHB), Shenzhen A-share (SZA), Shenzhen B-share (SZB), and the Hong Kong H-share (HK) markets; one for a rising market, and one for a declining market:
$CSSD_t^U = \alpha + \gamma_1^U |R_{m,t}^U| + \gamma_2^U (R_{m,t}^U)^2 + \gamma_3^U CSSD_{t-1}^U + \varepsilon_t$
$CSSD_t^D = \alpha + \gamma_1^D |R_{m,t}^D| + \gamma_2^D (R_{m,t}^D)^2 + \gamma_3^D CSSD_{t-1}^D + \varepsilon_t$
where $R_{m,t}^U(R_{m,t}^D)$ is the equal-weighted average portfolio return during period $t$ when the market is up (down). $CSSD_t^U(CSSD_t^D)$ is the cross sectional standard deviation, and $CSSD_{t-1}^U(CSSD_{t-1}^D)$ is the 1-day lag of the dependent variable ($CSSD_t$) when the market is up (down). The sample period is from 1/1/2014 to 31/12/2015. Numbers in parentheses are the power of the coefficients based on Newey & West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. *(0.01)*, *(0.05)*, and *(0.1)* represent statistical significance at the 1%, 5%, and 10% levels respectively.

Herding asymmetry has been examined in previous studies. The results of this study are in line with CKK (2010), Chiang et al. (2007), and Chiang et al. (2009) who found herding to be more pronounced in rising markets. However, Yao et al. (2014), and Fu and Lin (2010) found herding to be more pronounced in declining markets.

### 5.2.2 Hong Kong

Table 8 compares the regression results of the Hong Kong up-market with the down-market. Since the chosen subsamples in section 5.1 mainly show statistically significant results for the herding coefficient ($y_2$), the same subsamples are used to measure the regression model.

**Table 8**
Analysis of herd behavior in rising in declining Hong Kong stock markets
Period 1/1/2011 - 31/12/2015

*Panel A: regression results when market rises ($R_{m,t} \geq 0$), Eq. (8)*

| Market | 2011 | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|---|
| $\alpha$ | 0.630 | 0.669 | 0.698 | 0.700 | 0.779 |
| | *(0.000)* | *(0.001)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.529 | 0.737 | 1.369 | 1.782 | 0.405 |
| | *(0.000)* | *(0.051)* | *(0.000)* | *(0.002)* | *(0.007)* |
| $y_2$ | 0.006 | -0.400 | -0.981 | -1.736 | 0.065 |
| | *(0.950)* | *(0.015)* | *(0.000)* | *(0.037)* | *(0.021)* |
| $y_3$ | 0.220 | 0.270 | 0.154 | 0.092 | 0.161 |
| | *(0.000)* | *(0.024)* | *(0.000)* | *(0.237)* | *(0.044)* |
| Adjusted $R^2$ | 0.519 | 0.157 | 0.200 | 0.197 | 0.576 |

*Panel B: regression results when market declines ($R_{m,t} < 0$), Eq. (9)*

| Market | 2011 | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|---|
| $\alpha$ | 0.561 | 0.668 | 0.614 | 0.806 | 0.653 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.472 | 0.929 | 0.976 | 1.428 | 0.322 |
| | *(0.000)* | *(0.002)* | *(0.000)* | *(0.010)* | *(0.000)* |
| $y_2$ | -0.074 | -0.411 | -0.430 | -1.121 | 0.025 |
| | *(0.116)* | *(0.038)* | *(0.015)* | *(0.038)* | *(0.361)* |
| $y_3$ | 0.301 | 0.168 | 0.222 | 0.040 | 0.296 |
| | *(0.000)* | *(0.112)* | *(0.009)* | *(0.455)* | *(0.000)* |
| Adjusted $R^2$ | 0.424 | 0.191 | 0.242 | 0.079 | 0.516 |

Table 8 reports the coefficients and the adjusted $R^2$ of the following regression model for the Hong Kong H-share (HK) market; one for a rising market, and one for a declining market:
$CSSD_t^U = \alpha + \gamma_1^U |R_{m,t}^U| + \gamma_2^U (R_{m,t}^U)^2 + \gamma_3^U CSSD_{t-1}^U + \varepsilon_t$
$CSSD_t^D = \alpha + \gamma_1^D |R_{m,t}^D| + \gamma_2^D (R_{m,t}^D)^2 + \gamma_3^D CSSD_{t-1}^D + \varepsilon_t$
where $R_{m,t}^U(R_{m,t}^D)$ is the equal-weighted average portfolio return during period $t$ when the market is up (down). $CSSD_t^U(CSSD_t^D)$ is the cross sectional standard deviation, and $CSSD_{t-1}^U(CSSD_{t-1}^D)$ is the 1-day lag of the dependent variable ($CSSD_t$) when the market is up (down). The sample period is from 1/1/2014 to 11/6/2015. Numbers in parentheses are the power of the coefficients based on Newey & West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. *(0.01), (0.05),* and *(0.1)* represent statistical significance at the 1%, 5%, and 10% levels respectively.

Table 5 reports statistically insignificant results for 2011, and also under both market conditions individually the herding coefficients remain insignificant. Furthermore, in 2012-2014, in both rising and declining markets, the negative, statistically significant $y_2$ coefficients indicate herding. In 2012-2015 the magnitude and the significance is clearly larger in the up-market, except for 2012 that shows a slightly larger magnitude in the down-market.

Interestingly, these results are (more or less) consistent with the herding asymmetry in the B-share markets. In both the B-share markets and the Hong Kong markets, the negative herding coefficient has a larger magnitude in the up-market, providing evidence that herding is more pronounced under rising market conditions. The herding coefficient in the A-share market also is significantly larger in the up-market, but positive. As argued before, the results in the A-share market are more consistent with the rational asset pricing theories.

### *5.3 Crisis effect*

Table 9 reports the regression results of regression Eq. (8), where a dummy variable is used to examine the potential effect of the stock market crash on the test results. Since the crash has occurred in the Shanghai, Shenzhen, and Hong Kong market, the crisis effect for all three are tested on the same sample periods. Only the 1/1/2014 – 31/12/2015 sample period is analyzed. Clearly, Appendix 14 shows that for the total sample the dispersion has increased for all markets, but the results remain statistically insignificant.

