Information asymmetry and Herding: insights from the US and Chinese stock markets

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Abstract

The academic research has highly focused on examining the investor's behavior in stock markets. Many theories in psychology and sociology are used in the so called "Behavioral Finance" in order to explain the limits of the efficient market hypothesis and the financial market fragility. By analyzing the herding behavior, the researchers try to explain the market anomalies and the large market movements.

Although the existing herding literature has mainly focused on the existence (or nonexistence) of herding, our study focuses on the effect of information availability on herding. We aim to examine if herding is more pronounced in a high information asymmetry context. In other words, we investigate if herding is really driven by investors' lack of information. We use the matching methodology in order to construct portfolios with different information asymmetry levels, yet with comparable firms' characteristics. We treat different information asymmetry portfolios to examine herding in a developed and an emerging market (the US and Chinese stock markets). The study covers an overall period from 2004 to 2012, which we split into pre-crisis, post-crisis and crisis period.

Main findings of CH 95 model show no evidence of herding regardless of the level of information asymmetry between firms and investors in both the US and Chinese stock markets. On the other hand, the CCK 2000 model detects herding differences in the Chinese stock market depending on the information asymmetry level. The findings suggest that the emerging markets are affected by herding during the crisis period, regardless of the firm size and information availability.

Keywords: Herding behavior, Behavioral finance, Information asymmetry, Portfolio choice, Asset pricing.

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1. Introduction

Understanding the investors' behavior and their decision-making is crucial for pricing assets in stock markets. The decision-making beyond diverse asset allocation and hedging strategies can affect prices in stock markets and affect market volatility. For both academia and regulators, it is necessary to understand crowd behavior and the different dynamics among investor groups in order to better interpret economic phenomena (Brunnermeier, 2001). Herding behavior is a largely treated topic in the financial literature. This behavior occurs when investors imitate their peers, or follow the market trend, in their investment decision making. (Economou et al., 2011) argue that market participants are more expected to manifest herding during periods of extreme market conditions. For example, the survey of (Shiller et al., 1987) shows that the crash of October 1987 was provoked by the investors' psychology. Even the 1990's dot com bubble was in part explained by the mutual fund's herding behavior, as mentioned by (Dass et al., 2008). Indeed, the last financial crisis is another good example of this period where prices largely move away from fundamental values. As a result, the real economy has been largely threatened by the financial crisis between 2007 and 2008 (Economou et al., 2011). This financial crisis was the most severe since the Great Depression of the 1930'. Markets are, in this period, highly affected by frictions as liquidity problems and information asymmetry. Consequently, the market instability raises the systemic risk that participants can not hedge.

Herding behavior is largely used to explain some market anomalies as bubbles and large price deviation from fundamentals. (Christie and Huang, 1995) define herding as the tendency of investors to imitate the decision of other investors or to follow the market trend. As reported by (Khanna and Mathews, 2011), when herding exists in a stock market, it could induce a poor decision quality, and the aggregate information may be inferior compared to a free herding market. As an illustration, if a group of market participants herd, the accumulated private information could not be inferred by the following investors. (Devenow and Welch, 1996) state that a coordination mechanism is required for investors to herd. The mechanism could be a signal received by most of investors, as a price movement for example. Alternatively, the herding represents social interactions when investors make their investment decision based on observing a partner's decision. In both cases, the authors confirm that it is fiction to think that investors take their investment decision independently. Indeed, numerous influential traders confirm that their investments are largely influenced by other traders.

Herding occurs because of two principal reasons as explained by (Bikhchandani and Sharma, 2001). First, intentional herding takes place whenever investors prefer to chase the mean crowd move and neglect their private information. Second, spurious or unintentional herding arises when traders invest based on identical public information. Although it is crucial for regulators to identify the causes of the different herding types, it is difficult to empirically distinguish between them. As long as the number of factors that affect investment decisions, and the reasons behind a trade stay hidden, regulators could find difficulties in identifying the herding type (Kremer and Nautz, 2013).

In this paper, we can examine the investors' incentives behind the existence of herding by introducing a new dimension, which is the information asymmetry. Using several proxies for information availability, that is, dividend policy, bid ask spread, firm size and market sophistication along with considering the market condition (pre, post or during crisis period), this study allows us to investigate herding in different information availability contexts. Depending on information availability, investors could herd to compensate their lack of information and to feel more confident. Otherwise, they could herd by neglecting their information, that is, they herd when information asymmetry is low and information is at hand.

Policy makers and market regulators, with the intention of reducing the information asymmetry between firms and investors, have proposed major reforms. For example, the US Securities and Exchange Commission (SEC) has promulgated the Reg FD (Regulation Fair Discloser) to enforce the information disclosure between firms and investors. Even the 2001 Nobel Prize Laureates in Economics, George Akerlof, Michael Spence, and Joseph Stiglitz were nominated due to their crucial work in which they analyze the markets with information asymmetry[3]. The Laureates explain many market anomalies using a theoretical framework based on the assumption of asymmetric information. The agents in this framework possess different information level; one party has superior information compared to the other one. Consequently, the well-informed party can use its private information, in order to improve its payoff compared to the low informed party. Managers are supposed to have more inside information about the investment opportunities available to their firms (their stocks' value).

Therefore, the literature review dealing with corporate finance defines the information asymmetry as the existence of differences in possessing information whether between managers and other market participants or among investors. (Ravi and Hong, 2014) explain how information asymmetry could arise among investors, or between the firm insiders and investors. In their study, they show how the asymmetry between investors is empirically related to the asymmetry firm-investors. When firms decrease their information disclosure, the firm-investors asymmetry is high but the between investors asymmetry is low because all investors need to get financial information. When the firm-investors asymmetry is low, all investors have access to information so the between investors asymmetry is low too.

The between investors information asymmetry exists when some investors get nonpublic information about the firm financial situation. The market maker changes the price sensitivity depending on this information asymmetry among investors (Chae, 2005). In our study, we implement two herding models using different proxies for information asymmetry. Among others, we use the dividend policy as a proxy for the information asymmetry firm-investors, and the bid ask spread to measure the between-investors information asymmetry. We also treat herding depending on firms' size and market sophistication, as we include data for both a developed and an emerging market.

Although the existing herding literature has mainly focused on the existence (or nonexistence) of herding, our study focuses on the effect of information availability on herding. We use the matching methodology in order to construct portfolios with different information asymmetry levels, yet with comparable firms' characteristics. We aim to examine if herding is more pronounced in a high information asymmetry context. In other words, we investigate if herding is really driven by investors' lack of information. We treat different information asymmetry portfolios to examine herding in a developed and an emerging market

[3]See the http://www.nobelprize.org web site for further information.

(the US and Chinese stock markets). The study covers an overall period from 2004 to 2012, which we split into pre-crisis, post-crisis and crisis period.

The rest of the paperis organized as follows. The first section starts by developing the hypotheses to link herding and information asymmetry. The second section presents the research methodology. We start the section by a brief recall of the CH 95 and CCK 2000 models. Next, we present the propensity score matching method. Finally, we present the proxies we use for information asymmetry.The last section presents data and empirical findings. We first start the section by presenting both the Sample date and the period. Next, we present descriptive statistics for the herding models' variables and the covariates we use to match firms. Finally, the last section provides empirical findings and ends with a conclusion.

2. Literature review and hypotheses development

For each individual stock, our study needs an information asymmetry measure. This measure should represent the degree of market informed trading, because information asymmetry cannot be directly observed. Following the previous literature, we use several proxies in order to measure information asymmetry, such as dividend payment, bid-ask spread and firm size along with the market sophistication.

