UNIVERSITY OF VAASA

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HERDING BEHAVIOR AND MARKET OVERREACTION IN CHINESE STOCK MARKET

Evidence from China 2007-2018

Master's Thesis in

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ABREVIATIONS

CAPM	Capital Asset Pricing Model
CBOE	Chicago Board Options Exchange
CSAD	Cross Sectional Absolute Deviation
CSSD	Cross Sectional Standard Deviation
EMH	Efficient Market Hypothesis
P/E	Price-to-Earnings
SE	Stock Exchange
SHA	Shanghai A-share
SHB	Shanghai B-share
SIC	Standard Industrial Classification
SML	Security Market Line
SZA	Shenzhen A-share
SZB	Shenzhen B-share

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ABSTRACT

The Chinese stock market is one of the largest and most liquid markets in the world, but it is also highly volatile. One of the main reasons for the high volatility is the large portion of individual investors in the market. Unlike in other major markets, the Chinese stock market is dominated by individual investors and not by institutional investors. When compared to the institutional investors, individual investors tend to prefer short-term trading strategies and react easily during times of high market volatility.

The purpose of this study is to identify whether the market-wide herding behavior has been present in the Chinese stock markets in 2007 - 2018. The study will also try to examine the reasons behind the phenomena and observe how and when the herding behavior occurs.

The CSAD (cross-sectional absolute deviation) method developed by Christie & Huang (1995) is used to detect market-wide herding. The studied sample includes 2766 observations from the review period (2008-2017) for 821 Shanghai A-share firms, 51 Shanghai B-share firms, 570 Shenzhen A-share firms and 52 Shenzhen B-share firms.

The results indicate that the market-wide herding behavior is present in the Chinese stock market. The results suggest that the investors herd around A-shares during periods of high market stress. There is also significant evidence that the herding behavior varies between different industries and time periods.

The differences in presence of herding behavior between A and B-shares indicate that the different investor base and experience in investing has an influence on the existence of herding behavior between the share classes.

Keywords: Herding behavior, Market-wide herding, Cross-sectional absolute deviation, Behavioral finance, Chinese stock market, Shanghai stock exchange, Shenzhen stock exchange

1. INTRODUCTION

"It is impossible to produce superior performance unless you do something different from the majority" (Sir John Templeton).

Individual people make often decisions based on what others think. Peer pressure and other peoples' opinions may have a strong effect on the way we think. Similar process of decision making can be applicable to the financial markets. Investors are often wondering whether it is a right time to sell the stock or not. In many cases, investors like to observe the behavior of their colleagues, imitate them or follow the direction of the market. Such behavior where people like to follow the example of others is called herding behavior. It is very important to understand this kind of psychological behavior because it can have a powerful effect on market, especially in less development countries.

The herding behavior on the financial markets can lead to significant mispricing of the assets. Investors may herd and rush to buy a security whose fundamentals do not really support the price of A-share or an asset. Respectively, during the bear market, investors may sell their investments in panic and forget the value of the security. The most famous instrument associated with herd behavior during this decade is Bitcoin. Bitcoin has been seen as the most unprecedented global economic bubble and pyramid scam since the tulip mania in 17th century. The valuation of bitcoin is speculative because it has no real economic basis and very few practical applications. Despite the speculative nature of bitcoin, its value rose to nearly $20,000, before starting to decline in in 2018. (Poyser 2018.)

During the summer and early fall of 2015, the headlines of the financial press were covered about news concerning the Chinese stock markets. The Chinese stock exchanges in Shanghai and Shenzhen had experienced their latest and largest drops measured by market capitalization. In just few months Shanghai Stock Exchange lost over 30 percent and Shenzhen Stock Exchange over 35 percent of its total value. Estimated losses for investors were over $3.5 trillion. (Lleo & Ziemba 2015; World Federation of Exchanges 2016; U.S.-China Economic Review Commission 2015.)

The effects of Chinese stock market crash remained quite limited due to the small number of foreign investors in the market. The impact on domestic consumption was also limited since only 15 percent of household funds are invested on the stock market. Nevertheless, the rapid drop in share prices was enough to scare investors around the world and raised concerns about the efficiency of Chinese stock markets and overall economic fundamentals. (U.S.-China Economic Review Commission 2015.)

The stock crash on Chinese stock markets showed in a horrible way what kind of destruction panic can cause when it hits the investors. Some investors had used debt leverage to buy stocks and when stock prices began to fall, the investors faced margin calls and many were forced to sell off their shares in a lower price and in hurry, which precipitated the crash. (Bendini 2015.)

There are two different views which describe the investment behavior in financial markets. These views are called the traditional and behavioral finance views. The traditional view is based on efficient market hypothesis (EMH) and its applications which were developed by Eugene Fama in 1970.

According to the Fama's (1970) famous theory, market is defined as efficient if prices always fully reflect all available information. Theory is based on assumptions about investor rationality and arbitrage. The behavioral view is more focused on investor psychology and limits to arbitrage. (Barberis & Thaler 2003.)

It has been stated by academics that behavioral finance has originally been developed as response for different psychology related anomalies which are not explained by traditional finance models. After several stock crashes and financial crises, the influence of human psychology has been recognized as an important part of the investment decision making process. Many of the behavioral finance related studies have focused on the fact that humans tend to imitate the actions of their peers. (De Bondt, Muradoglu, Shefrin & Staikouras 2008.)

Nowadays, the common opinion is that the herding behavior can be strongly linked to different kind of crises and crashes. The existence of investor herds is also one frequently used explanation for the volatility of stock returns. (Christie & Huang 1995.) Researchers have also often expressed their concern that herding behavior by market participants can destabilize markets, inflate bubbles, and can therefore, lead to serious meltdowns on markets. (Xu, Jiang, Chan & Wu 2016.)

The size, volatility and significant share of individual investors combined to large differences in experience and availability of information make the Chinese stock markets interesting object to focus on this study.

1.1. Research Hypothesis

The purpose of the study is to examine whether herding behavior exists on Chinese stock markets, compare which share class experiences herding and measure if possible herding has been stronger during periods of extreme market movements. The objective is also to reflect the causes that make the herding behavior exist in Chinese stock market.

The intended contribution of the study is to provide results that can add value to previous studies. The examination of the newest data should also help us to understand current situation on Chinese stock market. The situation in financial markets around the world and the significance of China provides us with an interesting basis for research.

In order to reach the objectives, the following hypotheses are formed:

H1: Herding behavior exists in Chinese stock market

H2: Herding behavior is linked to investor structure and share classes

H3: Herding behavior is stronger during extraordinary market conditions

2. LITERATURE REVIEW

2.1. The Efficient Market Hypothesis

An efficient market hypothesis is an idea often associated with neoclassical economics and especially finance related research, that financial markets are an effective tool for channeling capital to the most profitable investments. Economist Eugene Fama's article Random Walks in Stock Market Prices (1965), played an important role in raising the idea of an efficient market for the mainstream of financial research.

The hypothesis and forms of market efficiency are based on theories about investor rationality and arbitrage. According to EMH, the prices quoted for the securities in the markets at any given time reliably reflect the actual value of the securities and their potential future returns. This is possible if investors are thought to always have up-to-date information on the content and risks of each security. The EMH also presumes that investors who are participating financial markets are rational utility maximizers. Even if some investors act in irrational ways, the effects of their trades should be invalidated by the effects of other irrational investors. If the effects of irrational investors reach markets, the arbitrageurs should eliminate their impact on prices. (Fama 1970; Shleifer 2000.)

There are three forms of market efficiency: weak, semi-strong and strong. The weak form of EMH assumes that the prices reflect all historical information. The semi-strong form speculates that the prices are based on all publicly available information. The third and strongest form of hypothesis presumes that prices reflect all information including the private information which is yet to reach the markets. (Fama 1970.)

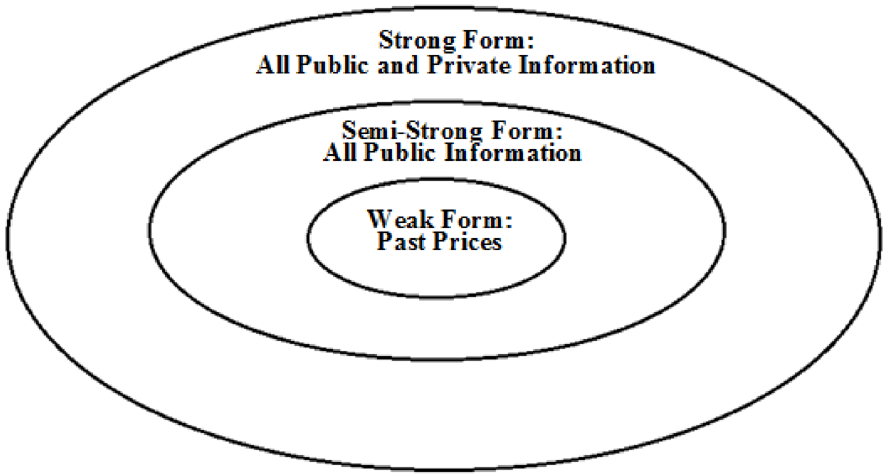


Figure 1: Three forms of Efficient Market Hypothesis: weak, semi-strong and strong (Fama 1970).

The first and lowest level in EMH categorization is the level of weak market efficiency. In this form the markets use all past information in pricing of stocks, commodities and other assets. This implies that investors shouldn't be able to utilize any trading models or price patterns based on historical information to earn abnormal returns. (Poshakvale 1996.)

The second level of EMH states that in addition to past pricing the prices also reflect all publicly available information. This level of efficiency is called semi-strong. According to semi-strong level of market efficiency, the investors are able to use all historical information and all public information in pricing as soon as it's made available. Public information includes for example earnings statements, company news and stock issues. (Brealey, Myers & Allen 2011.)

The third and last level of market efficiency is called the strong form. In the state of strong market efficiency, prices reflect all information. That includes all information that can be acquired about company and economy overall. Depending on investor's personal skills, he or she should be able to make the necessary analysis and win the market in at least some occasion. (Brealey, Myers & Allen 2011.)

For a long time, the EMH was considered to be the core of the rational market theory. EMH was and still is largely used as a basic framework while modeling the behavior of stock markets. It creates a base for different kinds of analyses and rationalizes the mechanisms of stock markets. However, during the last decades researchers have started to recognize that there are also psychological and sociological factors that influence investors' investing behavior. Since 1970, researchers have found multiple anomalies that violate the principles of neoclassical finance and EMH. For example, momentum and contrarian strategies as well as diversification and indexing, all violate the principles of efficient market theory. (Fama 1991; Wang, Shi & Fan 2006)

Researchers have started to understand that investors are not solely bounded by rationality as the EMH and classical finance theories have previously assumed. In 1986, Simon (1986) argued investor irrationality may be caused by fundamental limitations in humans' information processing capabilities. Also, Kahneman and Tverksy (1982) had already earlier suspected that humans have tendency to use heuristic shortcuts in order to avoid the burden of complex processing. One of the non-rational psychological phenomena's behind investors' behavior is the herding effect.