**Table 9**
Analysis of the effects of the June - October stock market crisis
Period 1/1/2014 - 31/12/2015

*Regression results under modified model including crisis dummy, Eq. (10)*

| Market | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| $\alpha$ | 0.449 | 0.269 | 0.581 | 0.370 | 0.769 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.161 | 0.266 | 0.164 | 0.342 | 0.426 |

| | | | | | |
|---|---|---|---|---|---|
| | *(0.002)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_2$ | -0.009 | -0.026 | 0.006 | -0.018 | 0.034 |
| | *(0.549)* | *(0.012)* | *(0.762)* | *(0.040)* | *(0.079)* |
| $y_3$ | 0.483 | 0.470 | 0.381 | 0.354 | 0.186 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_4$ | 0.154 | 0.032 | 0.226 | 0.035 | 0.084 |
| | *(0.004)* | *(0.239)* | *(0.013)* | *(0.343)* | *(0.074)* |
| Adjusted $R^2$ | 0.587 | 0.678 | 0.562 | 0.626 | 0.392 |

This table reports the coefficients and the adjusted $R^2$ of the following regression model for the Shanghai A-share (SHA), Shanghai B-share (SHB), Shenzhen A-share (SZA), Shenzhen B-share (SZB), and the Hong Kong H-share (HK) markets;
$CSSD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2 + \gamma_3 CSSD_{t-1} + \varepsilon_t + \gamma_4 DM_t R_{m,t}^2 + \varepsilon_t$
where $R_{m,t}$ is the equal-weighted average portfolio return during period *t*. $CSSD_t$ is the cross sectional standard deviation, and $CSSD_{t-1}$ is the 1-day lag of the dependent variable ($CSSD_t$). $DM_t$ is the dummy variable that takes the value of unity between 12/6/2015 and 2/10/2015 and zero otherwise. The sample period is from 1/1/2014 to 31/12/2015. Numbers in parentheses are the power of the coefficients based on Newey & West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. *(0.01), (0.05),* and *(0.1)* represent statistical significance at the 1%, 5%, and 10% levels respectively.

For three out of the five markets, the A-share markets and the Hong Kong market, the estimated coefficients for the dummy variable ($y_4$) is found to be positively significant at the 5% and the 10% level. These positive coefficients suggest that over the period of the crash, the return dispersion in these markets has increased. The B-share markets show insignificant results for $y_4$. The results do not suggest that investors exhibit herding behavior during the crash/crisis period. These results are, carefully, in line with the results in Table 4. The results in Table 4 show that the herding coefficients for the B-share markets have got a larger magnitude than the herding coefficients in Table 3, meaning that herd behavior appears to be stronger when the crisis period is excluded from the sample. Since the results suggest that investors do not exhibit herd behavior during the crisis period, this could explain why the herding coefficients are smaller for the sample including the crisis period and larger for the sample excluding the crisis period.

# Chapter 6 Conclusion

In response to rational asset pricing models arguing that investors are rational, behavioral finance is a rather new approach that has proven that prices could deviate from their fundamentals, and that these deviations are the result of the presence of investors who are less-than-fully rational. In light of this, the focus of this thesis is the examination of investment behavior of investors within the Chinese stock market. The observed tendency among investors to conform towards the market consensus, without regard for their own beliefs – also known as herd behavior – has been investigated in the Shanghai, Shenzhen, and Hong Kong stock markets. Significant herd behavior among investors has the potential to push prices away from fundamentals, and could lead to large price swings, resulting in excess volatility and bubble-like patterns in the stock market.

The testing methodology used in this thesis is based on the empirical models developed by CH (1995) and CKK (2000), where the relationship between market returns and return dispersions is used to detect herding. Return dispersions are measured by the cross-sectional standard deviation, as proposed by CH (1995). The regression model proposed by CK (2000) is used to estimate the herding coefficients. A modified regression model that corrects for multicollinearity is used to perform the tests. The dataset consists of stock prices from the A-share, B-share, and H-share markets, and cover the sample period 1/1/2011 to 31/12/2015.

The empirical results provide some interesting findings about herd behavior among investors in the Chinese stock markets. The test results reveal significant evidence of herd behavior toward the market consensus in the B-share market, but not during the whole sample period. Herd behavior is only present in the B-share market during the subsample 1/1/2014 to 31/12/2015, the period that is characterized by a more volatile stock market. The herding coefficients show a larger magnitude when the period after the stock market crash is excluded from the sample. The results provide even stronger evidence for market-wide herding in the H-share market, during (almost) the whole sample period. These results indicate that investors tend to suppress their own beliefs and investment decisions in favor of the market consensus and are in line with the behavioral finance framework. In contrast, the results do not provide evidence for herding in the A-share market, during the whole sample period. Returns seem to deviate from the market consensus, indicating localized herding. This finding more or less supports the hypothesis of the rational asset pricing models that predict that periods of market stress lead to increased levels of dispersion, whereas herd behavior among investors leads to decreased levels of dispersion.

In addition, considering the B-share and H-share markets, herding significantly exists under both rising and declining market conditions. However, herding is significantly stronger in the up-markets. Also the results for the A-share markets reveal that the herding coefficient has a larger magnitude in the up-market. Hence, the level of dispersion proves to be larger during periods of a rising market. The test results for the crisis reveal that crisis has had a positive effect on the A-share market and the Hong Kong market, meaning that the return dispersion has increased over the period of the crash. In contrast, the crisis did not have a significant effect on the results in the B-share market.

In this thesis four hypotheses are tested. Since evidence of herd behavior is found in the B-share and H-share markets, herd behavior exists in the Chinese stock market. Hypothesis 1 'Herding significantly exist in the Chinese stock market' is accepted. Though, the results show evidence against herd behavior in the A-share market. As a result, Hypothesis 2 'Herding is more pronounced in the B-share market than in the A-share market' is accepted. Hypothesis 3 'Herd behavior is less pronounced in the Hong Kong market than in both Shanghai and Shenzhen markets' is rejected. The herding coefficients of the H-share market are significantly larger than the herding coefficients of the B-share markets in both the Shanghai and Shenzhen stock exchange. So herd behavior is more pronounced in the Hong Kong market. Hypothesis 4 'For all three shares, herd behavior is more pronounced under conditions of rising markets than under declining markets in the Chinese stock market' is rejected. Herd behavior is only more pronounced under conditions of rising markets for the B-shares and the H-shares.