In our empirical investigation, we use several information asymmetry proxies for some reasons. In the first place, previous literature does not agree about the “best” proxy. We believe it is more accurate to use many proxies in order to reduce the result doubtfulness of relying on only one proxy. Second, when using different information asymmetry proxies, we are able to detect the result's sensitivity to those proxies. In the following part, we connect herding concept with information asymmetry and its proxies, then we form our study hypothesis.

2.1. Herding relation with information asymmetry

In the literature, we find many papers that investigate the information asymmetry and confirm its effect on financial markets. Herding behavior is also widely cited as one of the investors' attitudes that affect the market. However, these studies do not make a direct association between herding and information asymmetry. These studies mention briefly the need for information as a possible explanation of herding occurrence, but they do not develop the link between herding and information asymmetry. In this section, we try to link investors' herding behavior and the information asymmetry considering the results of previous studies.

A wide literature investigates the relation between information asymmetry and information quality. If we look closely to the studies, we notice that many authors use the volume in order to measure the degree of information asymmetry. Others use the firm size in order to evaluate firm's information asymmetry. For example, (Suominen, 2001) build his theoretical model by suggesting that a high trading volume is related to a high information quality. This is because informed traders reveal their private information when they trade assets. Inversely, in a market characterized by a low level of liquidity (low transaction volume), information quality is poor, thus information asymmetry will be more prevalent, as it is also predicted by (Diamond and Verrecchia, 1991).

Consequently, (Kremer and Nautz, 2013) use trading volume as a proxy to measure the level of information quality, in order to determine if the herding behavior level is greater when institutional investors herd. In view of linking the herding level and the information quality, previous literature uses the hypothesis of the intentional herding theory. This theory suggests that herding behavior is present when the trading volume is low. For that, they suppose the presence of an inverse relationship between the information quality and the herding level. In this case, when the market is liquid and the trading volumes are high, that suggests a low level of information asymmetry (good information quality), and thus it can only involve a low herding behavior degree. Otherwise, when the volumes are low, we can assume that the information asymmetry level is high, so the level of herding behavior might also be high.

According to (Dornbusch et al., 2000), contagion behavior among investors is caused either by liquidity problems or information asymmetry. Also, as explained by (Park, 2011), when investments are made based on non-financial information, they may be associated with herding behavior. This is because investors are more prompt to herd when they collect imperfect signals about an asset, and when they face sources of uncertainty about the future (Khanna and Mathews, 2011). Comparatively, when market participants hold poor information about an asset, their trading activity may lead to a weak herding level (Park, 2011).

On the other hand, and based on a Sample of US equity funds, (Lakonishok et al., 1992) split up their Sample in order to sort the firms based on their level of information access, using the firm market capitalization. Like (Kremer and Nautz, 2013), they expect to detect more herding in small stocks compared to the firms with a large market capitalization. They find strong evidence that supports the presence of intentional herding compared to the existence of unintentional herding. Additionally, other recent researchers, namely (Venezia et al., 2011) and (Choi and Sias, 2009), approve that markets exhibit less herding in large companies and more herding in small stocks. Moreover, using a market simulation, (Zhou and Lai, 2009) findings are in the line with the previous assumption, that is, herding is more present in small firms where information is less available.

In this paper, we can test whether the intentional herding behavior exists more in the US and Chinese stock markets. In fact, detecting a high herding level in a market with high information asymmetry will suggest the existence of the intentional form of herding, given that investors lack information. In contrast, if herding does exist in a low information asymmetry market (where information is available), it could be considered as an unintentional herding, since all investors use the same available information. It is also considered intentional if they neglect the information and follow the crowd. The unintentional herding type is generally driven by the use of identical information and through the investors' reaction to the same public signal, as explained by (Bikhchandani and Sharma, 2001).

Furthermore, as cited by (Lux, 1995), besides the investor psychology, the level of access to financial information is important in driving herding behavior. For example, investigating the features of herding behavior using an experiment, (Fernández et al., 2011) examine the interaction between the investor cognitive profile and his level of access to information. Their findings show that, in an exactly alike cognitive profile, the herding differences are explained by the divergences in the investors' level of access to information. Furthermore, according to (Wärneryd, 2001), investors are generally unable to process all the signals and information in their possession. In addition, investors are often not certain about the securities value while trading, because of the uncertainty about the quality of the information they receive. They believe that other investors have information that is more accurate. They consequently tend to infer the accurate security value by observing the decision of other market participants (Fernández et al., 2011). This behavior can lead to herding. The results of (Christoffersen and Tang, 2009) paper confirm the existence of a high herding level when the information context is poor.

In other words, when information asymmetry is high and investors lack information or face uncertainty about the market signal's quality, they are more prompt to herd. Inversely, when investors have good information quality, and have confidence in their information treatment capabilities, they are less prone to herd. Therefore, our first hypothesis is as follows:

H1: *Herding is more prevalent in a context characterized by a high information asymmetry level compared to a low asymmetry context.*

2.2. Information asymmetry and dividend policy

In the first empirical part of this article, we use the dividend policy as an information asymmetry proxy in order to examine the herding level in both the US and Chinese markets. In general, dividends signal information, and changes in dividend policy are important in reducing information asymmetry (Khang and King, 2002). (Miller and Modigliani, 1961) suggest that firms pay dividends notably because they can convey inside information to outsiders about future cash flows. In other words, a positive change in dividends would signal management's confidence about the future earnings increase. Likewise, managers decrease dividends only if they expect a decline in future earnings. (Bhattacharya, 1979), (Miller and Rock, 1985), and (John and Williams, 1985) suggest that dividends reduce information asymmetry by acting as a signaling mechanism. (Lintner, 1956) suggests that managers prefer to raise rather than reduce dividend levels, and this has been widely interpreted as indicating that dividend decreases are associated with negative signals, while dividend increases signal positive news. If insiders/managers of a firm know more about the firm's future prospects than outsiders/investors, then changes in dividends, or the fact that dividends do not change, may convey some information to investors.

Changes in market perception of firm value triggered by dividend change announcements have been largely reported. Among many others, (Pettit, 1976), (Aharony and Swary, 1980), (Michaely et al., 1995) and (Lee and Ryan, 2000) found evidence showing that changes in dividends are positively associated with contemporaneous abnormal stock returns, probably because such announcements convey inside information to outsiders. (Brav et al., 2005) present findings based on an extensive survey indicating that managers believe that dividend payments have information content about firms' future earnings. (Dasilas et al., 2009) report that dividend initiations result in significant positive abnormal stock returns, and that the market reaction to dividend initiations is inversely associated with the firms' information environment.

Based on these findings, dividends have information content and firms that pay dividends regularly are expected to face less information asymmetry problems than dividend non-payers. Thus, according to our first hypothesis and linking the firm's dividend policy to the herding behavior, we can examine if investors are less likely to herd when they invest in dividend payers' firms. In other words, we examine if they are more likely to herd when they invest in dividend non-payers. Accordingly, the second hypothesis we test in this paper is:

H2: *Herding is more pronounced in firms that do not pay dividends compared to dividend payers*

2.3. Bid-Ask Spread and Information asymmetry

Bid-ask spread has been viewed, for a long time, as a proxy for information asymmetry costs. The intuition behind this proxy lies in the fact that, market makers ignore if investors, that are facing them, are better informed, and if they hold more precise opinion about firms' value or not. The market maker charge fees (a spread) in response to the information asymmetry.

Even though the spread reflects a compensation for varied components (order processing costs, information asymmetry costs and inventory costs), (George et al., 1991) show that the bid-ask spread information asymmetry cost is the second predominant component after the order processing costs. Therefore, the prevailing information asymmetry component is largely used in the literature as a proxy to measure information asymmetry.