2.3.1. Security Market Line and Capital Asset Pricing Model

The financial markets provide opportunities to invest in either risky or risk-free destinations. In the case of a risk-free investment, the investor already knows the return at the time of the investment. On the other hand, there is no information about the returns on risky investments at the time of the investment. However, the investor has expectations about the return and the deviation from the expected return is the risk of the investment. (Malkamäki & Martikainen 1989.) The security market line displays the expected rate of return of an individual security as a function of systematic risk which cannot be diversified.

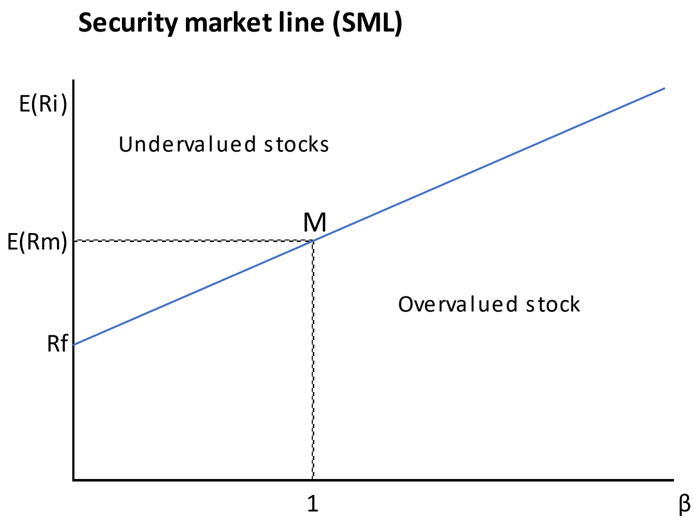


Figure 2: Security market line presents the correlation between the expected return and systematic risk (Sharpe 1964).

Capital Asset Pricing Model (CAPM) developed by economists Jack Treynor (1962), William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966) is a pricing model used to calculate the expected return for a security. It has been built on the portfolio theory model developed by Harry Markowitz (1952). The model describes the trade-off between the risk and return. According to the model, the expected return is obtained by adding the average risk premium of the market multiplied by the company-specific beta to the risk-free interest rate. In the model, beta represents systematic risk related to an individual stock in comparison for the market. (Treynor 1962; Sharpe 1964; Lintner 1965; Mossin 1966.)

The model indicates the long-term average return that investors demand for the security. Volatility may cause deviations from the expected returns in the short and medium term, but according to the theory, in the long term, the return on the model should be on average the same as the real return. (Treynor 1962; Sharpe 1964; Lintner 1965; Mossin 1966.) The formula of the CAPM is as follows:

$$(1) \qquad E(r_i) = r_f + \beta_i \, [r_m - r_f]$$

Where, $E(r_i)$ is the expected return on a security, r_f is the risk-free interest rate, β_i is the beta of the security and r_m is the expected market return.

In short, according to CAPM, the risk and return expectations for the investment go hand in hand. By diversifying investments, it is possible to lower unsystematic risk related to individual securities.

2.3.2. EMH and Behavioral Finance

It is commonly known, that to work, the efficient market hypothesis usually needs two assumptions to be true. These two assumptions are that the price changes are nearly random (there are no detectable trends) and the prices reflect market fundamentals. (Delcey 2017.)

As we all know, both of the assumptions mentioned above are not exactly true or accurate in real life. This is why the efficient market hypothesis and traditional asset pricing models, like CAPM, are not able to predict development of stock prices accurately.

One of the reasons why the assumptions do not come true is human mind and human behavior in particular. Behavioral economics is a line of study in economics that studies the impact of psychological, social, cognitive, and emotional factors on the economic decision-making of people and institutions, and their consequences for the market and the allocation of resources. (Kahneman & Tversky 1979; Thaler 1993.)

Behavioral finance is a closely related research field that seeks to provide psychological and cognitive explanations for various anomalies in the financial markets. The behavioral finance framework considers the fact that a human being is not capable of completely rational decision-making process. Contrary to the mainstream theories of academic finance research and the School of Market Efficiency, behavioral finance sees that, despite the rational efforts of investors, their rationality is limited at best. (De Bondt, Muradoglu, Shefrin & Staikouras 2008.)

The traditional asset pricing models presume that investors are rational utility maximizers. According to behavioral finance, even if one tries to act "rationally" and in accordance with the traditional financial theory, from the point of view of behavioral financing, however, investors' behavior and thinking are guided by different cognitions and emotions. Therefore, instead of studying irrationality, the behavioral finance is typically more interested in the limits of rational decision-making by economic operators and how different heuristics and cognitive skewers affect investor decision-making. (Kahneman & Tversky 1979; Thaler 1993; Hirshleifer 2001.)

Behavioral finance recognizes the role of a human in the asset pricing and market movements. Humans are often prone to irrational psychological biases, such as overconfidence, anchoring, loss aversion, mental accounting and over & under-reaction.

This study concentrates on how people behave irrationally by mimicking other people and copying their investment decisions. In behavioral finance, this phenomenon is called herding behavior.

2.3. Herding Behavior in Financial Markets

In 1995 Thomas Lux found out that stock prices usually experience more volatility than what is expected based on market conditions or fundamentals. The unexplained volatility raised questions about the efficiency of the stock market (Lux 1995). Phenomenon has usually been explained as an outcome of investor herding in the financial market (Christie & Huang 1995).

Herding is seen as irrational investing behavior which usually increases in low information cost environment. Banerjee (1992) defines herding as following “everyone doing what everyone else is doing, even when their information suggests doing something different”. In other words, individual people like to imitate the actions of others. Actions might be rational or irrational, though usually even herding towards rational direction leads to overreaction, and therefore, to inaccurate valuation of assets. (Fu & Lin 2010.)

Often, after a financial crisis there is an increased interest in the existence of herding behavior. Some of the scholars even argue widespread herding might have contributed to the births of financial crises. (Chari & Kehoe 2004.) Economists and researchers believe that market-wide herding occurs in financial markets (Devenow & Welch 1996).

Theoretical models of herding behavior have been developed by Bikhchandani, Hirshleifer & Welch (1992), Scharfstein & Stein (1990) and Devenow & Welch (1996) but the most notable papers are probably made by Christie & Huang (1995) and Chang, Cheng & Khorana (2000). Their papers have paved the way for the behavioral approach and modern herding research.

The most notable Finnish researchers in the area of herding behavior are Kultti and Miettinen (2006). They developed a decision model which links the cost of the information about their predecessors’ actions and the signals that agents use in their decision making. They reason that if investors face financial panic, they may not have enough time to collect and analyze information and end up acting in panic. In other words, they expose themselves to herding behavior.

The Chinese stock market provides an interesting base for research. The growing rate of Chinese economy has been very high for years and the amount of citizens’ wealth has grown with the economy. The development of the Chinese financial system has also been quite fast. Monetary policy is still under the state rule but is going in a more free and flexible direction.

Government influences decisions concerning industrialism and structural reforms, which has had a positive impact on country's development. (Kolodko 2002.)

In their earlier work, researchers Shleifer and Summers (1990) propose that herding is possible or even likely for individual investors if they follow similar signals, like analyst recommendations. The herding is also possible if they practice positive or negative feedback trading. Institutions, on other hand, are more likely to herd in under-valued stocks, assuming that they are better informed than individual investors. (Bailey, Cai, Cheung & Wang 2006.)

Zheng, Li & Chu (2015) propose that investor herding is stronger on actively traded stock. The effect is stronger if investors are less experienced and have less information. It is common for less sophisticated investors to follow the behavior of their more experienced peers and make actions based on trends. They might prefer to trade towards common trend rather than to act based on information they have processed themselves. The herding behavior tends to be more common and the effect is usually stronger on less advanced markets. The results indicate that this kind of irrational behavior can cause pricing anomalies on short run but the anomalies are likely to adjust on the long run. (Zheng, Li & Zhu 2015.)

Yao, Ma & He (2014) found out that return dispersions are often lower during extreme negative market movements. This indicates that herding behavior is more common during negative surprises than during positive surprises.

2.3.1. Different Forms of Herding Behavior

The herding behavior does not only concern individual people or people who are investing their own savings. The herding behavior might also concern institutional investors, although, the institutional investors are usually more aware about the fundamentals behind the asset prices. (Contreras 2019.)

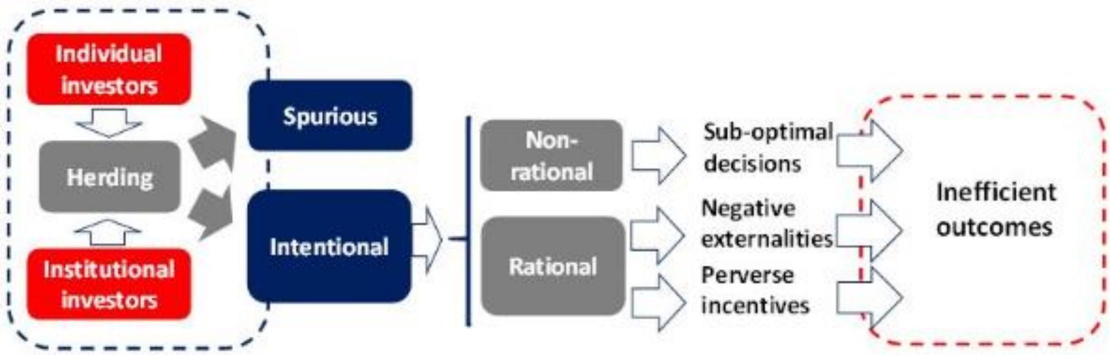


Figure 3: Different forms of herding behavior (Contreras 2019).

Herding behavior can be split into two categories based on the underlying reasons for herding. In spurious herding, the investors react to widely known public information (e.g. Brexit referendum results) and adopt similar investment decision with each other. In intentional herding, the investors make decisions solely based on actions of others, without additional knowledge. In practice, it might be difficult to distinguish one from another. (Bikhchandani & Sharma 2001).

Contreras (2019) presents that the intentional herding can be further divided into non-rational and rational herding. Rational herding refers to situations where the investor does not have perfect information about the true state of the asset or market and deems that it is better to follow the market.

Number of scholars have identified situations where the individual investors and institutional investors might show non-rational herding behavior:

<u>Individual investors</u>

- Sociological factors may drive investors to imitate each other's actions during periods of high market uncertainty (Keynes 1936).