Concluding, herd behavior exists among investors in the Chinese stock markets on a total market level, but it depends on the timeframe and the particular share.

The evidence of herd behavior may have some policy implications. In the B-share and H-share market, where herd behavior is prevalent, a greater number of assets may be needed in order to see portfolio strategies be diversified. A herd-free market may need a reduced amount of assets to achieve the same level of diversification. Besides, the presence of herd behavior suggest that the quality of information disclosure has not been optimal yet in certain markets. Evidence of herd behavior would suggest that the government involvement and reforms have not proven their desired effects. However, these reforms could have positively affect the Chinese retail investors at least, since evidence against herding is found in the A-share market.

### *6.1 Discussion*

A couple of factors make research in herd behavior in stock markets a complex phenomenon. First, literature shows mixed results of herd behavior in different markets, both developed and emerging markets. Second, literature proves that different herding models applied on the same dataset provide different results. Third, herding could be influenced by market capitalization, trading volume, government policies, rising/falling markets, etc. Besides, the empirical literature and the experimental literature have hardly been combined.

There are some decisions that have been made while writing this thesis that could be argued. Certain decisions could affect the statistical results of the tests or the explanation of those results. Therefore, the most important decisions will be discussed below.

While obtaining the data I realized that the list of constituents of an index usually changes over time, and so do the constituents lists of the examined indices in this thesis. As a result, the indices do not contain the same constituents list over the full sample period. Therefore, I have made the decision to exclude al constituents listed on July 1, 2016, from the dataset, that were not listed on the index at the beginning of the sample period, January 1, 2011. Evidently, the excluded percentage of constituents is different for all five examined indices. As such, for each individual index the list of constituents remains the same for the whole sample period and each chosen subsample period. For every trading day, the average market portfolio return ($R_{m,t}$) and the cross-sectional standard deviation ($CSSD_t$) are calculated based on the same constituents list. The dataset does not include any missing data. Moreover, the results have not faced the potential bias caused by new companies entering the index at a certain point in time during the sample period. However, the exclusion of a percentage of the constituents could have a downside. The type of excluded constituents has not been explored. It is possible that excluded constituents belong to a certain sector or industry where herd behavior appears to be particularly strong or weak, and, as a result, could positively or negatively affect the results.

No constituents from both B-share markets needed to be excluded from the dataset, as opposed to both A-share markets and the H-share market. A survival bias could have affected the results. The base date of all constituents of both B-share markets is long before the beginning of the sample period. The duration of the constituents list of a certain index could possibly affect herd behavior. This thesis has not controlled for the duration of the constituents list. Possibly, the number of years a company listed on an index could affect herd behavior in the stock market.

In the methodology part I also made certain decisions that could affect the results. The model used to test for herd behavior is based on the herding models of CH (1995) and CKK (2000).

Another empirical model that showed much attention in the herding literature is the model developed by Hwang & Salmon (2004). They state that their method is able to separate herding from common movements in asset returns induced by movements in fundamentals. Since the results of this thesis provide evidence for herd behavior in the B-share and H-share market - markets that are characterized by (more) sophisticated, institutional investors, generally using fundamental analysis rather than technical analysis – the Hwang and Salmon method could be an appropriate, and maybe better approach to detect herd behavior in these markets. The models used in this thesis are not capable of separating herding from common movements in stock price returns due to movements in fundamentals.

The results of this thesis are in line with some studies, but contradict the results of other studies. These mixed results of studies investigating herd behavior during different time frames suggest that herding is only present in certain periods. Often studies have overlaps in time periods. This could be a reason why studies have different conclusions regarding herd behavior in stock markets. The results of this thesis show that one or a couple of years can drive the results of the entire period investigated. The herding results of some chosen subsamples in this thesis showed differences compared to the herding results of the total sample. Apparently, significant herd behavior in stock markets could be present during one period, and could be disappeared during the next period. This gives reasons to believe that studies should consider focusing on short time frames rather than long time frames. Carefully, most likely there is no perfect time frame to investigate herd behavior. One should regard multiple factors when determining subsample periods.

Not only could the chosen time interval affect the herding results, also market conditions or market characteristics could affect the test results. Next to choosing certain subsample periods to get a better view on herd behavior in the Chinese stock market, this thesis investigated possible differences in herd behavior under conditions of rising and declining market returns. Moreover, the crisis effect has been examined. Admitted, due to the limited scope of this thesis, more research extensions have not been included in the study. Future studies could extend this research by investigating herd behavior in different market sectors or industries. Moreover, herding research could be extended by investigating herding under conditions of high/low trading volume or high/low volatility. The latter could be of particular interest since the results in this thesis suggest that herd behavior is stronger in periods of high volatility.

Since the sample period is a period with differences in market sentiment, future research could pay attention to investigating differences in herd behavior under different conditions of market sentiment. Differences could exist in bull and bear markets. A method that has been developed to examine firm-size-related differences in abnormal returns and systematic risks in bull and bear markets is the dual beta market model of Bhardwaj and Brooks (1993). This model could be combined with one of the existing herding models to get more insights into differences in herd behavior under different market sentiments.

Lastly, since herd behavior is present in the B-share and H-share markets, both dominated by foreign investors, it could be interesting to see whether foreign capital markets, that have investors in the Chinese stock markets and companies listed on the Chinese indices, could have certain impact on herd behavior in these markets. Due to the ongoing globalization, the Chinese stock markets increase integrating with Asia Pacific, US and Western stock markets.

Future research that could possibly compensate for the limitations of this research, together with the suggested research extensions, could potentially give improved and more detailed insights in herd behavior in the Chinese stock markets.