There exists many models called asymmetric information models treating the spread relation to information asymmetry. In these models, the authors explain how the market maker uses the spread to deal with better informed investors. Market makers use the spread as a compensation to cover the losses made when trading against the well informed market participants. When trading with investors having different information levels, the market maker may lose money if he is facing better informed agents. These potential losses are covered by the spread because the market maker quotes a lower bid price compared to ask price.

(Roll, 1984) built a model to associate the spread to the stock return's variance. Return's variance does not seize the asymmetry between market makers and investors, but only the risk of holding the stock. (Klein et al., 2002) enlarge Roll's model by including a variable measuring the information asymmetry. The authors assume to have different market participants in their model. These participants diverge in their aptitude to process information about firm's performance. The market maker cannot determine if the agent he is dealing with is more or less informed, so he uses the total order demand to deduce the investors' private information. Accordingly, the market maker adjusts the spread depending on the amount of information held by investors. When public information is precise, the market liquidity increases and the spread is low. On the other side, the divergence in information through possessors leads to higher spreads (Kim and Verrecchia, 1994). The information asymmetry among the market participants reduces the market maker chance to have an information advantage compared to the well informed investors, thus the market maker protects himself from the well informed participants by increasing the spread.

As mentioned first by (Bagehot, 1971), to stay in the market, the losses generated by trading with informed agents are neutralized by the market maker, using gains from trading with low informed agents. (Glosten and Milgrom, 1985) argue that, the more the market maker is dealing with better informed investors, the greater the risk of potential loss is. Thus, market makers cover those potential losses using a wide spread. In other words, high information asymmetry among agents leads to a wide spread to cover the market maker. When information asymmetry is low, the spread is also low because the transaction risk stays low.

Many other papers try to explain the information asymmetry effect on market maker behavior (ex. (Bagehot, 1971), (Glosten and Milgrom, 1985), among others). (Stoll, 1978) argue that the stocks with high volume expose the market maker to greater losses when trading against better informed participants. In addition, the market makers use the volume signal in order to anticipate the market movement and the returns to come in the future. (Kim and Verrecchia, 2001) investigate the relationship between trading volume and returns when information is rare. They found a negative influence of market value and trading volume on the market spread. The (Biais, 1993) model (among others) explain how a volatile asset price affects the risk of holding inventory. This latter risk is higher when the price volatility is high. As a result, market makers adjust the spread to take account of this risk, and it is shown that market uncertainty is positively correlated with spread.

Following the literature above, we can consider that investors infer the degree of firms' information asymmetry using the size of the spread. To do so, investors believe that market makers enlarges the spread when they face asymmetry between market participants. Consequently, we expect that herding behavior will increase when asymmetry is high because investors lacking information will follow the market consensus. Thus, we can test the following hypothesis:

H3: *Herding behavior will be greater when the spread is high, and inversely a low bid-ask spread will indicate a low herding level*

2.4. Size & Information asymmetry

Previous studies report a positive relation between firm size and firm informational environment. The large firms disseminate more information to investors in comparison to small firms. Private information is therefore less valuable for investors, as information asymmetry between large firms and investors is shown, theoretically and empirically, to be low. (Collins et al., 1987) mention that the investor interest in getting and using private information depends both on the cost of acquiring the information, and the number of agents holding the stock. This is because the price becomes less sensitive to investors' private information when the stock is largely held. This is generally the case for big firms.

(Atiase, 1985), among others, argue that the flow of information is higher for large firms, and that institutional investors assign more resources and time to collect, analyze and disseminate information on large firms. Consequently, information about large firm's activities is more available to investors, since professionals and analysts devote considerable resources to large firm activities.

Investor incentives to collect private information depends on the firm size, as it is confirmed by the theory of (Atiase, 1980). Investors are less motivated to collect small firm's private information. Even the empirical evidence of (Atiase, 1985) is consistent with this theory. For example, (Bamber, 1987) mention the study of (Grant, 1980) where it shows that the Wall Street Journal publishe regularly information about large firms, and less often about small firms.

(Wermers, 1999) examines herding level in small stocks. The author argues that herding would be more predictable in small firms than in large stocks. This is due to the low accuracy of the earnings information transmitted to the market. This low information quality prompts investors to neglect the signal when the consensus opinion diverges. Furthermore, herding level is high on the small stocks, since fund managers exhibit aversion to holding these stocks because of their low liquidity.

Referring to the previous literature (see also (Bamber, 1987), and (Chae, 2005)), empirical evidence shows that the set of information disclosure should increase in function of the firm size. In consequence, herding behavior should be lower for larger firms, since information asymmetry is low, and inversely, herding behavior should be higher for smaller firms because information asymmetry is high. This can be explained by the lack of information the traders face when they trade small size stocks. Investors should compensate the lack of information by expressing herding movement and by following the market consensus. Accordingly, we hypothesize that:

H4: *Herding behavior will be greater when the firm is small, and inversely a large firm will exhibit a low herding level.*

2.5. Herding behavior in emerging vs. developed markets

As mentioned by (Fernández et al., 2011), in addition to the limited capability of treating information, limited access to information leads investors to herd. In fact, the encompassing information uncertainty influences investors' decision-making. Accordingly, herding behavior helps investors' in filling its information gap, and in feeling more comfortable when they make their investment decisions. According to our first hypothesis, herding is expected to occur when uncertainty and information asymmetry levels are particularly high. The information asymmetry could therefore be an important factor that encourages the appearance of herding behavior.

According to (Khanna and Mathews, 2011), herding could arise when investors gather imperfect signals and face uncertainty. Similarly, according to (Voronkova and Bohl, 2005), herding highly persists in emerging markets compared to developed markets, because of the poor information quality and inferior market transparency. Particularly, when an investor notices a considerable number of trading operations, but he is uncertain about the asset's value and gets a weak signal, this investor will be attempting to follow the market, as mentioned by (Bikhchandani et al., 1992).

Examining an emerging market, the results obtained by (Kim and Wei, 2002) suggest that investors limited access to information in the Korean market leads them to herd. Also, according to (Black, 1986), herding is encouraged by the noise in prices. The same result has been found by (Borensztein and Gelos, 2000) using an emerging market mutual fund data base, where their conclusion states that herding exists and is related to market's information deficiency.

The Chinese stock market is considered as an emerging market. It is a recent market compared to the old markets in the developed countries. For example, both the Shanghai and the Shenzhen markets start trading in the early nineties (Shanghai in 1990 and Shenzhen in 1991). As mentioned by (Hilliard and Zhang, 2015), the Shanghai stock market represents a Main Board Market as it is for the NYSE in the U.S Market, and the Shenzhen Stock exchange is a Growth Enterprise Market as its counterpart, the NASDAQ exchange in the American Market.

The difference between the American and the Chinese findings could be due to the differences in the characteristics of these markets. As reported by (Ni et al., 2015), the Chinese individual investors represent over 80% of the overall Chinese market participants. In addition, the Chinese companies often exhibit a high level of state ownership and information asymmetry. In the Chinese market, the dominant investors are Chinese, and their investing knowledge is generally limited. The Chinese investors and market characteristics give rise to the ideal environment for herding appearance.

According to (Hilliard and Zhang, 2015), unlike the investors in the American market who require a high return, Chinese investors mainly require lower returns for small versus large stocks because of the lower bankruptcy cost. This is because the government is a large shareholder and holds important capital parts in many firms. This large government participation prevents firms' bankruptcy by assisting the firm that faces financial difficulties.