- Investors may place more weight on recent news (Scleifer & Summers 1990).
- Investors like to think that past returns are a good indication of the future (Lakonishok et al. 1994).
- Investors make conjectures based on decisions made by past decisionmakers and ignore the non-salient aspects of their decisions (Hirshleifer 2001; Simonsohn & Ariely 2008).
- Investors have tendency seek comfort or approval from the general market opinion or consensus (Lakonishok et al. 1994; Devenow & Welch 1996).
- Investors tend to sell past winners (assets that have increased in value) and keep losers (assets that have decreased in value) (disposition bias) (Shefrin & Statman 1985).

Institutional investors

- Investors tend to act irrationally based on noise (e.g. news headlines) (Scleifer & Summers 1990).
- Traders tend to follow certain trading strategies (e.g. momentum or contrarian), which are based on past performance. This may lead to overpricing or underpricing of certain assets. (Grinblatt et al. 1995.)
- Investors might ignore their prior opinions and follow other investors without evidence to support their view. This may happen for instance when there is significant information scarcity. (Dedenow & Welch 1996.)

3. SPECIAL CHARACTERISTICS OF CHINESE STOCK MARKET

China, as the most populated and one of the fastest growing economies, has an enormous impact on world economy. Despite its status as an emerging market, China has one of the largest stock markets in world. Mainland China has two separate stock exchanges, the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE). Both exchanges were established in early 90s. (Lee, Li &Wang 2010; Ng & Wu 2006.) At the end of 2015, the combined domestic market capitalization of SSE and SZSE was over USD 8.1 trillion surpassing the Tokyo Stock Exchange by over USD 3 trillion (World Federation of Exchanges 2016).

China’s stock market enjoyed a long bull-market run during 2000-2007 before turning bearish after the financial crisis in 2008. The bull market was short lived and the market has experienced a significant recovery but is still far from the highest peak on 2007. The volatility in Chinese stock markets has been remarkably higher after the crisis compared to the preceding years. Also, the price swings haven’t shown notable correlation to the overall performance of the economy or surprises in other market areas. (KPMG 2011.)

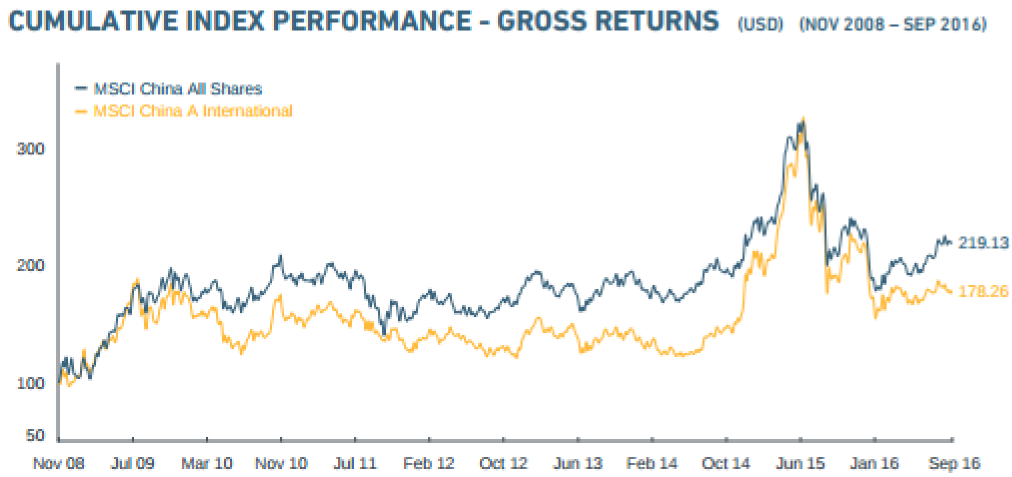


Figure 4: Cumulative performance of MSCI China All Shares Index. The index captures large and mid-cap representation across China A-shares, B-shares, H-shares, Red-chips, and P-chips (MSCI Inc. 2016).

The history has shown that the Chinese stock market has been really volatile during its lifetime. Researchers Lleo & Ziemba (2015) found out that Shanghai Composite Index (SHCOMP) has experienced multiple extreme market movements during the exchanges 25-year-old lifespan. Since the SHCOMP started trading, the index has recorded 26 market movements with cumulative returns over 10 % or more and 24 market movements with losses of 10 % or more. (Lleo & Ziemba 2015.)

3.1. Individual Investors Dominate the Market

Unlike in developed markets, individual investors in China seem to dominate the equity market. At the end of 2014, over 200 million individuals and institutions had an active trading account in China with millions more being opened each month. More than 90 percent of these accounts are owned by individual investors. According to KPMG’s report, individual investors own about 40 percent of China’s tradable stocks by value and are responsible for

60 percent of trading volume (SSE & SSZE combined). (China Depositary and Clearing Corporation 2015; KPMG 2011.)

Demirer and Kutan (2006) question the efficiency of Chinese stock markets in their study. They suspect that less developed components like weak legal framework, heavy government involvement, and strong state ownership on Chinese stock markets could result in more speculative investment behavior. Large portion of individual investor on markets can strengthen the effect.

According to Yao, Ma & He (2014) individual investors are more eager to forget their own beliefs, and instead base their investment decisions on market consensus during periods of extreme market stress. This causes individual stock returns to shuffle near the overall market return. Theory about rational asset pricing models would anticipate increase in return dispersions. Herding behavior biases rational models and distorts returns. (Yao, Ma & He 2014.)

3.2. Two Share Classes and Limitations for Foreign Capital

Apart from rest of the world, Chinese equity markets still face many restrictions with political background. Probably most significant of these is the share classification which divides equity owners to different classes depending of their origin. The two share classes with most significance are A-shares and B-shares. (KPMG 2011.)

A-shares are the most common stock class in Chinese equity market and are listed on Shanghai Stock Exchange or on Shenzen Stock Exchange. A-shares are always denominated in Chinese Renminbi (RMB). Only nationals from mainland China and Qualified Foreign Institutional Investors (QFIIs) are able to trade A-shares. (KPMG 2011; Lleo & Ziemba 2015.)

B-shares are Chinese stocks denominated in foreign currencies but listed on domestic stock exchanges. B-shares on Shanghai Stock Exchange are nominated in US Dollars (USD) whereas B-shares in Shenzen are nominated in Hong Kong Dollars (HKD). Until 2001, the foreign investors were the only ones permitted to trade B-shares but the legislation has changed since, and nowadays it is also possible for domestic citizens. However, only a small portion of domestic investors in China have access to foreign capital. (KPMG 2011; Lleo & Ziemba 2015.)

There are also additional share classes and instruments that foreign investors with interest in Chinese equity market can acquire. H-shares are Chinese stock traded on Hong Kong Stock Exchange and denominated in HKD. L-chips, N-chips and S-chips are share classes for companies with substantial operations in China, but the shares are traded in London, New York or Singapore. (Lleo & Ziemba 2015.)

Although all share classes are actively traded in China, A-shares owned by Chinese nationals and Qualified Foreign Investors continue to have most significance since their number, market capitalization and trading volumes are superior compared to B-shares. (KPMG 2011; Ng & Wu 2006.)

The study from Chen, Kim, Nofsinger & Rui (2007) shows that Chinese investors own less stocks on average compared to Americans but prefer much quicker trading frequency. They find that that between years 1998-2002 average Chinese investors owned stocks of 2.6 companies, whereas U.S. investor hold stocks of 4 companies on average. The Chinese investors are also less-likely to diversify their investments in different companies. (Chen et al. 2007.)

Instead, the Chinese investors seem to be more active in trading stocks. It seems that fast-trading individual investor is the most common investor type on Chinese stock markets. The average monthly turnover ratio for investor in China was 27,3 percent. For the average investor in U.S. the same ratio was only 7,59 percent during same period. Investors in China prefer to buy stocks when the market is rising and to sell when market is falling. Government involvement seems to strengthen the effect. (Chen et al. 2007.)

3.3. Investing Behavior

According to previous studies, investors in developed countries have tendency to simplify their decision-making process when investing. This might stem from brain's aptitude to avoid long and complex process making. Instead, humans are prone to mental shortcuts and usually favor more likeable solutions. Given the rapid development of economy and short history of investing, Chinese investors are probably less experienced and less sophisticated than their counterparties in developed countries, which may make them even more exposed to these cognitive errors. Inexperience combined to these tendencies might in turn lead to irrational decision making and mistakes while investing. (Ng & Wu 2006; Chen et al. 2007.)

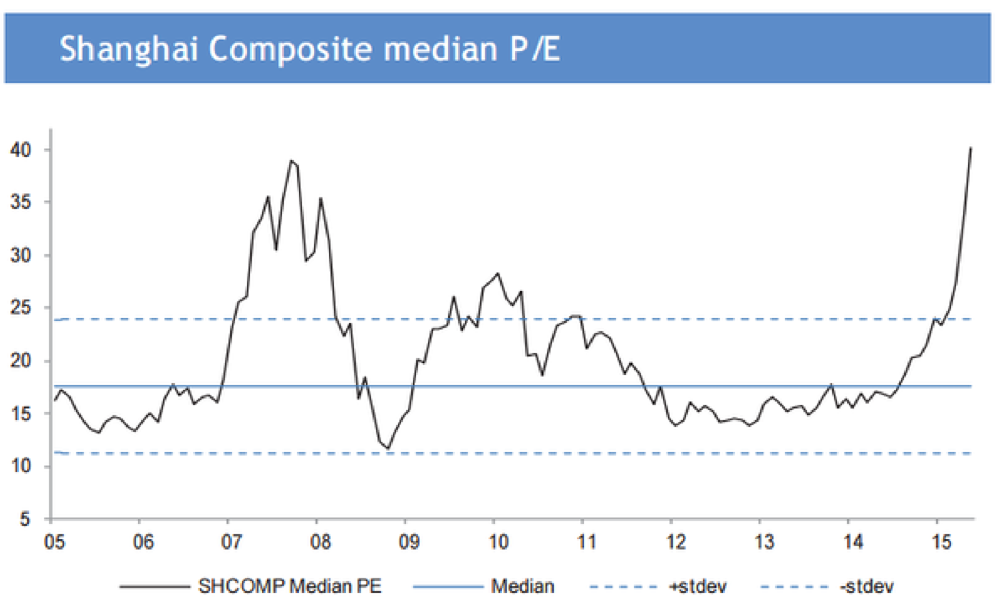


Figure 5: Shanghai Composite Index median P/E 2005-Q1/2016. (Shanghai Stock Exchange 2016).

Consistent with the previous findings, researchers Lee, Li & Wang (2010) find that individual traders respond stronger to return shocks, while response from institutional traders is not so aggressive. They reason that it could be explained by the fact that institutional traders are usually more sophisticated, and therefore do not overreact so easily.