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# Appendices

**Appendix 1**
Descriptive statistics of Cross Sectional Standard Deviation (CSSD) and average Market Return ($R_{m,t}$)
Period: 2011

| Market | No. obs. | Variable | Mean | Std. dev. | Skewness | Kurtosis | Jarque-Bera | ADF |
|---|---|---|---|---|---|---|---|---|
| SHA | 247 | $R_{m,t}$ | -0.055 | 0.636 | -0.555 | 3.352 | (13.964)*** | (-15.063)*** |
| | 247 | CSSD | 0.851 | 0.178 | -0.428 | 8.744 | (347.171)*** | (-12.937)*** |
| SHB | 244 | $R_{m,t}$ | -0.065 | 0.637 | -1549 | 8588 | (415.114)*** | (-13.854)*** |
| | 244 | CSSD | 0.643 | 0.182 | 2.453 | 15.189 | (1755.452)*** | (-11.412)*** |
| SZA | 252 | $R_{m,t}$ | -0.067 | 0.658 | -0.544 | 3.475 | (14.840)*** | (-14.637)*** |
| | 252 | CSSD | 0.861 | 0.259 | 1.428 | 21.073 | (3515.629)*** | (-12.168)*** |
| SZB | 253 | $R_{m,t}$ | -0.077 | 0.581 | -0.780 | 4.602 | (52.755)*** | (-14.233)*** |
| | 253 | CSSD | 0.759 | 0.233 | -0.568 | 4.519 | (37.964)*** | (-10.912)*** |
| HK | 259 | $R_{m,t}$ | -0.069 | 0.741 | -0.337 | 5.732 | (85.515)*** | (-9.228)*** |
| | 259 | CSSD | 1.121 | 0.388 | -0.194 | 5.421 | (64.916)*** | (-4.356)*** |

Appendix 1 lists descriptive statistics of daily mean, standard deviation, skewness, kurtosis of the CSSD and the $R_{m,t}$ over the year 2011 for the Shanghai A (SHA), Shanghai B (SHB), Shenzhen A (SZA), Shenzhen B (SZB), and the Hong Kong (HK) markets. In addition, the Jarque-Bera test for normality and the Augmented Dicky-Fuller test for stationary are reported. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels respectively.

**Appendix 2**

Descriptive statistics of Cross Sectional Standard Deviation (CSSD) and average Market Return ($R_{m,t}$)
Period: 2012

| Market | No. obs. | Variable | Mean | Std. dev. | Skewness | Kurtosis | Jarque-Bera | ADF |
|---|---|---|---|---|---|---|---|---|
| SHA | 243 | $R_{m,t}$ | 0.006 | 0.640 | -0.078 | 3.977 | (9.934)*** | (-14.701)*** |
| | 243 | CSSD | 0.855 | 0.188 | 4.757 | 39.902 | (14704.510)*** | (-12.854)*** |
| SHB | 243 | $R_{m,t}$ | 0.021 | 0.586 | -1.061 | 10.863 | (671.758)*** | (-8.063)*** |
| | 243 | CSSD | 0.664 | 0,173 | 0.707 | 10.328 | (661.859)*** | (-4.668)*** |
| SZA | 247 | $R_{m,t}$ | -0.003 | 0.678 | -0.324 | 3.996 | (14.555)*** | (-14.273)*** |
| | 247 | CSSD | 0.865 | 0.229 | 3.899 | 49.576 | (22952.390)*** | (-11.806)*** |
| SZB | 252 | $R_{m,t}$ | 0.024 | 0.590 | -0.982 | 7.875 | (290.149)*** | (-13.365)*** |
| | 252 | CSSD | 0.808 | 0.265 | 0.053 | 4.922 | (38.936)*** | (-8.982)*** |
| HK | 260 | $R_{m,t}$ | 0.033 | 0.437 | -0.144 | 3.811 | (8.039)*** | (-15.985)*** |
| | 260 | CSSD | 1.114 | 0.343 | -1.054 | 6.426 | (175.319)*** | (-11.461)*** |

Appendix 2 lists descriptive statistics of daily mean, standard deviation, skewness, kurtosis of the CSSD and the $R_{m,t}$ over the year 2012 for the Shanghai A (SHA), Shanghai B (SHB), Shenzhen A (SZA), Shenzhen B (SZB), and the Hong Kong (HK) markets. In addition, the Jarque-Bera test for normality and the Augmented Dicky-Fuller test for stationary are reported. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels respectively.

## Appendix 3

Descriptive statistics of Cross Sectional Standard Deviation (CSSD) and average Market Return ($R_{m,t}$)

Period: 2013

| Market | No. obs. | Variable | Mean | Std. dev. | Skewness | Kurtosis | Jarque-Bera | ADF |
|---|---|---|---|---|---|---|---|---|
| SHA | 244 | $R_{m,t}$ | 0.015 | 0.575 | -0.936 | 5.508 | (99.638)*** | (-14.685)*** |
| | 244 | CSSD | 0.915 | 0.211 | -1.221 | 10.209 | (589.070)*** | (-10.161)*** |
| SHB | 238 | $R_{m,t}$ | 0.036 | 0.585 | -0.474 | 5.546 | (73.220)*** | (-15.124)*** |
| | 238 | CSSD | 0.716 | 0.259 | 5.124 | 52.905 | (25739.160)*** | (-8.031)*** |
| SZA | 241 | $R_{m,t}$ | 0.039 | 0.619 | -0.947 | 5.304 | (89.350)*** | (-15.094)*** |
| | 241 | CSSD | 1.001 | 0.298 | 6.429 | 78.773 | (59316.380)*** | (-15.221)*** |
| SZB | 248 | $R_{m,t}$ | 0.041 | 0.511 | -0.214 | 5.777 | (81.596)*** | (-14.816)*** |
| | 248 | CSSD | 0.719 | 0.212 | -0.565 | 5.024 | (55.539)*** | (-11.133)*** |
| HK | 260 | $R_{m,t}$ | 0.026 | 0.404 | -0.477 | 4.819 | (45.763)*** | (-14.744)*** |
| | 260 | CSSD | 1.095 | 0.354 | -1.035 | 6.603 | (187.197)*** | (-12.223)*** |

Appendix 3 lists descriptive statistics of daily mean, standard deviation, skewness, kurtosis of the CSSD and the $R_{m,t}$ over the year 2013 for the Shanghai A (SHA), Shanghai B (SHB), Shenzhen A (SZA), Shenzhen B (SZB), and the Hong Kong (HK) markets. In addition, the Jarque-Bera test for normality and the Augmented Dicky-Fuller test for stationary are reported. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels respectively.