There are reasons that make the Chinese Market dominated by the individual investors. In particular, compared to the rest of the world, China has one of the highest saving rate. The saving rate is almost half of GDP in 2013 and that is the same since 2000[4]. That makes the individual investors in possession of a huge amount of money available for investing. On the other hand, the stock market is one of the rare investment opportunities that have the Chinese residents associated with the investment in real estate and in bank deposits. The Chinese individual investors flee the bank deposits because interest rates are kept lower than market rates to seek a strengthened economic development. They also flee the real estate, because the regulation on the private ownership of properties is rigid. Accordingly, Chinese individual investors find a substitute in using stock markets as an investment opportunity (Kang et al., 2002).

The global flow of funds related to Chinese resident investment is globally turned toward stocks and real estate. The amount invested in real estate is deeply affected by the governmental regulations. Therefore, the supply and demand fluctuate as funds are widely oriented into trading on stock markets (Burdekin and Siklos, 2012).

As mentioned by (Hilliard and Zhang, 2015), emerging markets (and less developed markets) are more likely to be affected by herding behavior because investors in this countries have low information flow, and in consequence, they are more inclined to follow the trends. For example, in their research, (Chang et al., 2000) find evidence of herding in the studied emerging markets (that is, in Taiwan and south Korea), and no herding evidence in the U.S

[4]Information about savings data source: world development indicators from The World Bank web site: data.worldbank.org (2013 rate).

and Hong Kong Markets (the evidence was week in Japanese market). The researchers indicate that in the emerging markets, the difference in herding is due to the investor lack in getting firm-specific information.

The literature shows how a market that is dominated by individual investors is more exposed to herding behavior. This is due to their restrained market knowledge. As in the Chinese market, those dominant individual investors are more likely to assimilate the positions taken by other investors and to follow the market trend (Hilliard and Zhang, 2015). Consequently, it is possible to expect more herding in the Chinese stock market, as long as this market is dominated by individual investors, who face limited investment opportunities. The same authors justify the existence of a speculative environment in the Chinese market by the dominant presence of individual investors and the lack of information, which drive the herding behavior.

(Luo and Schinckus, 2015) examine whether or not the US market affects the Chinese market herding behavior. The authors analyze a Sample of Chinese firms over the period 2006 to 2012. This study intentionally targets this period as long as the financial crisis that originates in the US market had spread throughout the rest of the world. Therefore, the authors suppose that herding behavior could arise in this situation in the Chinese stock market. They attend to determine if the fragile emerging markets, as the Chinese stock market, could be somehow affected. Even if the impact of the US market on the Chinese market exists, the herding contagion was not documented. They explain the absence of contagion by the difference in the structure of the investigated markets. Indeed, the government can quickly interpose in the Chinese stock market because of its micro and macro unique structure. Inversely, the US stock market is independent of the US government that cannot directly interfere during the destabilizing periods.

Regarding the characteristics of the Chinese market compared to the US market, the information asymmetry level may be higher in the Chinese market because of the listed firms' corporate governance low quality, and because of the large earnings management. Furthermore, the Chinese investors are less experienced, and the fund industry does not have a long history compared to the US one. For example, junior fund managers follow their predecessors, that is, they follow the seniors in their investment strategy giving more chance to the market dysfunction persistence (Chen et al., 2007). Consequently, and according to the previous empirical literature review, we can test if herding behavior is more likely to be stronger in the Chinese stock market compared to the US market. Thus, the next hypothesis we are testing is:

H5: *Herding behavior is stronger in the Chinese stock market compared to the US stock market.*

3. Research Methodology

In our study, we examine herding behavior using different models that we present in the following part. Moreover, we review the propensity score matching methodology. We use this method to get sub-Samples with close characteristics but different information asymmetry level. Furthermore, we discuss the covariate variables that we use to match dividend payers with non-payers, and high bid-ask spread firms with low bid-ask spread firms. Finally, we present the methodology. We explain the basis for classifying firms into dividend payers and non-payers, and to distinguish high bid-ask spread firms from low bid-ask spread firms.

3.1. Herding models

Based on the previous empirical literature, we perform herding tests using two main models: the Christie and Huang model, established in 1995, and Chang, Cheng and Khorana model, formed in 2000. Those empirical models are presented in the next section.

3.1.1. Christie and Huang (1995) model

The first model we use to test for herding is developed by (Christie and Huang, 1995) (CH 95 hereafter). The researchers use the stock returns' cross-sectional standard deviation (CSSD) as a dependent variable in a linear regression in order to capture herding.The dispersion is mathematically determined using the following formula:

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

Where: $R_{i,t}$ is the return of the firm i at the date t, $R_{m,t}$is the market return at the date t, Nis the total number of firms present in day t, $CSSD_t$ is the Cross-sectional standard deviation of individual stock returns at day t. The linear model of CH 95 is formulated as follows:

$$CSSD_t = \beta_0 + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t \qquad (2)$$

Where: D^L_t is equal to 1 if the market return on day "t" is lying in the lower tail of the market return distribution, and 0 otherwise. D^U_t is equal to 1 if the market return on day "t" is lying in the upper tail of the market return distribution, and 0 otherwise. $CSSD_t$ is the Cross-sectional standard deviation of individual stock returns at day t.

This linear model can be explained with a simple intuition. The researchers try to test if during the extreme market movement, the dispersion around the market would decrease. That is, when the market return is in the extreme tails (1% - 99% or 5% - 95%) of the market return distribution, we expect a decreasing dispersion. This would help us in examining whether or not herding exists. If the investors trade around the market move, a significant negative β_1 and β_2 coefficients can accordingly capture herding.

3.1.2. Chang, Cheng and Khorana (2000) model

The model of (Chang et al., 2000) (CCK 2000 hereafter) is based on a non-linear regression model. They use the cross sectional absolute deviation (CSAD) to capture the individual stock returns' dispersion around the market return. The dispersion is calculated as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{3}$$

Where: $R_{i,t}$is the return of the firm i at the date t, $R_{m,t}$is the market return at the date t, N is the total number of firms present in day t, $CSAD_t$ is the Cross-sectional absolute deviation of individual stock returns at day t. This dispersion variable is used in the following non-linear model, to test for the existence of herding behavior:

$$CSAD_t = \beta_0 + \beta_1\left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + \varepsilon_t \tag{4}$$

Where: $R_{m,t}$ is the market return during the date t, $|R_{m,t}|$ is the absolute value of the market return at the date t.

The CCK 2000 model is built on the evidence that it exists a positive linear relationship between the market return and the dispersion of individual stock returns. Although this may be true, the situation is different when investors trade around the market move. In this latter case, when herding is present, an increase in the absolute value of market returns may produce either a decrease or an increase in the dispersion of individual stock returns at a decreasing rate. This effect leads to the violation of the linear relationship. The result will be a change in the dispersion shape along with a non-linear effect at high returns. The CCK 2000 model uses this fact by implementing a non-linear term equal to the square of the market return ($R_{m,t}^2$) to capture herding. The case when there is lack of linearity, herding would be present in the market. This situation implies a coefficient β_2 of the formula (4) significantly negative.

3.2. Propensity Score Matching

The origin of this method dates back to the study of (Rosenbaum and Rubin, 1983) when they start considering the selection bias problem related to the observational studies. Unlike the experimental studies, the non-randomized observational studies suffer from an evaluation problem, because the units' allocation to the different groups is not randomized. The authors present the Propensity Score Matching method (PSM hereafter) in order to offer a solution to this problem. Accordingly, we use the PSM in order to match the different information asymmetry portfolios.