In addition, researchers find that individual investors are often net buyers of stocks during following periods of large market movements, both positive and negative. Moreover, they observe that individual investors also react more strongly to firm-specific announcements. This indicates that individual investors are more easily influenced by one-time and firm-specific events than their institutional peers. (Lee, Li & Wang 2010.)

Lee, Li & Wang (2010) also discover significant reversal relationships between return shocks and individual trading. Their results indicate that individual investors put more weight on market returns and tend to overreact to return shocks. They find that individual trading and market returns have strong Granger causality relationship. Similarly, they find evidence on Granger causality between institutional investors and daily market returns but in longer time horizons.

According to their results, past individual trading has predictive power for future daily market returns, while past institutional trading has predictive power for market returns in long run. Both, Chinese institutional and individual investors seem to base their trading decisions more on past trades than past returns. (Lee, Li & Wang 2010.)

4. METHODOLOGY

The approach in this paper is based on prior models developed to investigate market wide herding. Primary objective is to use statistical methods to detect market wide herding in Chinese stock market. Secondary objective concentrates on measuring if herding is stronger during periods of extreme volatility.

4.1. Market-Wide Herding Behavior

Market wide herding occurs when investors are following the movements of the market instead of acting rationally and tracking the characteristics of individual stocks. (Henker J., Henker T. & Mitsios 2006). In order to detect herding behavior, the study exploits the same models as Christie & Huang (1995) and Chang et al. (2000) used in their famous papers.

4.1.1. CSSD-model

The first researchers to detect market-wide herding were Christie & Huang (1995) and Chang et al. (2000). Both teams proposed that investors herd during periods of high market volatility. In their paper, Christie & Huang (1995) reason that in the cases of herd, the returns of individual stocks and the return on the market index would aggregate. In other words, herding effect should result in smaller differences between returns of individual stocks and the return on the market index.

The method Christie & Huang (1995) used to measure the dispersion of returns is the cross-sectional standard deviation (CSSD). CSSD measures the dispersion between individual returns of stocks and the return of the market index. When individual returns are significantly greater or lower than the return of the market index the dispersion increases.

In normal situation, the returns of individual stocks follow random walk and thus, they show greater dispersion from each other and the market index. However, in cases of market-wide herding, returns from individual stocks move in the same direction with the market index and dispersion decreases.

(2) $$CSSD_t = \sqrt{\frac{\sum_{i=t}^{N}(R_{i,t} - R_{m,t})^2}{(N-1)}}$$

Where $R_{i,t}$ is the observed stock return on firm i at time t and $R_{m,t}$ is the cross-sectional average return for market portfolio at time t.

The earlier results indicate that individual investors are more likely to herd and follow market movements during periods of extreme volatility. In other words, investors are likely to base their investment decision solely on performance of the market. This results in smaller differences in returns of individual stocks and market index. In times like this, CSSD-model should show lower return dispersions than during normal market conditions. Normal asset pricing models usually assume that dispersions strengthen during extreme market movements.

4.2. CSAD-model

In addition to CSSD-model, Chang et al. (2000) propose other, more complex model to detect market-wide herding behavior. Cross-sectional absolute deviation (CSAD) is less stringent test but demands more linearity between returns of individual stocks and market.

(3) $$CSAD_t = \frac{1}{N}\sum_{i=t}^{N}|R_{i,t} - R_{m,t}|$$

Where the left-hand-side variable, CSAD, represents the return dispersion and is measured by the cross-sectional absolute deviation, $R_{i,t}$ is the computed return of industrial index i at time t and $R_{m,t}$ is the cross-sectional average return of market index at time t.

Assuming that rational asset pricing models are right and market stress should increase the dispersion between individual and market returns, Chang et al. (2000) argue that the dispersion between returns should be linear. In other words, dispersions should act as an increasing function of the market return. In their study, Chang et al. (2000) use CSAD-model based on conditional form of the capital asset pricing model (CAPM) to measure this possible linearity.

According to model, the herd behavior would not only be shown as a decrease in dispersion but also as a non-linear relation between dispersions and the market return. In order for the non-linear relationship to exist, dispersions should decrease or increase at less-than-proportional rate with the market return. CSAD-model should be able to detect herding behavior, or be able to prove it better, in more normal market conditions.

4.2.1. Regression Model for Market-Wide Herding

Motivated by the CSAD-model, the following regression is constructed for each of the two share classes and stock exchanges:

$$(4) \qquad CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \varepsilon_t$$

Where the left-hand-side variable, CSAD, represents the return dispersion and is measured by the cross-sectional absolute deviation. $R_{m,t}$ is the cross-sectional average return of market index at time t, whereas the $|R_{m,t}|$ is the return for absolute term of the cross-sectional average return of market index at time t. As stated previously, herding behavior is more likely to occur during large market movements and therefore, a non-linear term $R_{m,t}^2$ is included in the regression.

The investor herding should occur as a negative CSAD value or the value should at least increase at less-than-proportional rate with the market return. To herding effect to be consistent, the γ3 must be negative and statistically significant value of R^2.

4.2.2. Herding Across Different Industries

In addition to just repeating the regression for A- and B-share classes in Shanghai and Shenzhen stock exchanges, I want to investigate the herding behavior across the different industries. Therefore, the equation (3) is estimated for the main industries amongst both stock exchanges.

Due to relatively small number of B-share firms in the exchanges, it does not make sense to run the equations for both of the share classes, so I will focus on A-shares listed in Shanghai and Shenzhen stock exchanges.

The main industries are defined by the prime standard industry classification (SIC) codes and include 1) agriculture, forestry and fishing, 2) mining, 3) construction, 4) manufacturing, 5) transportation, communications, electric, gas and sanitary services, 6) wholesale trade, 7) retail trade, 8) finance, insurance and real estate, and 9) services.

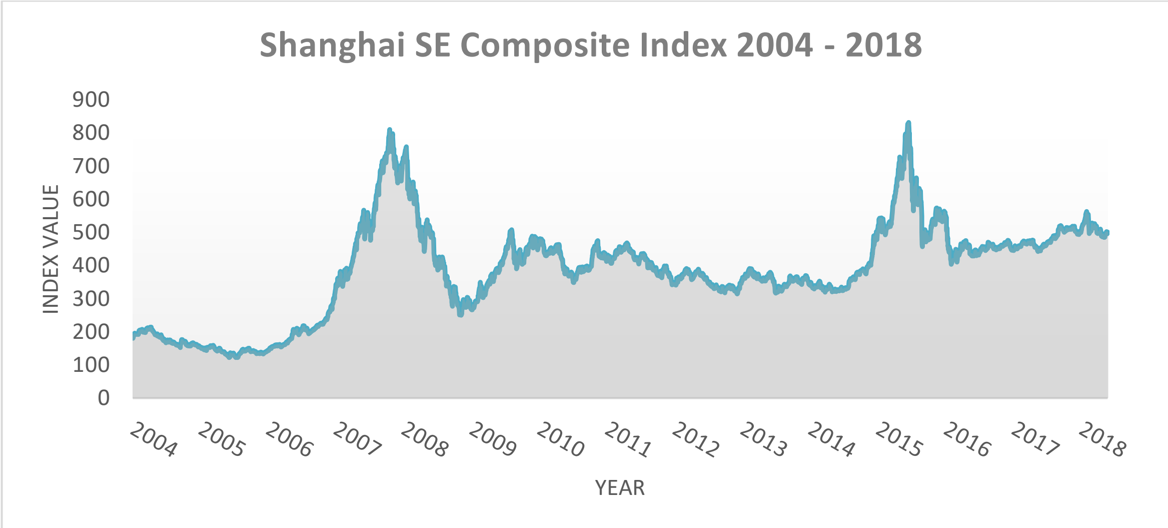
4.3. Asymmetric Herding Behavior

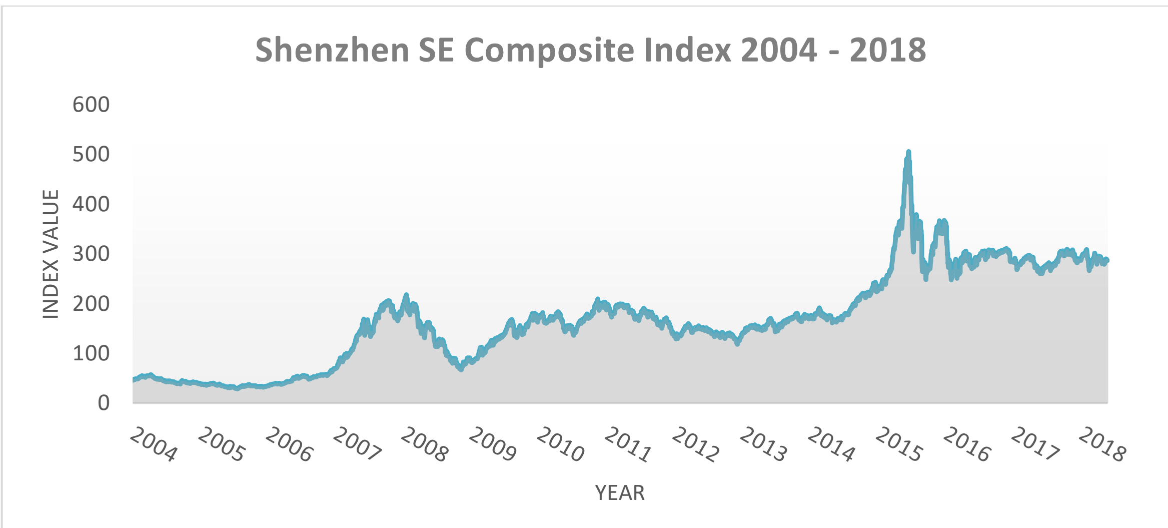
As numerous researchers have concluded before, investors are more likely to display herding behavior during extreme market movements (Chiang, Li & Tan 2010). In addition to just examining the herding behavior in long term, my object is to study whether herding behavior has been more common during market-wide crisis or large ascensions. Furthermore, I also want to resolve if herding is stronger during periods of market stress.

4.3.1. Herding Behavior During Large Market Movements

Chinese stock market has experienced various unexpected market movements since establishment of the Chinese stock exchanges and the speed and direction of the movements have varied during different years.

The time period of the study (2007-2018) is interesting as it includes the Chinese stock bubble in 2007, the global financial crisis in 2008-2009 and Chinese stock market turbulence in 2015-2016.





Figures 6-7: Shanghai and Shenzhen SE Composite Index values 2004 – 2018. (Thomson Reuters Datastream).

In order to assess whether the possible herding behavior is stronger during large market movements, the review period (2007-2018) is split into 2-year sub-periods. These sub-periods include the market movements from the last 12 years in the Chinese equity market. The regression for market-wide herding is then repeated for the 2-year sub-periods to assess whether the possible herding has been consistent throughout the review period.