## Appendix 4

Descriptive statistics of Cross Sectional Standard Deviation (CSSD) and average Market Return ($R_{m,t}$)

Period: 2014

| Market | No. obs. | Variable | Mean | Std. dev. | Skewness | Kurtosis | Jarque-Bera | ADF |
|---|---|---|---|---|---|---|---|---|
| SHA | 245 | $R_{m,t}$ | 0.060 | 0.505 | -0.778 | 4.314 | (42.401)*** | (-15.007)*** |
| | 245 | CSSD | 0.919 | 0.241 | 4.543 | 38.715 | )13864.410)*** | (-6.822)*** |
| SHB | 245 | $R_{m,t}$ | 0.030 | 0.336 | -0.565 | 5.394 | (71.548)*** | (-14.750)*** |
| | 245 | CSSD | 0.596 | 0.170 | 0,959968 | 4.154 | (51.242)*** | (-6.901)*** |
| SZA | 245 | $R_{m,t}$ | 0.052 | 0.558 | -1.030 | 4.748 | (74.609)*** | (-14.430)*** |
| | 245 | CSSD | 0.961 | 0.166 | 1.526 | 6.601 | (227.557)*** | (-8.462)*** |
| SZB | 253 | $R_{m,t}$ | 0.026 | 0.302 | -0.840 | 5.417 | (91.339)*** | (-16.250)*** |
| | 253 | CSSD | 0.654 | 0.196 | -0.001 | 3.899 | (8.531)*** | (-13.392)*** |
| HK | 259 | $R_{m,t}$ | 0.004 | 0.329 | -0.557 | 3.553 | (16.720)*** | (-10.233)*** |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 259 | CSSD | 1.082 | 0.388 | 1.088 | 13.844 | (1320.294)*** | (-13.485)*** |

Appendix 4 lists descriptive statistics of daily mean, standard deviation, skewness, kurtosis of the CSSD and the $R_{m,t}$ over the year 2014 for the Shanghai A (SHA), Shanghai B (SHB), Shenzhen A (SZA), Shenzhen B (SZB), and the Hong Kong (HK) markets. In addition, the Jarque-Bera test for normality and the Augmented Dicky-Fuller test for stationary are reported. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels respectively.

**Appendix 5**

Descriptive statistics of Cross Sectional Standard Deviation (CSSD) and average Market Return ($R_{m,t}$)

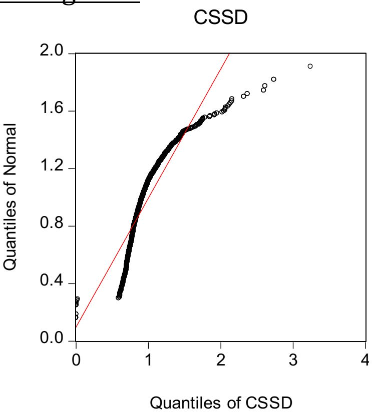
Period: 2015

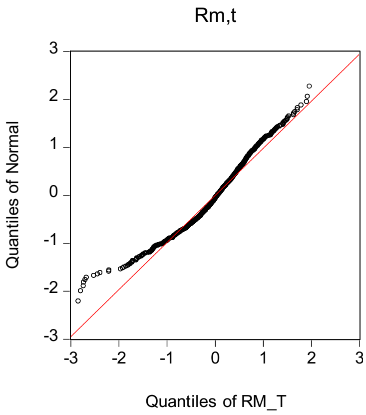
| Market | No. obs. | Variable | Mean | Std. dev. | Skewness | Kurtosis | Jarque-Bera | ADF |
|---|---|---|---|---|---|---|---|---|
| SHA | 248 | $R_{m,t}$ | 0.051 | 1.290 | -0.854 | 4.193 | (44.922)*** | (-12.229)*** |
| | 248 | CSSD | 1.286 | 0.401 | 0.479 | 4.818 | (43.678)*** | (-3.022)** |
| SHB | 244 | $R_{m,t}$ | 0.087 | 1.300 | -0.683 | 4.983 | (58.999)*** | (-11.366)*** |
| | 244 | CSSD | 0.932 | 0.369 | 0.963 | 4.135 | (50.838)*** | (-4.555)*** |
| SZA | 245 | $R_{m,t}$ | 0.085 | 1.237 | -0.886 | 3.931 | (40.932)*** | (-12.092)*** |
| | 245 | CSSD | 1.410 | 0.430 | 1.680 | 10.173 | (640.660)*** | (-3.481)*** |
| SZB | 248 | $R_{m,t}$ | 0.059 | 1.045 | -0.662 | 5.806 | (99.534)*** | (-11.145)*** |
| | 248 | CSSD | 0.955 | 0.398 | 0.889 | 3.964 | (42.300)*** | (-3.401)** |
| HK | 257 | $R_{m,t}$ | -0.006 | 0.805 | 0.411 | 13.705 | (1234.533)*** | (-12.866)*** |
| | 257 | CSSD | 1.193 | 0.504 | 1.813 | 14.210 | (1486.649)*** | (-5.276)*** |

Appendix 5 lists descriptive statistics of daily mean, standard deviation, skewness, kurtosis of the CSSD and the $R_{m,t}$ over the year 2015 for the Shanghai A (SHA), Shanghai B (SHB), Shenzhen A (SZA), Shenzhen B (SZB), and the Hong Kong (HK) markets. In addition, the Jarque-Bera test for normality and the Augmented Dicky-Fuller test for stationary are reported. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels respectively.