(Heckman et al., 1997) helped in developing the PSM method by focusing on selection bias problems. This method is a Sampleing procedure useful when the researcher needs to control some Sample characteristics. It allows to generate a control subsample which, compared to the treated group, has a very similar covariate distribution. In other words, with propensity score matching method, a researcher can pair a treatment unit with a control one that has the same characteristics measured by the propensity score. Even though the PSM method is usually used to analyze two groups, a researcher can apply the method to compare several groups of subjects.

There exists a number of other methods, but PSM remains appealing for many reasons. Firstly, as it is stated by (Rosenbaum and Rubin, 1983), this method allows performing a simple pair analyses based on the treated and control groups, in order to measure their equivalence when there exists some confounding variables. Secondly, because of the similarities between the treated and the control group distributions, the variance of the average treatment effect is low, that is, a decreasing difference between the two groups averages, results in a decreasing variance of the covariance estimate. In addition, while examining the same element before and after taking a treatment, the results are generally different compared to the case where the examined elements are already different. This is because the difference between the treated group and the non-treated one may come not from the treatment, but from the elements' own characteristics.

As stated by (Austin, 2011) the observational studies have a limitation because even though it is possible to have a random subject selection, it is almost impossible to do a random treatments' allocation. For this reason, researchers cannot make inferences from non-randomized Samples, since the difference in the outcome could be due either to the treatment effect or to the differences among subject characteristics. We need to deal with the same issue when we treat herding among dividend payers and non-payers and bid-ask spread. Herding could be due to the differences in firm's characteristics and not to the information asymmetry level. Using a matching Sample, we are sure to have firms of similar characteristics that differ only in information asymmetry level.

A researcher may use a variable called "covariate" if the units he is examining in the experiment differ because of the influence of this variable. Thus, the covariates measures are taken before the treatment application, and then used in the analyses in order to consider the differences among units. This may give more appropriate outcome about the treatment. The researcher is not interested in the covariates' relationship with the dependent variable, but it is rather used in order to remove the differences between units. As an example, suppose we need to examine animals living in cages that differ in temperature. We can take into account the cages temperature as a covariate variable in order to perform a regression where the cages temperature is statistically matched. The same reasoning applies to business and investment. In order to compare very similar companies that have similar characteristics (same size, same industry …) we perform propensity score matching.

In this study, we employ the PSM method in order to classify companies into two portfolios that have different information asymmetry level. First, the selected portfolios contain firms that do not differ, except in terms of dividend payment. That is, companies that have the same covariates' distributions and do pay dividend are assigned to the payers group, whereas the firms that never pay dividend are assigned to the non-payers group, since the two portfolios should contain companies that are very close in their characteristics, but do have distinct dividend policy. This allows us to distinguish the two information asymmetry levels: on one hand the high asymmetry level in the group containing dividend non-payers, and on the other hand, the group representing the low asymmetry level contains dividend payers. Second, we perform another matching for the high bid-ask spread companies to compare them with the low bid-ask spread ones. This distinction between dividend payers/non-payers matched groups, and between high/low bid-ask spreads is done for both US and Chinese firms. Thus, it is important to select the covariate variables that explain the differences in the firm dividend policy, and the determinants of bid-ask spread.

First, using the same database collected from Datastream Advance, the selected covariate variables are downloaded for all the US and the Chinese payers/non-payers firms and high/low Bid-ask spread firms. Second, for each of the four subgroups (ex. payers or non-payers, US or Chinese firms), the probability of paying dividends as a function of the selected firm's characteristics has been estimated using a Logit regression[5]. For each firm, a propensity score is generated using the estimated values. The same procedure is used with the bid-ask spread portfolios.

The estimated model is as follows:

$$P(X_{i,t}) = \beta_0 + \beta_1 \text{ Covariates }_{i,t} + \varepsilon_{i,t}$$

Where :

- The "i" identifies the firm i, and "t" is the year t.
- P(X i,t): depends on the matching process:
  - ⇨ Matching of payers vs. non-payers:
    P(X i,t) equals 1 if firm "i" is a dividend payer in year "t", 0 if the firm is a dividend non-payer,
  - ⇨ Matching of high vs. low Bid-ask spread:
    P(X i,t) equals 1 if firm "i" has a Low BAS in year t, 0 if the firm has a High BAS,
- Covariates: depends on the matching process:
  - ⇨ Matching of payers vs. non-payers:

    Size: logarithmic market capitalization
    Profitability: Earnings before Interest and Taxes scaled by Total Assets ($EBIT_t/TA_t$)
    Growth opportunities: Market to book value (MTBV)
    Borrowing ratio: total loans scaled by equity capital and reserves
    Sector: the Global Industry Classification Standard (GICS) classification
  - ⇨ Matching of High vs. Low Bid-ask spread

    Firm size: log of market capitalization
    Share turnover: number of traded shares scaled by shares outstanding
    Return variability: coefficient of variation of spread mid-point
    Sector: the Global Industry Classification Standard (GICS) classification

We then select for each dividend payer, a dividend non-payer that has a similar propensity score. That is, we form a Sample of non-payers with the nearest neighbors that have the closest propensity score. We choose a matching without replacement technique in order to avoid using the same non-payer firm with different payers. Once the matched Samples are built, we use the same models we present in the last section in order to test for herding

[5]This regression has been performed using the Stata software.

behavior among matched payers and non-payers. The same method is used to produce the matched high and low spread firms[6].

In our study, the difficulty arises from the differences among the firms that pay dividends and the non-payers, and the different characteristics that affect the spread. We need to select firms that are similar but follow different dividend policies. We also need to get close firms by controlling the covariates that affect the bid-ask spread. We use the propensity score matching in order to solve this problem. This method allows limiting the comparison to a single dimension that is the propensity score. Rather than selecting firms according to many variables that explain the dividend policy or the spread, we reduce the comparison to a single factor. We get better propensity scores by including all the covariates that influence the probability of paying dividend and the size of the spread.

3.2.1. Covariate variables controlling for dividend payment

The literature treating dividend policy suggests many factors to explain the firm dividend policies. These factors include leverage level, growth opportunities, the firm size and the profitability as suggested by (Fama and French, 2001) and (Deangelo and Deangelo, 2006), among others.These factors are determinants of dividend payment decision. In order to control for the dividend payment differences, we use different variables to control these firms' characteristics. Accordingly, we are controlling for the profitability, the growth opportunities, the size, the leverage and the sector in order to explain the firm's dividend policy.

3.2.1.1. Size

As suggested by the life cycle theory, a firm's size affects its dividend policy since large firms are expected to be more profitable, mature and are more likely to have large retained earnings. Consequently, those firms could easily raise funds since they have more access to capital markets. Their dividend policy is therefore more flexible compared to small firms. The relation between size and dividend policy is consequently positive as suggested by the life cycle theory (Deangelo and Deangelo, 2006).

Furthermore, it is possible to measure the large firm's manager performance when dividends are paid as argued by (Damodaran, 2011). Shareholders face difficulties in monitoring manager's activities when ownership is dispersed. Therefore, large firms try to convey information to shareholders and to the market by paying dividends. We use the market value as a covariate variable to match firms by size. This value equals the stock price multiplied by the number of outstanding shares. We take the logarithm of market capitalization for our first covariate.

3.2.1.2. Profitability

When companies reach a high maturity level, they generally become more profitable, and according to the life cycle theory, the high profitability level allows firms to pay dividends (Mueller, 1972). As a result, the level of firm profitability explains the firm's dividend policy

[6]We require the matched firms for bid-ask spread to be in the same quarter in order to avoid matching the firm with itself.

since the stable future earnings allow a consistent dividend payment. For example, Chinese listed firms' dividend payment decisions are strongly influenced by the level of earnings (Wang et al., 2011). In addition, the signaling theory suggests that dividend changes can predict a future change in earnings. (Liu and Chen, 2015) examine this latter theory using US market data and find a significant impact of dividend changes on changes in earnings.