Previous studies have found evidence that the herding behavior usually differs between the positive and negative market sentiments (i.e. bull / bear market) (Batmunkh et al. 2018; Tan et al. 2007).

In order to asses if the asymmetry in herding between positive and negative market return days exists, the following specified regression are estimated for both stock exchanges and share classes:

(5) $$CSAD_t^{UP} = \gamma_0 + \gamma_1{}^{UP}\, R_{m,t}^{UP} + \gamma_2{}^{UP}\gamma_2 \left|R_{m,t}^{UP}\right| + \gamma_3{}^{UP}\, R_{m,t}^{2\,UP} + \varepsilon_t$$

(6) $$CSAD_t^{DOWN} = \gamma_0 + \gamma_1{}^{DOWN}\, R_{m,t}^{DOWN} + \gamma_2{}^{DOWN}\gamma_2\, |R_{m,t}^{DOWN} + \gamma_3{}^{UP}\, R_{m,t}^{2\,DOWN} + \varepsilon_t$$

In the equation, $R_{m,t}^{UP}$ is the cross-sectional average return of market index, $\left|R_{m,t}^{UP}\right|$ is the absolute term of the cross-sectional average return and $R_{m,t}^{2\,UP}$ is the squared term of the cross-sectional average return of market index when the market rises. Variables with the superscript "down" refer to same formula when the market declines. As before, for herding to exist during positive and negative market periods, γ_3 must be negative and statistically significant.

4.3.2. Herding Behavior During High and Low Volatility

In addition to examining whether the herding behavior is affected by the prevalent market sentiment, I will also study what effects the volatility has on herding behavior. The volatility is measured by the Chinese equivalent of VIXX called CBOE China ETF Volatility Index. The index values are categorized into seven different quantiles representing market volatility at 5 %, 10 %, 25 %, 50 %, 75 %, 90 % and 95 % levels. In other words, 5 % present the situation when the volatility is at its lowest and 95 % situation when the volatility is at its highest.

To assess the effect of the volatility to the herding behavior, the following specified regression is estimated for both stock exchanges and share classes:

$$(7) \qquad CSAD_t^{\hat{\sigma}5\%} = \gamma_0 + {\gamma_1}^{\hat{\sigma}5\%} R_{m,t}^{\hat{\sigma}5\%} + {\gamma_2}^{\hat{\sigma}5\%}\gamma_2 \left|R_{m,t}^{\hat{\sigma}5\%}\right| + {\gamma_3}^{\hat{\sigma}5\%} R_{m,t}^{2\,\hat{\sigma}5\%} + \varepsilon_t$$

In the equation, $R_{m,t}^{\hat{\sigma}5\%}$ is the cross-sectional average return of market index, $\left|R_{m,t}^{\hat{\sigma}5\%}\right|$ is the absolute term of the cross-sectional average return and $R_{m,t}^{2\,\hat{\sigma}5\%}$ is the squared term of the cross-sectional average return of market index when the volatility is at 5 % quantile. The same regression is estimated for all the quantiles mentioned above (5 %, 10 %, 25 %, 50 %, 75 %, 90 % and 95 %).

5. DATA AND DESCRIPTIVE STATISTICS

5.1. Data

This study uses data on Chinese stock market in order to measure the relationship between the returns of individual stocks and the return on the market index. Data in this study has been obtained via Thomson Reuters Datastream.

Data contains information on daily closing prices, share classes, standard industry classification (SIC) codes and main exchanges of A- and B-share listed stocks listed in Shanghai stock exchange and Shenzhen stock exchange for the period 1.1.2007 – 18.5.2018. The period contains 2766 observations for each of the stocks and indices. In addition to the data of individual stocks, the daily closing prices of Shanghai SE Composite index, Shenzhen SE Composite index, Shanghai A-share index, Shanghai B-share index, Shenzhen A-share index and Shenzhen B-share index are collected. Furthermore, the daily closing price of CBOE China ETF Volatility Index for the period 16.3.2011 – 18.5.2018 is also gathered.

The original data contains information from 1927 Shanghai A-share firms, 61 Shanghai B-share firms, 2344 Shenzhen A-share firms, and 65 Shenzhen B-share firms (SZB). After removing the shares that have not been listed for the entire review period (2007-2018), 821 Shanghai A-share firms, 51 Shanghai B-share firms, 570 Shenzhen A-share firms and 52 Shenzhen B-share firms remain in the sample.

All returns are recorded as U.S. Dollars (USD) for all instruments. The respective Dollarized values for instruments nominated in local currency (RMB) are calculated by using the prevalent exchange rate. In the first phase, the individual stock returns are allocated to Shanghai A-share, Shanghai B-share, Shenzhen A-share and Shenzhen B-share portfolios. In the second phase, A-share returns for both A-share stocks are also allocated into industry sector portfolios by using the prime SIC codes for individual stocks.

The log return formula is applied in order to calculate the returns for the industry indices and individual stocks:

(8) $$R_t = 100 * (\log(P_t) - \log(P_{t-1}))$$

Where R_t is daily change in the stock price/market index (i.e. return), P_t is the price of the stock/market index at time t and P_{t-1} is the corresponding value day before.

Once the returns have been defined for the individual stocks and the market index, the CSAD values are calculated.

5.2. Descriptive Statistics

Table 1.

Descriptive statistics of daily cross-sectional absolute deviations

Statistic	SHA		SHB		SZA		SZB	
	CSAD	Rm	CSAD	Rm	CSAD	Rm	CSAD	Rm
Statistics for daily CSADt								
No. of companies	821		51		570		52	
No. of observations	2766		2766		2766		2766	
Mean	1,708	0,044	1,216	0,032	1,733	0,047	1,370	0,028
Median	1,544	0,238	1,109	0,132	1,564	0,244	1,252	0,100
Maximum	5,449	8,639	5,171	8,823	5,794	8,325	4,801	8,746
Minimum	0,816	-9,135	0,254	-9,508	0,863	-9,174	0,300	-8,881
Std. Dev.	0,598	1,995	0,555	1,963	0,614	1,940	0,620	1,665
Skewness	1,545	-0,916	1,707	-0,646	1,676	-0,933	1,419	-0,648
Kurtosis	6,458	6,296	9,096	8,691	7,058	6,099	6,192	7,891
Jarque-Bera	2478,447	1639,264	5626,538	3924,905	3192,488	1508,361	2102,579	2950,972
Probability	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000

Descriptive statistics of daily cross-sectional absolute deviations and average market index returns for A and B-shares in Shanghai and Shenzhen stock exchanges.

Table one is presenting descriptive statistics for daily $CSAD_t$ and $R_{m,t}$ values which have been derived for A and B-class shares in Shanghai and Shenzhen stock exchanges. The review period used in this study covers a period from 1.1.2007 to 18.5.2018 (i.e. c. 11,5 years) and includes 2766 observations when the non-trading days and weekends are omitted from the sample.

The descriptive statistics show that the mean and median values of $CSAD_t$ for A-shares are higher than the respective values of B-shares. The mean and median $CSAD_t$ values for A-shares in Shanghai and Shenzhen are close to each other, whereas, the mean and median values for B-shares differ slightly between the two stock exchanges. The highest mean value in the sample belongs to Shenzhen A-shares and lowest mean value to Shanghai B-shares. The standard deviations for $CSAD_t$ values range from 0,555 to 0,620 and are relatively similar to each other across the stock exchanges and share classes. Both exchanges and share classes have a positive skewness and have excess kurtosis.

The equally weighted average market returns range from -9,508 % for the Shanghai B-shares to 8,746 % for the Shenzhen B-shares. Daily market returns of the B-shares seem to have lower mean values compared to A-shares. The standard deviations of market returns for Shanghai A- and B-shares, and Shenzhen A-shares are similar to each other. However, the standard deviation of the market return for Shenzhen B-shares is low (1,665 %) compared to other investigated markets.

Table 2.

Correlation of daily cross-sectional absolute deviations

Statistic		SHA	SHB	SZA	SZB
Statistics for daily CSAD					
	SHA	1			
	SHB	0,760	1		
	SHZNA	0,972	0,740	1	
	SHZNB	0,735	0,796	0,739	1

Correlations of daily cross-sectional absolute deviations for A and B-shares in Shanghai and Shenzhen stock exchanges.

The table 2 presents the correlations of $CSAD_t$ values across the share classes and stock exchanges. Interestingly, the correlation between the Shanghai A-shares and Shenzhen A-shares seems to be relatively high (0,972), whereas, the correlation between the B-shares is lower (0,796). The correlations between the share classes of same stock exchanges are around 0,74 – 0,76.

Table 3.

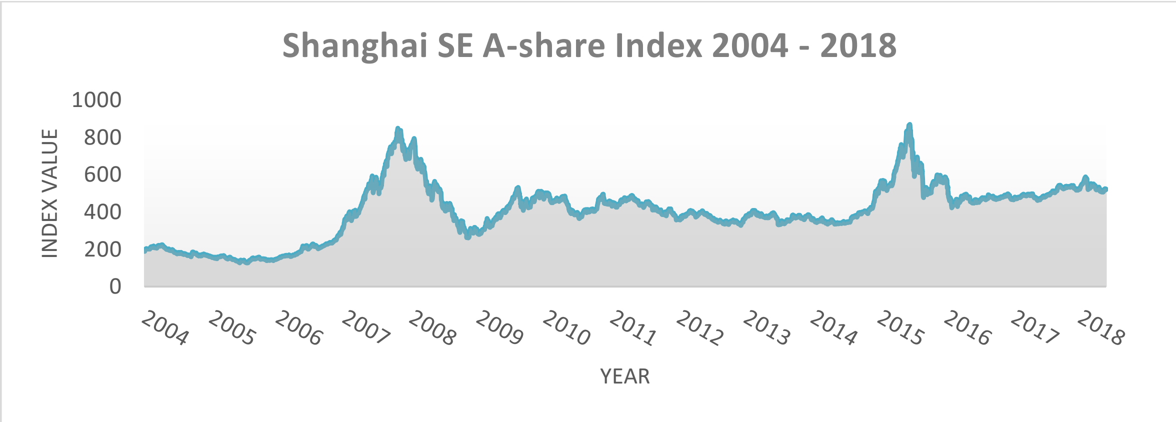
Correlation of daily equally weighted market returns