## Appendix 6

### Shanghai A

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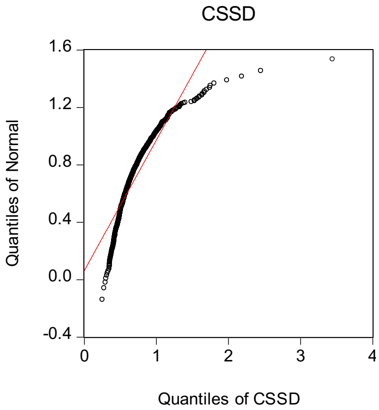


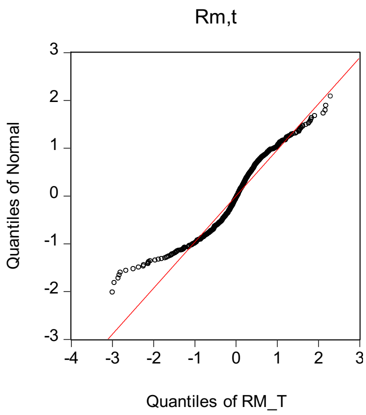


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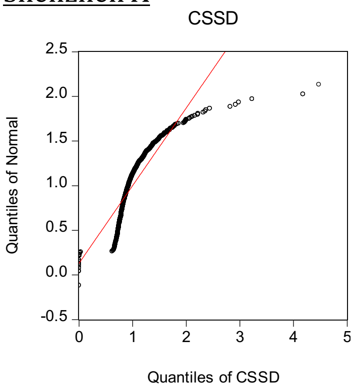
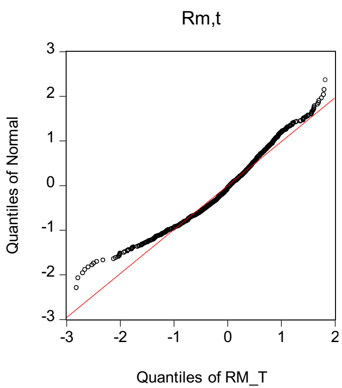
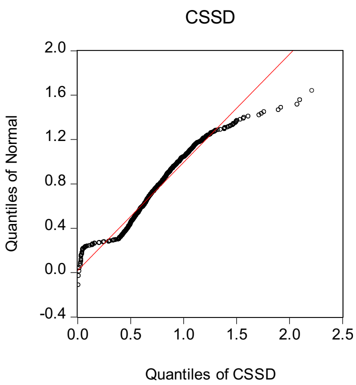
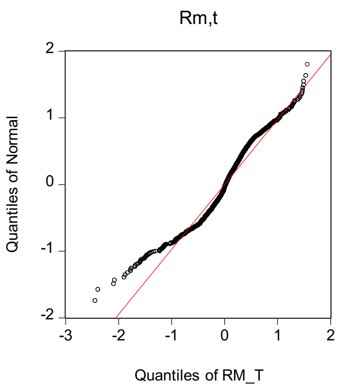


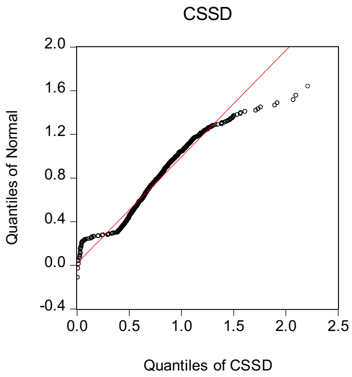



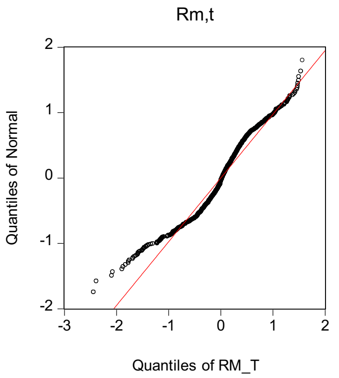

### Shenzhen B



## Hong Kong




Appendix 6: QQ-plots of the Cross-Sectional Standard Deviation (CSSD) and the average market return ($R_{m,t}$). The quantiles of the CSSD and the $R_{m,t}$ are plotted against the quantile values of normality for the Shanghai A-share (SHA), the Shanghai B-share (SHB), the Shenzhen A-share (SZA), the Shenzhen B-share (SZB), and the Hong Kong (HK) market. The red line is the line of normality.

**Appendix 7**
Autocorrelation of the Cross-Sectional Standard Deviation (CSSD) and the average market return ($R_{m,t}$)
<u>Period 1/1/2011 – 31/12/2015</u>

| Market | Variable | 1 lag | 2 lags | 5 lags | 20 lags |
|---|---|---|---|---|---|
| SHA | $R_{m,t}$ | (0.155)*** | (-0.037)*** | (0.055)*** | (0.027)*** |
| | CSSD | (0.656)*** | (0.573)*** | (0.509)*** | (0.439)*** |
| SHB | $R_{m,t}$ | (0.156)*** | (-0.073)*** | (0.079)*** | (0.076)*** |
| | CSSD | (0.584)*** | (0.523)*** | (0.428)*** | (0.350)*** |
| SZA | $R_{m,t}$ | (0.157)*** | (-0.026)*** | (0.060)*** | (0.015)*** |
| | CSSD | (0.551)*** | (0.492)*** | (0.478)*** | (0.451)*** |
| SZB | $R_{m,t}$ | (0.188)*** | (-0.043)*** | (0.051)*** | (0.089)*** |
| | CSSD | (0.558)*** | (0.438)*** | (0.348)*** | (0.261)*** |
| HK | $R_{m,t}$ | (0.145)*** | (0.061)*** | (0.005)*** | (0.056)*** |
| | CSSD | (0.343)*** | (0.228)*** | (0.103)*** | (0.055)*** |

Appendix 7 lists the descriptive statistics of the autocorrelation (serial correlation) of the CSSD and the $R_{m,t}$ over the total sample period for the Shanghai A (SHA), Shanghai B (SHB), Shenzhen A (SZA), Shenzhen B (SZB), and the Hong Kong (HK) markets. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels respectively.