Similarly, examining the relation between changes in dividend payment and future earnings, (Benartzi et al., 1997) demonstrate that a firm's decrease in dividend can signal a future increase in earnings. Therefore, we include a variable in our model in order to match the firms having the same profitability level.

When comparing several firms, it is important to measure the companies' profitability in percentage because the information provided in the income statement expresses the level of profitability only in terms of absolute values (Damodaran, 2011). We then measure the profitability using the pretax return on assets (ROA) calculated as the earnings before interest and taxes ($EBIT_t$) scaled by the value of total assets (TA_t). This measure excludes the effect of taxes, which allows us to compare the portfolios.

3.2.1.3. Investment/Growthopportunities

The growth and the investment opportunities are important in explaining the dividend payment policy. As suggested by the life cycle theory, when a firm reaches its maturity level, its growth rate starts to decline and the firm is expected to begin paying dividends. Therefore, the information concerning the transition to the maturity level is conveyed by dividend initiation. Thus, profits are retained when the firms have investment opportunities, otherwise they pay dividends.

Many studies examine the relation between firms' dividend policy and their growth opportunities. For example, (Baker, 1989) explains how dividend non-payers retain their cash in order to avail investment opportunities. As suggested by (Von Eije and Megginson, 2006), companies that have a fast growth are less likely to initiate dividends. According to (Bruce Payne, 2011), firms are less likely to pay dividends when they have a high market-to book ratio, (i.e. when they face more growth opportunities). On the other hand, the results obtained by (Fama and French, 2001) report a positive relation between dividend payment and growth opportunities. (Denis and Osobov, 2008) report that the relation between the dividend payment decision and the investment opportunities varies among countries.

In our article, we use the market-to-book ratio as a proxy for the firms' growth opportunities. According to (Block, 1995), this ratio is important since it gathers both the internal and external factors related to price, and thus it helps in analyzing firms at market and company levels. For example, firms with low book-to-market value, that announce an omission or a decrease in dividend payment, have a greater exposition to the new negative information, as it is shown in the study of (Van Eaton, 1999). Following (Fama and French, 2001) and (BC Payne, 2011), we compute the ratio by dividing market value by book value of firms.

3.2.1.4. Leverage

We use the borrowing ratio to control for the extent of external funding. As stated by (Jensen and Meckling, 1976), firms that have conflicts of interest between stockholders and managers can reduce their agency costs using the leverage. By debt contracts, stockholders can monitor managers' use of firms' cash flows. This is in line with the agency models that explain how capital structure along with dividend payments can help reducing information asymmetry. That is, the more a manager relies on debt contracts and pays dividend, the less the cash flow that remains under his control. That leads us to confirm that the capital structure is associated to the dividend policy. (Von Eije and Megginson, 2006) show that, the firm contracting high debt level is generally less likely to pay dividends and pays less dividend amount.

The capital structure can further affect firms' dividend policy because the firms get restrictions from lenders, as the later need to secure their funds. This postulate is supported by the agency costs theory. Not only this theory confirms the effect of leverage on dividend policy, but also the signaling theory explains this effect. For example, (Rhee and Chang, 1990) suggest that, many firms do pay dividend using the borrowed money, in view of signaling their interesting future prospects. In addition, it has been argued by (Bruce Payne, 2011) that dividend initiators are mostly less risky firms, unlike the riskier firms who tend to reduce their payout ratio. Therefore, given that leverage increases firm risk, the authors confirm that dividend policy is associated with the firms' debt level.

In order to include the debt level in our model, we use borrowing ratio as a covariate variable for leverage. Following (Ali, 2013), we use total loans scaled by equity capital and reserves to measure the leverage level.

3.2.1.5. Sectors

We include in the model a variable that controls for industries, to ensure that the sub-Sample companies are as similar as possible. We aim also to ensure that the stocks classified as "financial" (40 GICS code) will be matched only with their peers. We use the Global Industry Classification Standard code (GICS) to define the different industries. This variable is used for both the matching of payers/non-payers and low/high bid-ask spread.

3.2.2. Covariate variables controlling for Bid-ask spread

There exist a comprehensive literature that examines the bid-ask spread relation to information asymmetry. This literature outlines the many variables that we can use in order to take into consideration the determinants of the spread (Chung et al., 1995). Those variables are usually used as control variables. Empirical research about bid-ask spread is consistent with market microstructure theory as it shows correlation of the spread with variables such as share price, trading volume, share turnover and volatility (Agrawal et al., 2004). In order to form our matched Samples, we use those control variables, namely, firm size, share turnover and return variability.

3.2.2.1. Firm size

On average, big firms convey more frequently information to market participants compared to small firms. Big firms are closely followed by a large number of financial analysts compared to small firms. These characteristics suggest that information asymmetry should be low for large firms. Accordingly, the literature suggests that the spread is inversely related to firm size.

Market makers have to provide liquidity to market participants and risk to deal with traders having an information advantage. They need to compensate their losses from trading with informed traders by setting an adequate spread. The spread always exists because the component of bid-ask spread in relation with adverse selection exists even when there is no order processing cost or inventory costs (Hanousek and Podpiera, 2003). In the other hand, the magnitude of the demand for a stock is reflected in its market value, thus, many authors consider the market value as a spread determinant. The firms that present a high market value are commonly characterized by a deep market, as there are many agents trading their equity frequently. These firms benefit also from outsized analysts' monitoring, therefore, they reduce the firms' information asymmetry. The spread is consequently low for these firms because their stocks are very liquid, and market makers are less exposed to the risk of adverse selection.

(Agrawal et al., 2004) mention many models such as (Glosten and Milgrom, 1985) and (Kyle, 1985) where the authors argue that market makers face two groups of market participants: the informed and the uninformed noise traders. Market makers, on average, lose money when facing informed traders because the prices do not reflect their private information. Thus, market makers cover those loses by the profits they earn from the uninformed traders. Market makers widen the spread to cover their losses and therefore the bid-ask spread is large on average when the number of informed traders is low, that is, when the information asymmetry between investors is high.

The profit resulting from trading on the basis of "information related to big firms" is likely to be higher compared to the profit resulting from trading in "comparable information about small firms". Accordingly, comparing the same information type, investors will find the one related to big firms more valuable compared to the information related to small firms. Furthermore, financial analysts focus on big firms because the larger part of market participants invest and are interested in holding large stocks. Even empirical evidence shows that spread is inversely related with firm size, since small firms are less frequently traded by investors ((Demsetz, 1968), (Tinic, 1972), (Copeland and Galai, 1983) among others).

We control for the size factor using matching method, in order to test for herding using the bid-ask spread as a measure of information asymmetry. We use the logarithmic market capitalization as a market value variable to include the firm size in the matching model.

3.2.2.2. Share turnover

Many basic studies such as (Demsetz, 1968), (Tinic, 1972) and (Lin et al., 1995) investigate the impact of variables (such as market price, risk and trading volume) over bid-ask spread. They admit that the bid-ask spread is wider when the between agent information asymmetry is high. In fact, (Copeland and Galai, 1983) argue that the level of spread rises up when there is a lift in the percentage of informed traders. (McInish and Wood, 1992) point out the existence of an inverse relation between spreads and trading volume. When trades are large, their information content is reflected in a narrow spread. In fact, liquidity is an important factor that explains the difference between ask and bid prices. Liquid assets are rapidly converted into cash, thus brokers require less compensation (narrow BAS) compared to when they execute trades for illiquid assets.