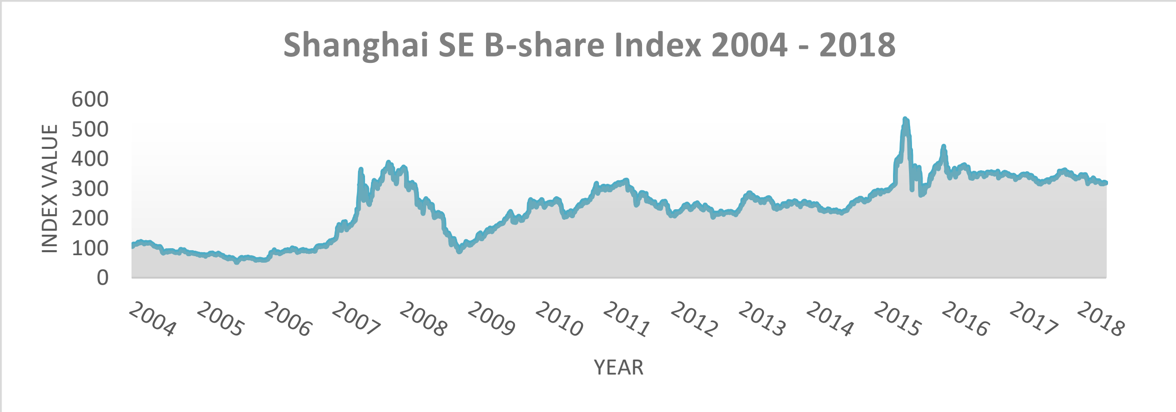
Statistic		SHA	SHB	SZA	SZB
Statistics for daily Rm					
	SHA	1			
	SHB	0,848	1		
	SHZNA	0,995	0,840	1	
	SHZNB	0,849	0,921	0,848	1

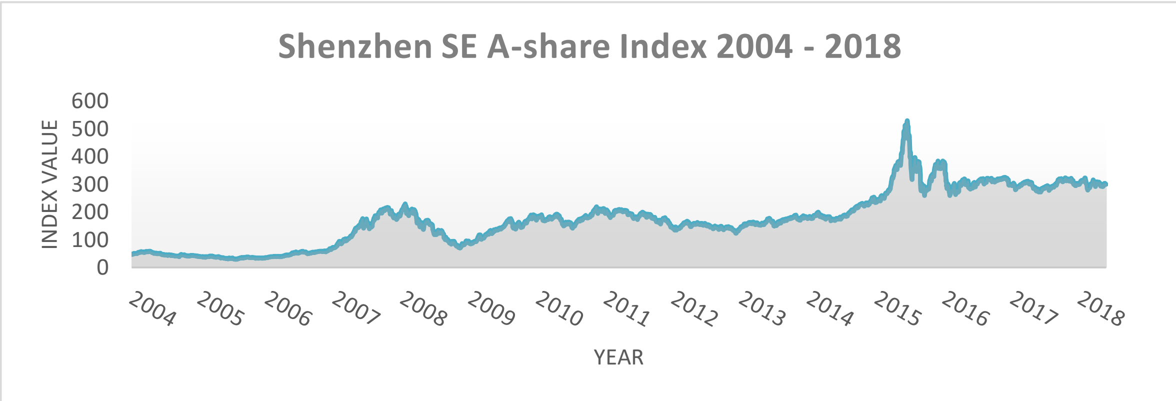
Correlations of equally weighted market returns for A and B-shares in Shanghai and Shenzhen stock exchanges.

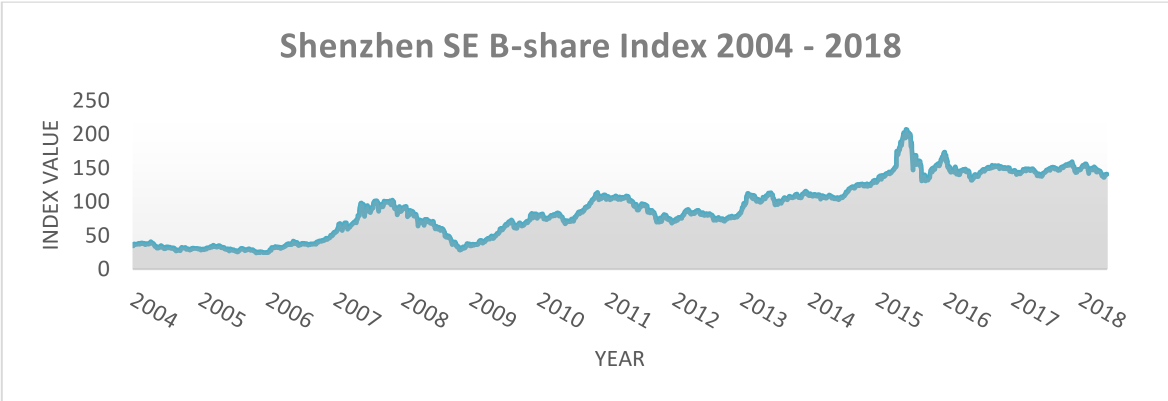
The table 3 presents the correlations of daily $R_{m,t}$ values across the share classes and stock exchanges. The Shanghai and Shenzhen A-shares seem to be more strongly correlated than the B-shares in the respective stock exchanges when the average daily equally weighted market return are inspected. A-shares in both stock exchanges share around 0,848 correlation with the B-shares in their own stock exchanges.

5.3. Historical Stock Market Returns









Figures 8-11: Shanghai and Shenzhen A-share and B-share Index values 2004 – 2018. (Thomson Reuters Datastream).

Figures 6-9 present the historical stock market developments of Shanghai and Shenzhen A- and B-shares. Being from the same country, it's no surprise, that all of the studied returns (Shanghai A- & B-shares and Shenzhen A- & B-shares) are similar to each other.

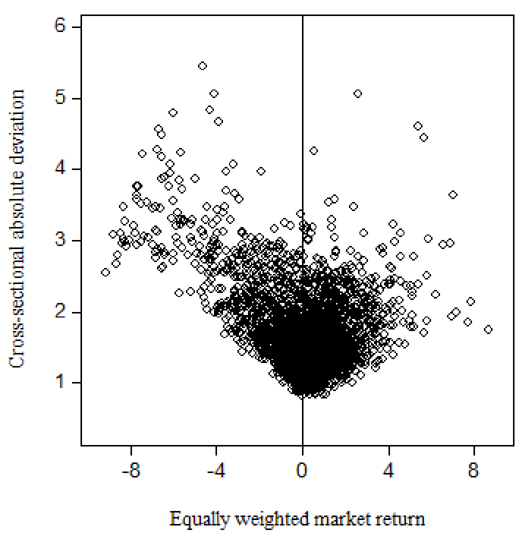
The review period of the study (2007-2018) is interesting because it includes several rapid developments in the Chinese stock markets during last two decades. The most prevalent market movements during the study period have been the bursting of Chinese stock bubble in 2007, the global financial crisis in 2008-2009 and Chinese stock market turbulence in 2015-2016. These events can be clearly seen from the above graphs as a rapid decline in the index price after a period of rising stock prices.

It seems that the above-mentioned market movements have been stronger with the A-shares than with the B-shares. This is not surprising considering that the A-shares are mainly owned by less sophisticated domestic (Chinese) investors, whereas, the B-shares are denominated in US Dollars (SHB) and Hong Kong Dollars (SZB) and owned mainly by foreign investors.

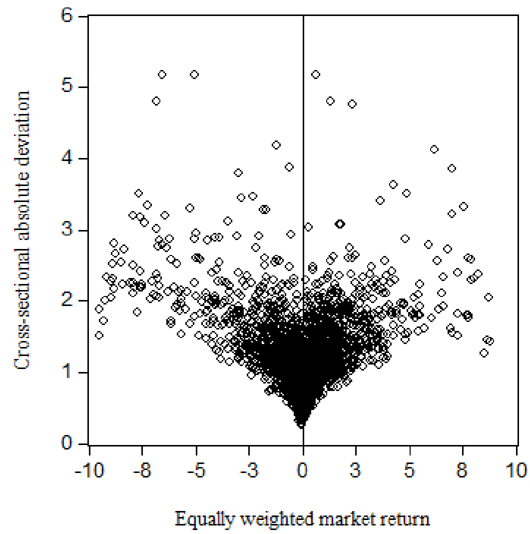
The large market movements enable the study to examine if the herding behavior is more prevalent during crisis periods as Christie and Huang (1995) proposed in their study.

5.4. Cross-Sectional Absolute Deviations and Equally Weighted Market Return

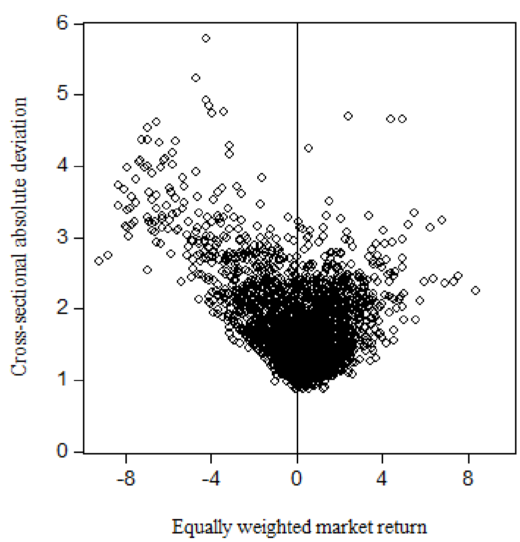
Shanghai A-share



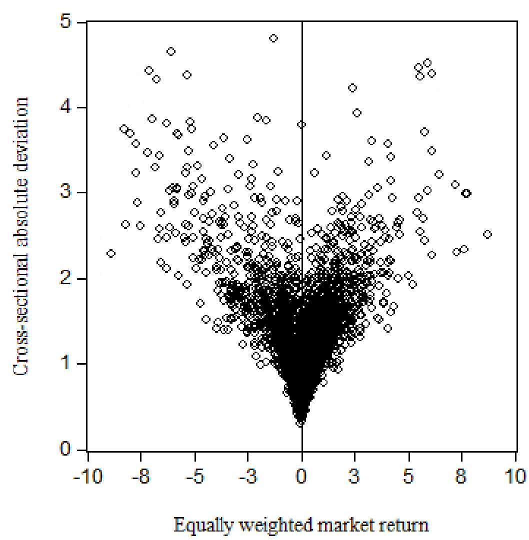
Shanghai B-share



Shenzhen A-share



Shenzhen B-share



Figures 12-15: The relationship between the cross-sectional absolute deviation and equally weighted market return for A and B-share classes in Shanghai and Shenzhen stock exchanges.

Figures 9-12 above present the relationship between the cross-sectional absolute deviation (which is used as a measurement of dispersion in the study) and equally weighted market return for A and B-share classes in Shanghai and Shenzhen stock exchanges.

According to Chang et al. (2000), the decrease or increase in dispersion and a non-linear relation between individual dispersions and the market return is an indicator of herding behavior. In order for the non-linear relationship to exist, dispersions should decrease or increase at less-than-proportional rate with the market return.