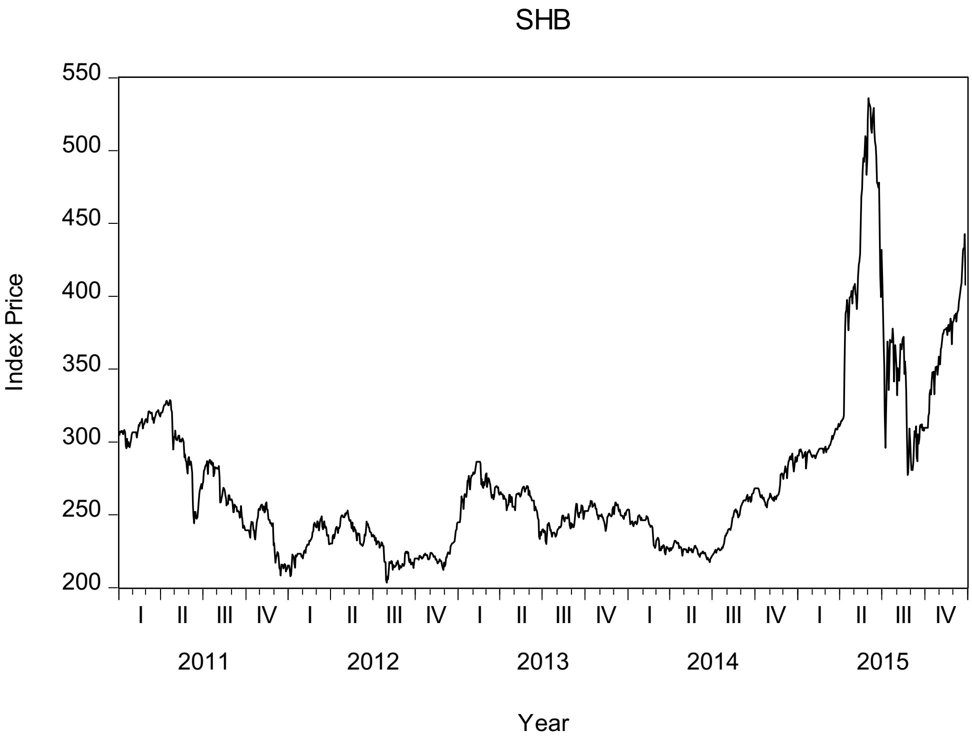
**Appendix 8**
Test for of Heteroscedasticity with the White test
Period: 1/1/2011 - 31/12/2015

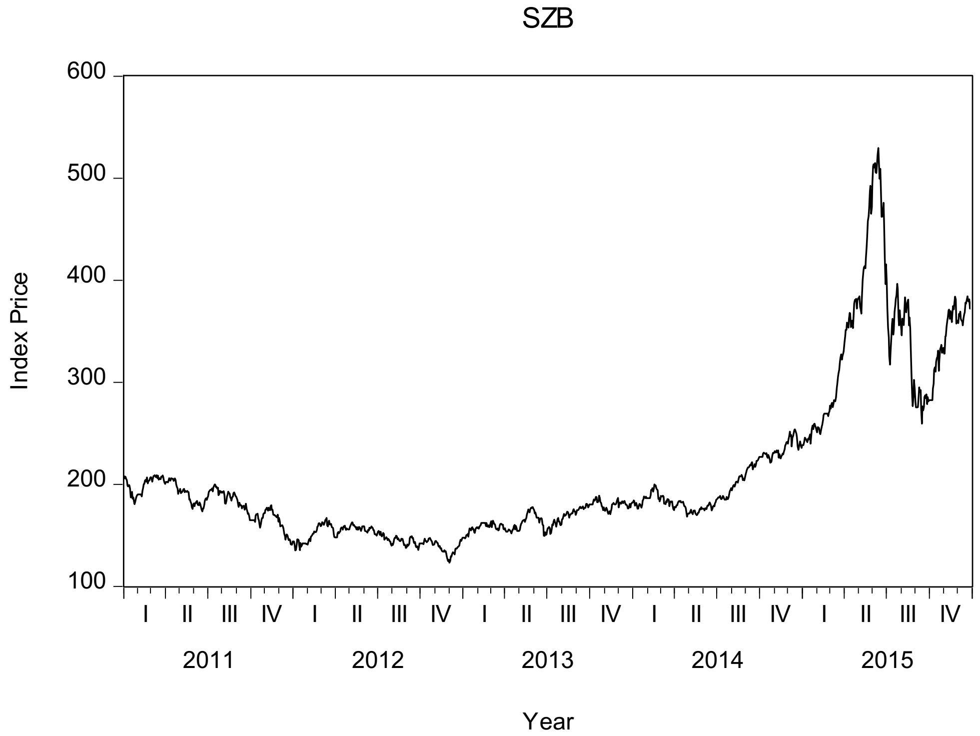
| | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| F-statistic | (10.647)*** | (10.454)*** | (5.149)*** | (3.629)*** | (1.742)* |

Appendix 8 lists the descriptive statistics of the test for Heteroscedasticity using the White test over the total sample period for the Shanghai A (SHA), Shanghai B (SHB), Shenzhen A (SZA), Shenzhen B (SZB), and the Hong Kong (HK) markets. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels respectively.

**Appendix 9**


SHA
900
800
700
600
500
400
300
Index Price
I II III IV I II III IV I II III IV I II III IV I II III IV
2011
2012
2013
2014
2015
Year


SHB
550
500
450
400
350
300
250
200
Index Price
I II III IV I II III IV I II III IV I II III IV I II III IV
2011
2012
2013
2014
2015
Year


Appendix 9: plot of the Shanghai A-share (SHA), Shanghai B-share (SHB), Shenzhen A-share (SZA) and Shenzhen B-share (SZB) markets. The charts represent the price evolution of the market index.

**Appendix 10**


Appendix 10: plot of the Hong Kong (HK) market price index. The chart represents the price evolution of the market index over the total sample period.

**Appendix 11**

Analysis of the change in herd behavior in the Hong Kong market in April 2015

*Panel A: regression results under modified model Eq. (7)*

| Period | 1/1/2011 - 7/4/2015 | 1/1/2011 - 8/4/2015 |
|---|---|---|
| $\alpha$ | 0,666 | 0,687 |
| | *(0.000)* | *(0.000)* |
| $y_1$ | 0,592 | 0,539 |
| | *(0.000)* | *(0.000)* |
| $y_2$ | -0,113 | -0,066 |
| | *(0,002)* | *(0,135)* |
| $y_3$ | 0,234 | 0,222 |
| | *(0.000)* | *(0.000)* |
| Adjusted $R^2$ | 0,251 | 0,256 |

*Panel B: regression results under modified model Eq. (7)*

| Period | 1/1/2011 - 7/4/2015 | 8/4/2015 - 31/12/2015 |
|---|---|---|
| $\alpha$ | 0,666 | 0,808 |

| | | |
|---|---|---|
| | *(0.000)* | *(0.000)* |
| $y_1$ | 0,592 | 0,300 |
| | *(0.000)* | *(0.000)* |
| $y_2$ | -0,113 | 0,059 |
| | *(0.002)* | *(0.002)* |
| $y_3$ | 0,234 | 0,184 |
| | *(0.000)* | *(0.005)* |
| Adjusted $R^2$ | 0,251 | 0,562 |

Appendix 11 reports the coefficients and the adjusted $R^2$ of the following regression model for the Hong Kong H-share (HK) market: $CSSD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2 + \gamma_3 CSSD_{t-1} + \varepsilon_t$
where $R_{m,t}$ is the equal-weighted average portfolio return at time *t.* $CSSD_t$ is the cross sectional standard deviation, and $CSSD_{t-1}$ is the 1-day lag of the dependent variable ($CSSD_t$). The sample period is from 1/1/2011 to 7/4/2015 and 1/1/2011 to 8/4/2015 in Panel A; and 1/1/2011 to 7/4/2015 and 8/4/2015 to 31/12/2015 in panel B. Numbers in parentheses are the power of the coefficients based on Newey & West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. *(0.01), (0.05),* and *(0.1)* represent statistical significance at the 1%, 5%, and 10% levels respectively.