Models about informed trading, as the (Subrahmanyam, 1991) model, where investors are supposed to have rational expectations, predict that large price movements may result from larger trade volumes. It has been documented in previous studies that bid-ask spread is inversely related to trading volume. For example, (Seyhun, 1992) empirical evidence shows an increase in trading volume when agents exploit their private information. This increased volume induces a narrow spread. Large trades generally are reflected in lower spreads, and result in an increase in the revealed adverse information.

Following (Conroy et al., 1990), the volume turnover we use is equal to the number of traded shares scaled by shares outstanding for a year.

3.2.2.3. Return variability

(Roll, 1984) built a model to associate the spread to the stock return's variance and according to many studies [(Zhang et al., 2008), (Hussain, 2011), amongothers], the bid-ask spread ispositivelyaffected by pricevariability. This positive relation can be explained by investors' need for private information when price is highly volatile. Indeed, investors risk to get a large inaccuracy when they forecast the share's price based only on public information, compared to the more precise price estimation they can get based on both the private and public information. Thus, the probability of getting considerable disparities in prices conditional on public/private information is more pronounced when firms' prices are volatile. Consequently, volatile prices lead to higher expected profits for the agents who use private information. Brokers can consequently charge higher spreads. In the opposite case, the BAS is narrow if price variability is low because of the low uncertainty level.

(Copeland and Galai, 1983) argue that a volatile price may present a positive relation to bid-ask spread changes. Following (Chung et al., 1995), we measure for each year the stock price variability. To do so, for each firm we calculate the daily mid-point of the quoted spreads, and then we determine their annual coefficient of variation[7].

3.3. Information asymmetry proxies

Concerning the matching portfolios, we need to form the groups of dividend payers/non-payers and the groups of high/low Bid-ask spread. We present in the next paragraphs the steps we follow in order to form those different information asymmetry level groups.

3.3.1. Dividend payers vs. dividend non-payers

From the overall Sample, we need to classify each of the stocks that pay dividend in a portfolio, and the non-payers in a second one. We obviously use the same procedure for both US and Chinese stocks. We require for our experimental design some conditions; as long as we need to ensure that the firm dividend policy is stable during the considered period.

We consider a firm as a dividend payer if it pays dividends during the considered year. Inversely, the non-payer is a firm that does not pay dividends. For the overall period (2004-2012), we require for the dividend payers a continuous dividend policy. The omission of dividends for one year (or the missing data) excludes the firm from the group of payers. Similarly, the non-payers have to omit payment during the overall period. On the other hand, we require for the sub-periods a constant dividend policy during the sub-period and at least during the five years before the sub-period. This condition helps in getting a steady dividend

[7] We also used other variables for size (total assets) and for return variability (stock return standard deviation). The herding results we obtain for the matched Samples are similar.

policy and larger sub-Samples for the regressions. The remaining firms that alternate between paying dividend and omitting payment are excluded.

3.3.2. Bid-Ask spread measure

We split our data into two portfolios according to the Bid-Ask Spread: low BAS vs. high BAS. Let us recall that we are aiming to test the following hypothesis: herding is more common in high BAS firms, that is, when the information asymmetry among investors is high, compared to the low BAS firms. We expect more herding in high BAS compared to low BAS.

To distinguish the two sub-Samples, we start by computing the daily percentage BAS for all companies, over the entire period (2004 to 2012). The daily BAS is calculated, for each firm, using the following formula:

$$\%\ \text{BAS}_{\ i,t} = \left[\frac{Ask_{i,t} - Bid_{i,t}}{(Ask_{i,t} + Bid_{i,t})/2}\right]$$

Where the characters represent:

"t" = the quotation day,

"i" = the firm's index,

$Ask_{i,t}$ = the price that a buyer accept to pay for an asset (dealers' sell price),

$Bid_{i,t}$= the price that a seller accept to sell an asset (dealers' buy price),

$\%BAS_{i,t}$ = represents the Bid-ask spread of firm "i" at day "t" in percentage.

In other words, the percentage spread is calculated using the bid-ask spread value scaled by the quotes' mid-point. Then, for each company, we calculate the quarters' median %BAS over the entire period (2004 to 2012). We use the median bid-ask spread percentage instead of using the mean percentage since the mean value is perturbed by outliers. Finally, we order the obtained quarter %BAS of all firms by quarter, in order to find a median spread value for each quarter. The median of the company on a given quarter is compared with that of other firms. If the spread of the company is greater than the median spread calculated on the whole Sample on the same quarter, the company goes in the high BAS portfolio ; alternatively, if its spread is lower, the firm belongs to the low BAS portfolio. As a result, we get the two sub-Samples of high and low BAS firms to test for herding. We repeat the same procedure with both US and Chinese stock markets.

3.3.3. Size and Market sophistication

The next information asymmetry measure we use is the classification of companies according to their size. We used both the firm capitalization (Market value) and total assets to classify firms into four portfolios. For each year, we split firms into:

Big firms: the top 25% biggest firms. The portfolio contains the largest firms in terms of market value or total assets. They have a size superior to 75% of market value or total assets' distribution.

Medium big firms: firms having a size under the third quarter (75%) and superior to the median (50%).

Medium small firms: this portfolio contains firms under the median (50%) but superior to the first quarter (25%).

Small firms: the smallest firms in the Sample. This portfolio contains the firms that have a market value or total assets under the first quarter of the distribution (under 25%).

We apply the herding models on these four portfolios to investigate herding at different information asymmetry levels. For both variables we use (market value and total assets), we test for herding in the full period (2004-2012) and the three sub-periods we present in the next section.

Concerning market sophistication, we perform all the previous regressions, with the different asymmetry measures, using both the US stock market and Chinese stock market data. These data (along with the findings) are presented in the following section.

4. Research Sample data and period

We present in this section the data we use to conduct our herding tests. We first present the different Samples and then the full and sub-periods we decide to use in order to take more advantage of our data.

4.1. Sample selection

A Sample of companies from the US stock market and Chinese stock market are used in this study. We select all the listed and delisted firms, between January 2004 and December 2012, for both the US and Chinese markets. The total number of firms in the US market, during the period we examine, is 7130. The Chinese Sample contains a list of 2603 listed and delisted firms. The number of firms fluctuates during the Sample period because of listing and delisting firms.

From the overall Sample, we first compose two similar portfolios of dividend payers and dividend non-payers. Those portfolios are used to get matched groups of dividend payers and non-payers. We also build the portfolios of low vs. high bid-ask spread firms, then we matched the firms. The number of firms in each group for each sub-period is presented in the following table:

[Insert Table 1 here]

The price we use to determine stock returns is provided by the Thomson Reuters Datastream database for the US Sample, and from the Compustat Global database for the Chinese Sample. The remaining variables we use for matching are drawn from Thomson Reuters Datastream.

To test for herding, we need the daily return for all companies, for each portfolio. We calculate the logarithmic returns both for firms and for the market index. Following (Yook and Kim, 2008), (Hwang and Salmon, 2004) and (Yamamoto, 2011) (among others), we use the

S&P500 composite index to measure the fluctuations of the US stock market. Furthermore, we follow (Lin and Fu, 2010), (Chiang et al., 2008) and (Demirer and Kutan, 2006) by using the Shanghai Stock Exchange composite index to measure to Chinese stock market movements.