Mathematically, the CSAD value should be zero if all individual stock returns in the sample move in perfect unison with the market return. Similarly, CSAD value should increase when the returns of individual stocks deviate from the market return. (Batmunkh et al. (2018.)

To no surprise, the graphs indicate that the relationship between CSAD and market return varies over time. The shape of the scatter cloud is similar between the Shanghai and Shenzhen A-shares, which both are indicating larger dispersion when the market return is negative. On the other hand, the scatter clouds of Shanghai and Shenzhen B-shares are more evenly spread. It also seems, that B-shares experience less dispersion compared to A-shares, when the market return is close to zero.

Based on the figure, it seems that that the return dispersion rises when the absolute average market returns become larger, but a less than proportional rate. This could indicate a non-linear relationship between dispersions and the market return, which would mean that both exchanges and share classes are experiencing at least some level of market-wide herding behavior.

6. EMPIRICAL RESULTS

This chapter presents the results, key findings and analysis based on the regression models presented earlier.

6.1. Market-Wide Herding

Table 4.

Analysis of market-wide herding behavior in Chinese stock markets

Panel A: regression results for daily data				
Market (no. of observations)	SHA (2766)	SHB (2766)	SZA (2766)	SZB (2766)
α	1,335	0,808	1,330	0,888
	(-85,517)***	(-64,898)***	(-86,126)***	(-70,733)***
γ1	-0,077	-0,017	-0,077	-0,006
	(-16,259)***	(-4,088)***	(-16,051)***	(-1,236)
γ2	0,313	0,435	0,332	0,533
	(-20,165)***	(-32,678)***	(-21,104)***	(-35,474)***
γ3	-0,015	-0,032	-0,013	-0,033
	(-5,879)***	(-16,566)***	(-4,693)***	(-12,423)***
Adjusted R2	0,430	0,466	0,481	0,574

Analysis of market-wide herding behavior in Chinese stock markets: regression result for daily data.

The table 4 presented above includes the regression result for formula (3) and includes all observations from the review period. According to the results, the coefficient γ_3 is negative and statistically significant for all the observed markets at 1 % level, which indicates that all markets are experiencing strong herding behavior. The results are similar to those what researchers Batmunkh et al. (2018) and Tan et al. 2007) discovered in their studies. The results can also be interpreted to be similar to findings of Chang et al. (2000), who did not investigate Chinese stock markets, but similar emerging markets which existed earlier in South Korea and Taiwan.

However, opposite to Batmunkh et al. (2018) and Tan et al. 2007), in this study the evidence suggests that the herding effect is stronger with the B-shares instead of the A-shares. This is interesting since the B-shares are mostly dominated by foreign institutional investors who should be more sophisticated investors. All in all, the empirical results support Hypothesis 1 and imply that the herding behavior is present in Chinese stock markets.

6.2. Market-Wide Herding Across the Industries

Table 5.

Analysis of herding behavior between industries in Chinese stock markets

Market	Industry	α	γ1	γ2	γ3	Adjusted R2	No. of observations
Panel A: regression results for different industries amongst Shanghai stock exchange A-shares							
Shanghai	Agriculture, forestry and fishing	1,053	-0,040	0,434	-0,012	0,469	2766
		(51,358)***	(-6,891)***	(21,383)***	(-3,637)***		
	Mining	1,220	-0,030	0,367	-0,009	0,366	2766
		(54,885)***	(-5,013)***	(16,992)***	(-2,400)**		
	Construction	1,262	-0,058	0,370	-0,023	0,371	2766
		(68,852)***	(-11,571)***	(21,650)***	(-8,695)***		
	Manufacturing	1,361	-0,074	0,286	-0,014	0,399	2766
		(86,968)***	(-16,064)***	(18,913)***	(-5,860)***		
	Transportation, communications, electric, gas and sanitary services	1,124	-0,061	0,361	-0,026	0,356	2766
		(70,511)***	(-12,402)***	(23,248)***	(-10,852)***		
	Wholesale trade	1,314	-0,073	0,376	-0,019	0,429	2766
		(73,256)***	(-13,257)***	(20,969)***	(-6,268)***		
	Retail trade	1,138	-0,039	0,344	-0,014	0,360	2766
		(62,209)***	(-7,040)***	(19,168)***	(-4,825)***		
	Finance, insurance and real Estate	0,890	-0,013	0,508	-0,018	0,383	2766
		(40,472)***	(-1,665)***	(21,132)***	(-4,162)***		
	Services	1,293	-0,068	0,388	-0,023	0,359	2766
		(63,515)***	(-11,887)***	(20,079)***	(-7,273)***		
Panel B: regression results for different industries amongst Shenzhen stock exchange A-shares							
Shenzhen	Agriculture, forestry and fishing	0,950	0,001	0,359	-0,027	0,155	2766
		(34,619)***	(0,215)	(16,156)***	(-8,787)***		
	Mining	1,161	-0,035	0,366	-0,003	0,447	2766
		(56,249)***	(-6,284)***	(17,805)***	(-0,744)		
	Construction	1,200	-0,049	0,446	-0,020	0,462	2766
		(64,427)***	(-8,744)***	(23,810)***	(-6,216)***		
	Manufacturing	1,340	-0,076	0,316	-0,014	0,446	2766
		(86,106)***	(-16,173)***	(20,498)***	(-5,556)***		
	Transportation, communications, electric, gas and sanitary services	1,150	-0,053	0,374	-0,020	0,361	2766
		(61,397)***	(-9,062)***	(20,227)***	(-6,756)***		
	Wholesale trade	1,331	-0,024	0,230	0,027	0,420	2766
		(60,429)***	(-3,677)***	(10,044)***	(6,620)***		
	Retail trade	1,204	-0,051	0,349	-0,020	0,285	2766
		(55,663)***	(-8,257)***	(17,015)***	(-6,086)***		
	Finance, Insurance and Real Estate	1,143	0,054	0,329	0,028	0,423	2766
		(45,159)***	(6,945)***	(13,180)***	(6,819)***		
	Services	1,214	-0,060	0,478	-0,033	0,388	2766
		(60,446)***	(-9,887)***	(23,607)***	(-9,731)***		

Analysis of market-wide herding behavior in Chinese stock markets: regression results for different industries amongst Shanghai and Shenzhen A-shares.

The regression result for market-wide herding behavior across different A-share industries in Shanghai and Shenzhen stock exchanges are presented in the table 5 above. From the table we can see that the herding behavior in Chinese stock markets is clearly stronger and more common with specific industries, whereas, some industries do not present signs of herding behavior.

The coefficients indicate that the herding behavior is most common amongst companies, which operate in construction, services and transportation, communications, electric, gas and sanitary services industries. The γ_3 coefficients for these industries are highly negative (≤ -0,020) and statistically significant at 1 % level in both Shanghai and Shenzhen stock exchanges.

In addition, the results suggest that in Shanghai stock exchange, the herding behavior is more or less prevalent within all industries and all industries have statistically significant γ_3 coefficients. The results for Shenzhen stock exchange are more interesting. In Shenzhen, companies related to mining, wholesale trade and finance, insurance and real estate industries do not have negative γ_3 coefficients or the results are not statistically significant. Based on the results, the herding behavior in Shanghai stock exchange is more extensive and concerns more industries.

6.3. Market-Wide Herding During Large Market Movements

Table 6.

Analysis of herding behavior in Chinese stock markets during different time periods

Panel A: results for the period	1.1.2007 - 31.12.2008				1.1.2009 - 31.12.2010			
Market (no. of observations)	SHA (488)	SHB (488)	SHZNA (488)	SHZNB (488)	SHA (486)	SHB (486)	SHZNA (486)	SHZNB (486)
α	2,098	1,361	1,963	1,454	1,581	0,986	1,598	1,090
	(-52,831)***	(-27,979)***	(-51,570)***	(-34,335)***	(-52,002)***	(-40,254)***	(-53,835)***	(-38,619)***
γ1	-0,097	-0,022	-0,093	-0,002	-0,098	-0,014	-0,102	-0,003
	(-13,732)***	(-2,625)***	(-13,055)***	(-0,228)	(-11,393)***	(-1,701)*	(-12,021)***	(-0,377)
γ2	0,154	0,291	0,220	0,408	0,153	0,329	0,155	0,357
	(-5,115)***	(-7,746)***	(-7,298)***	(-11,017)***	(-4,748)***	(-12,463)***	(-4,837)***	(-11,225)***
γ3	-0,012	-0,023	-0,013	-0,029	-0,009	-0,034	-0,004	-0,030
	(-2,946)***	(-4,804)***	(-2,985)***	(-5,262)***	(-1,407)	(-7,208)***	(-0,538)	(-4,711)***
Adjusted R2	0,395	0,220	0,500	0,415	0,383	0,339	0,452	0,392
Panel B: results for the period	1.1.2011 - 31.12.2012				1.1.2013 - 31.12.2014			
Market (no. of observations)	SHA (487)	SHB (487)	SHZNA (487)	SHZNB (487)	SHA (483)	SHB (483)	SHZNA (483)	SHZNB (483)
α	1,271	0,816	1,234	0,938	1,379	0,733	1,344	0,816
	(74,054)***	(46,437)***	(72,105)***	(42,897)***	(62,536)***	(36,945)***	(64,031)***	(44,804)***
γ1	-0,094	-0,034	-0,099	-0,006	-0,115	-0,025	-0,111	-0,010
	(-16,094)***	(-3,827)***	(-16,719)***	(-0,587)	(-11,297)***	(-2,370)**	(-11,327)***	(-0,889)
γ2	0,110	0,323	0,154	0,425	0,138	0,540	0,204	0,558
	(4,552)***	(14,989)***	(6,326)***	(14,338)***	(4,365)***	(15,563)***	(7,078)***	(15,383)***
γ3	0,002	-0,026	-0,003	-0,026	0,001	-0,075	-0,013	-0,068
	(0,328)	(-6,282)***	(-0,439)	(-3,564)***	(0,095)	(-7,723)***	(-1,717)*	(-5,947)***
Adjusted R2	0,532	0,491	0,588	0,566	0,401	0,498	0,436	0,566
Panel C: results for the period	1.1.2015 - 31.12.2016				1.1.2017 - 18.5.2018			
Market (no. of observations)	SHA (488)	SHB (488)	SHZNA (488)	SHZNB (488)	SHA (334)	SHB (334)	SHZNA (334)	SHZNB (334)
α	1,205	0,660	1,227	0,755	1,117	0,591	1,166	0,590
	(27,624)***	(21,587)***	(26,823)***	(28,363)***	(56,555)***	(36,386)***	(61,109)***	(31,885)***
γ1	-0,078	-0,014	-0,094	-0,024	-0,120	-0,027	-0,122	-0,052
	(-6,570)***	(-1,560)	(-7,162)***	(-2,459)**	(-9,360)***	(-1,931)*	(-9,784)***	(-2,481)**
γ2	0,517	0,480	0,586	0,554	0,146	0,426	0,124	0,759
	(12,529)***	(15,434)***	(13,282)***	(17,080)***	(4,217)***	(10,084)***	(3,794)***	(13,581)***
γ3	-0,035	-0,031	-0,043	-0,018	0,034	-0,043	0,030	-0,140
	(-5,748)***	(-7,290)***	(-6,308)***	(-3,275)***	(3,179)***	(-2,555)**	(3,088)***	(-4,867)***
Adjusted R2	0,554	0,599	0,571	0,755	0,661	0,574	0,658	0,625

Analysis of market-wide herding behavior in Chinese stock markets: regression results for different time periods.