**Appendix 12**

Analysis of herd behavior in Hong Kong stock markets, after removal of 1% outliers

Period: 1/1/2011 - 31/12/2015

*Regression results under modified model Eq. (7)*

| Year | 2011 | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|---|
| $\alpha$ | 0.578 | 0.585 | 0.633 | 0.688 | 0.640 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.733 | 0.822 | 1.038 | 1.497 | 0.566 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.012)* |
| $y_2$ | -0.236 | -0.406 | -0.551 | -1.246 | -0.120 |
| | *(0.083)* | *(0.030)* | *(0.000)* | *(0.002)* | *(0.414)* |
| $y_3$ | 0.238 | 0.298 | 0.226 | 0.135 | 0.268 |
| | *(0.002)* | *(0.000)* | *(0.006)* | *(0.010)* | *(0.002)* |
| Adjusted $R^2$ | 0.318 | 0.227 | 0.239 | 0.146 | 0.272 |

Appendix 12 reports the coefficients and the adjusted $R^2$ of the following regression model for the Hong Kong H-share (HK) market: $CSSD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2 + \gamma_3 CSSD_{t-1} + \varepsilon_t$
where $R_{m,t}$ is the equal-weighted average portfolio return at time *t.* $CSSD_t$ is the cross sectional standard deviation, and $CSSD_{t-1}$ is the 1-day lag of the dependent variable ($CSSD_t$). The sample period is from 1/1/2011 to 31/12/2015. The regression is performed after removal of the 1% outliers on both sides of the distribution. Numbers in parentheses are the power of the coefficients based on Newey & West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. *(0.01), (0.05),* and *(0.1)* represent statistical significance at the 1%, 5%, and 10% levels respectively.

**Appendix 13**

Analysis of herd behavior in Chinese stock markets

Period 1/1/2011 - 31/12/2013

*Regression results under modified model*

| Market | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| $\alpha$ | 0.568 | 0.451 | 0.657 | 0.394 | 0.633 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.034 | 0.160 | 0.112 | 0.325 | 0.564 |
| | (0.517) | *(0.000)* | (0.126) | *(0.000)* | *(0.000)* |
| $y_2$ | 0.064 | 0.006 | 0.028 | -0.043 | -0.099 |
| | *(0.031)* | *(0.534)* | *(0.426)* | *(0.563)* | *(0.006)* |
| $y_3$ | 0.304 | 0.230 | 0.203 | 0.334 | 0.263 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| Adjusted $R^2$ | 0.174 | 0.212 | 0.107 | 0.361 | 0.299 |

Appendix 13 reports the coefficients and the adjusted $R^2$ of the following regression model for the Shanghai A-share (SHA), Shanghai B-share (SHB), Shenzhen A-share (SZA), Shenzhen B-share (SZB), and the Hong Kong H-share (HK) markets: $CSSD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \gamma_3 CSSD_{t-1} + \varepsilon_t$
where $R_{m,t}$ is the equal-weighted average portfolio return at time *t*. $CSSD_t$ is the cross sectional standard deviation, and $CSSD_{t-1}$ is the 1-day lag of the dependent variable ($CSSD_t$). The sample period is from 1/1/2011 to 31/12/2013. Numbers in parentheses are the power of the coefficients based on Newey & West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. *(0.01), (0.05),* and *(0.1)* represent statistical significance at the 1%, 5%, and 10% levels respectively.

**Appendix 14**
Analysis of the effects of the June - October stock market crisis
Period 1/1/2011 - 31/12/2015

*Regression results under modified model*

| Market | SHA | SHB | SZA | SZB | HK |
|---|---|---|---|---|---|
| $\alpha$ | 0.444 | 0.348 | 0.567 | 0.382 | 0.711 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_1$ | 0.132 | 0.202 | 0.143 | 0.302 | 0.398 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_2$ | 0.003 | -0.006 | 0.014 | -0.012 | 0.022 |
| | (0.838) | (0.469) | (0.410) | (0.390) | (0.388) |
| $y_3$ | 0.450 | 0.366 | 0.335 | 0.349 | 0.228 |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* |
| $y_4$ | 0.212 | 0.081 | 0.326 | 0.059 | -0.042 |
| | (0.000) | *(0.000)* | (0.439) | (0.069) | (0.228) |
| Adjusted $R^2$ | 0.524 | 0.504 | 0.524 | 0.516 | 0.337 |

Appendix 14 reports the coefficients and the adjusted $R^2$ of the following regression model for the Shanghai A-share (SHA), Shanghai B-share (SHB), Shenzhen A-share (SZA), Shenzhen B-share (SZB), and the Hong Kong H-share (HK) markets; $CSSD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \gamma_3 CSSD_{t-1} + \varepsilon_t + \gamma_4 DM_t R_{m,t}^2 + \varepsilon_t$
where $R_{m,t}$ is the equal-weighted average portfolio return during period *t*. $CSSD_t$ is the cross sectional standard deviation, and $CSSD_{t-1}$ is the 1-day lag of the dependent variable ($CSSD_t$). $DM_t$ is the dummy variable that takes the value of unity between 12/6/2015 and 2/10/2015 and zero otherwise. The sample period is from 1/1/2011 to 31/12/2015. Numbers in parentheses are the power of the coefficients based on Newey & West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. *(0.01), (0.05),* and *(0.1)* represent statistical significance at the 1%, 5%, and 10% levels respectively.