The table number 6 above presents the results for six subsamples derived from the data, which each represent a subperiod of about two years. The last period (1.1.2017-18.5.2018) is a little bit shorter and includes observations from 334 days.

The two-year intervals are well suited for studying purposes. Years 2007-2008 include the rapid rise in stock prices and bursting of Chinese stock bubble, as well as, the start of the global financial crisis. Furthermore, the Chinese stock market turbulence took place in years 2015-2016. The rest of the review period (i.e. years 2009-2014 and 2017-2018) includes observations from steadier market periods in China.

Based on the results, it's evident that the large market movements have had an effect on investor behavior on Chinese stock markets. The γ_3 coefficients of A-shares in Shanghai and Shenzhen are only negative and statistically significant during the crisis periods of 2007-2008 and 2015-2016. This would indicate that the A-share stocks in Shanghai and Shenzhen are only experiencing herding behavior during extraordinary market conditions.

On the other hand, the γ_3 coefficients of the B-shares are negative and statistically significant throughout the review period. In other words, it seems that the B-shares in both stock exchanges seem to experience herding behavior even during less stressful market periods.

6.4. Market-Wide Herding During High and Low Volatility

Table 7.

Analysis of herding behavior in Chinese stock markets during low, median and high volatility

Panel A: results for the	5% volatility quantile				10% volatility quantile			
Market (no. of observations)	SHA (93)	SHB (93)	SHZNA (93)	SHZNB (93)	SHA (175)	SHB (175)	SHZNA (175)	SHZNB (175)
α	1,084	0,601	1,144	0,566	1,095	0,565	1,147	0,573
	(-32,363)***	(-20,745)***	(-36,086)***	(-19,098)***	(-44,211)***	(-25,457)***	(-47,506)***	(-23,394)***
γ1	-0,103	0,015	-0,085	-0,069	-0,103	0,005	-0,096	-0,055
	(-4,393)***	(-0,578)	(-3,841)***	(-1,848)*	(-6,285)***	(-0,238)	(-6,055)***	(-1,874)*
γ2	0,205	0,454	0,125	0,793	0,158	0,535	0,121	0,760
	(-3,239)***	(-5,540)***	(-2,116)**	(-7,083)***	(-3,312)***	(-8,591)***	(-2,617)***	(-8,182)***
γ3	0,025	-0,083	0,044	-0,164	0,036	-0,104	0,042	-0,141
	(-1,137)	(-2,227)**	(-2,189)**	(-2,266)**	(-2,064)**	(-3,551)***	(-2,523)**	(-2,191)**
Adjusted R2	0,695	0,486	0,692	0,666	0,617	0,500	0,605	0,579
Panel B: results for the	25% volatility quantile				median volatility quantile			
Market (no. of observations)	SHA (440)	SHB (440)	SHZNA (440)	SHZNB (440)	SHA (868)	SHB (868)	SHZNA (868)	SHZNB (868)
α	1,175	0,587	1,184	0,620	1,296	0,716	1,293	0,805
	(-53,690)***	(-36,075)***	(-53,041)***	(-35,054)***	(-67,471)***	(-49,061)***	(-69,817)***	(-54,228)***
γ1	-0,104	-0,003	-0,081	0,003	-0,093	-0,024	-0,093	-0,005
	(-8,244)***	(-0,247)	(-6,342)***	(-0,190)	(-11,629)***	(-2,896)***	(-11,965)***	(-0,491)
γ2	0,120	0,526	0,147	0,743	0,159	0,434	0,193	0,491
	(-2,728)***	(-15,741)***	(-3,335)***	(-17,210)***	(-5,437)***	(-21,439)***	(-6,957)***	(-19,097)***
γ3	0,041	-0,060	0,036	-0,096	0,007	-0,034	0,000	-0,025
	(-2,403)**	(-6,511)***	(-2,231)**	(-6,455)***	(-0,876)	(-8,753)***	(-0,001)	(-3,537)***
Adjusted R2	0,407	0,560	0,399	0,627	0,362	0,501	0,392	0,577
Panel C: results for the	75% volatility quantile				90% volatility quantile			
Market (no. of observations)	SHA (438)	SHB (438)	SHZNA (438)	SHZNB (438)	SHA (170)	SHB (170)	SHZNA (170)	SHZNB (170)
α	1,300	0,856	1,284	0,986	1,075	0,828	1,047	1,021
	(-24,927)***	(-24,915)***	(-23,026)***	(-30,395)***	(-13,324)***	(-17,378)***	(-12,178)***	(-18,795)***
γ1	-0,056	-0,009	-0,064	-0,015	-0,030	0,022	-0,040	0,005
	(-4,763)***	(-1,049)	(-4,857)***	(-1,594)	(-1,753)*	(-2,002)**	(-2,042)**	(-0,395)
γ2	0,359	0,338	0,429	0,387	0,421	0,256	0,476	0,324
	(-8,365)***	(-10,972)***	(-9,149)***	(-11,727)***	(-6,761)***	(-6,161)***	(-7,000)***	(-6,455)***
γ3	-0,014	-0,016	-0,020	0,000	-0,017	-0,003	-0,021	0,009
	(-2,252)**	(-3,895)***	(-2,859)***	(-0,014)	(-2,037)**	(-0,646)	(-2,233)**	(-1,223)
Adjusted R2	0,496	0,527	0,506	0,702	0,595	0,637	0,602	0,745
Panel D: results for the	95% volatility quantile							
Market (no. of observations)	SHA (81)	SHB (81)	SHZNA (81)	SHZNB (81)				
α	0,918	0,770	0,895	1,122				
	(-6,935)***	(-9,290)***	(-6,473)***	(-12,721)***				
γ1	-0,037	0,010	-0,045	0,016				
	(-1,409)	(-0,480)	(-1,565)	(-0,720)				
γ2	0,581	0,333	0,630	0,266				
	(-5,791)***	(-4,496)***	(-5,928)***	(-3,300)***				
γ3	-0,035	-0,012	-0,039	0,021				
	(-2,718)***	(-1,305)	(-2,768)***	(-1,709)*				
Adjusted R2	0,596	0,580	0,602	0,726				

Analysis of market-wide herding behavior in Chinese stock markets: regression results during low, median and high volatility.

The adjacent table (7) present the regression results during low, medium and high volatility. The strength of the volatility has been divided into seven different quantiles, where 5 % quantile presents lowest volatility and 95 % present highest volatility.

Surprisingly, the results for A-shares and B-shares differ from each other. It seems, that A-shares in both Shanghai and Shenzhen experience herding behavior when the volatility is high. Furthermore, the results indicate that the herding behavior with A-shares gets stronger when the volatility increases. On the other hand, the results indicate that the herding around B-shares is more common during low market volatility. The results are in line with the previous results where the A-shares experienced herding behavior during crisis periods.

7. CONCLUSIONS

The strong growth during recent decades has raised China to the center of attention of the entire world. Low costs, abundant supply of labor and huge growth potential of the market has attracted foreign investments. The market value of Chinese stock market has multiplied, and they have currently the second largest stock market in the world. Chinese stock market started to growth rapidly when the stock markets were opened at the beginning of 20th century in Shanghai and Shenzhen. However, the Chinese officials were afraid that the capital flows would distort the markets, and therefore, the separate share classes for foreign and domestic investors were presented. A-shares nominated in the local currency (renminbi) can be purchased only by domestic investors and selected foreign investors. B-shares nominated is foreign currencies can only be purchased by foreign investors. A-shares account for about 65 % of the domestic stock market.

The A-share market is dominated by individual retail investors who hold more than 75 % of the stocks in the market. The rapid rise of stock price has inspired individual investors, who are often regular Chinese nationals, to take risk and invest heavily in the stock market. Individual investors are rarely as sophisticated as institutional investors and their inexperience often leads to irrational decisions. Individual investors tend to base their trades more on news headlines and short-term development of the stock prices than on long-term fundamentals. This kind of behavior often leads to steep market movements which are escalated by mutual fund managers who are typically incentivized to chase short-term performance.

This study exploits the CSSD and CSAD models which researchers Christie & Huang (1995) and Chang et al. (2000) used in their famous papers. Christie & Huang (1995) proposed in their paper that in the cases of herding behavior, the returns of individual stocks and the return on the market index would aggregate. CSAD presented by Chang et al. (2000) is less stringent test but demands linearity between returns of individual stocks and market.

The results from this study support the doubts that the Chinese stock market is not functioning as well as the efficient market hypothesis would suggest. The study finds evidence that the market-wide herding behavior occurs in Chinese stock market and concerns both A and B-shares in Shanghai and Shenzhen stock exchanges. The evidence suggests that the herding behavior is clearly stronger and more common with specific industries (construction, services and transportation, communications, electric, gas and sanitary services). The herding behavior around A-shares occurs especially during periods of high market stress.

In the beginning of this paper, I listed three hypothesis which I have attempted to confirm. The hypotheses were as follows: H1: Herding behavior exists in Chinese stock market, H2: Herding behavior is linked to investor structure and share classes & H3: Herding behavior is stronger during extraordinary market conditions.

The first hypothesis concerns overall existence of herding behavior in the Chinese stock market. Based on the results presented in the tables four and five, it is clear that the market-wide herding behavior has occurred in the market during the review period. The aim of the second hypothesis was to find evidence that the herding behavior is linked to investor structure in the market. The differences in the results for A and B-shares listed Shanghai and Shenzhen stock exchanges give support to the presumption that the herding behavior is at least loosely associated to the investor structure. Finally, the purpose of the third hypothesis was to investigate whether the herding behavior is dependent on the prevailing market situation. Based on the results mentioned in tables six and seven, it is evident that the market conditions and especially volatility have a strong impact on the occurrence of the herding behavior. However, in this case, the impact mainly concerned A-shares.

As a suggestion for further research I want to mention examination of herding behavior amongst other share classes and industries in China. Furthermore, future herding related studies could concentrate on investigating whether the Chinese stock market herds around other stock markets (e.g. Japan, Hong Kong or US). In addition, it would be interesting to study if the herding effect will diminish in the future when Chinese investors become more professional and more informed.

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