4.2. Period selection

Following (Xie et al., 2015), we separate the main Sample period (2004-2012) into three sub-periods in order to isolate the crisis effect on herding behavior. This will help us to reduce the effect of crisis anomalies on herding, instead of only investigating the whole period. Despite the fact that there is no consensus in the literature, there are several studies which define 2007-2008 as a crisis period ((Poon et al., 2013), (Chen et al., 2012), (Huang et al., 2015), among others). We follow the same stream of studies and examine herding during the pre-crisis period (2004-2006), the crisis period (2007-2008) and the post-crisis period (2009-2012). The overall period starts from January 2004. We do not consider the pre-2004 period in order to; 1) avoid the effects of dot-com bubble on our results, 2) to cover the period for which data is available for the variables used in the study[8]. We run the herding models on both the overall period and the three sub-periods; hence, we could have a better perception of the herding phenomenon.

The following diagram illustrate the fluctuations of the Shanghai Composite Index during the period January 2004 to December 2012 (our overall Sample period). The diagram provides factual support to the partition we apply on the overall period.

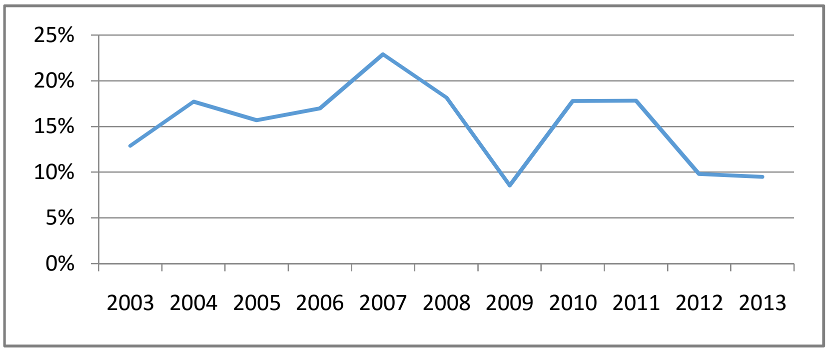
Figure 1: Shanghai Composite Index from 01/01/2004 to 31/12/2012

(source: Thomson Reuters Database)

We can easily observe a steady market movement during the periods 2004-2006 and 2009-2012 compared to the period 2007-2008. The latter period includes the financial agitation during the financial crisis where we observe the boom and crash movements. As claimed by (Xie et al., 2015), the crisis period illustrates a market stress period during which market volatility was high. The diagram gives support to the sub-partition we use in our study period. In fact, started by the end of 2006, Shanghai Index continued shifting up during the year 2007, and reached its historical peak of 6124.04 points, before the crash drives the market down until late 2008.

[8] Data for variables such as dividend payment and stock turnover is missing for many Chinese firms in early 2000s.

Figure 2: Percentage increase in Chinese GDP

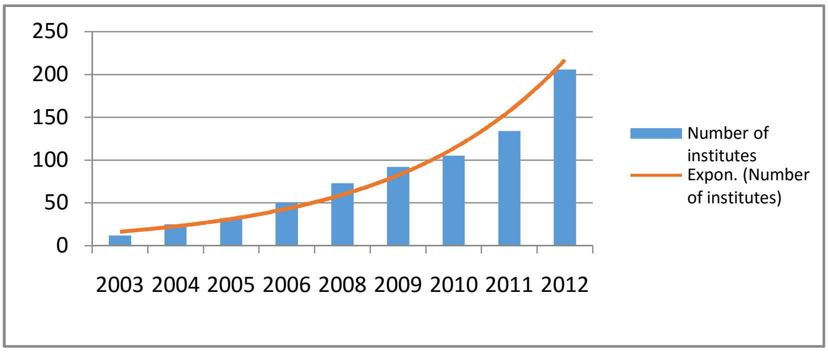


Source: "National Bureau of Statistics of China" web site

There are some reasons for this upward movement in the Chinese stock market. According to (Xie et al., 2015), the stock market boom was assisted by a considerable increase in Chinese GDP. As we can see in the following diagram, China achieved a very high percentage growth of GDP when it attains 22.88% in 2007. It is the highest economic growth in China during the last decade. This large economic growth has sustained the stock market upswing.

Moreover, the Chinese market has been influenced by the new shareholder structure reform. This reform could have induced a reinforcing effect as it helps correcting the market long-term assets mispricing. Moreover, the stock market capital resources have been increased thanks to the government. The raise in the number of Qualified Foreign Institutional Investors (QFII) has an exponential shape as we can see in the next diagram.

Figure 3: number of qualified foreign institutional investors

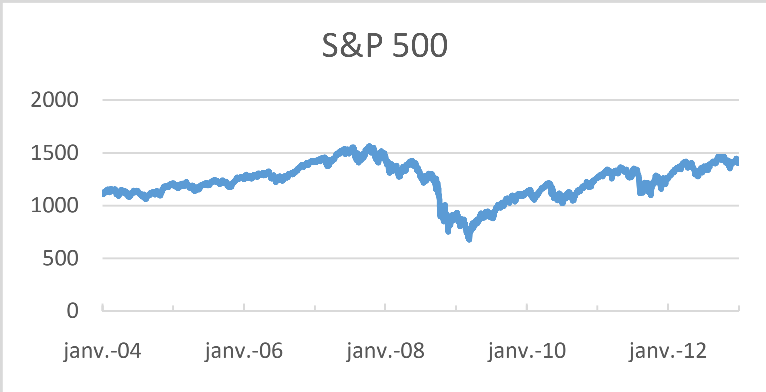


Source : Data from the China Securities Regulatory Commission web site

The number of QFII's has almost doubled between the year 2006 and 2009, and it is 10 times bigger in 2012 than it was in 2003. All these circumstances had boosted the Chinese market to reach the historical peak.

To a certain degree, it is possible to discuss some of the reasons of market collapse. For example, by the end of 2007 and till the end of 2008, the Shanghai Index dropped to 1664 points while the financial crisis that started in the US market were spreading around worldwide. Many authors such as (Arouri and Jawadi, 2010) explain the collapse by markets' integration. In fact, during the last decade, the emerging market's economic stability had increased their co-movement with the developed markets. This is also due to the emerging markets' integration, progress and positive perspectives.

Figure 4: S&P500 Index from 01/01/2004to 31/12/2012



Source: Thomson Reuters Database

According to Figure 4, the US market (here represented by S&P 500) shows a similar tendency compared to the Chinese index during the period 2007-2008, where we can observe the financial crash. We use the same sub-periods for the US and Chinese stock markets to have comparable results when we test for herding.

5. Descriptive statistics

In this section, we first present the descriptive statistics for the US and Chinese market returns. Second, we give some characteristics for the portfolio of dividend payers vs. non-payers and the portfolio of low vs. high bid-ask spread. To do so, we present the descriptive statistics for the covariate variables we use for matching. In other words, we examine the difference between portfolios in terms of profitability, growth opportunities, size and leverage for dividend payers/non-payers portfolios, and the differences in terms of liquidity, price variability and size for low/high portfolios. Third, we present the statistics of the variables we use to test for the herding existence, that is; the cross sectional standard deviation (CSSD), cross sectional absolute deviation (CSAD) and the returns for all portfolios. Statistics are presented for the full-period (2004-2012) and the three sub-periods (2004-2006), (2007-2008) and (2009-2012).

5.1. Market returns

As we mention in the previous section, we use the S&P500 and Shanghai Stock Exchange composite index to determine the market returns. The table below presents the mean return during the full period and for the sub-periods, along with the standard deviation and the tendency measures. Panel A provides summary statistics for the US stock market and Panel B is dedicated to Chinese stock market statistics.

The mean return for the US market is lower in the full period compared to the Chinese market return. Similarly, the return dispersion is higher in the Chinese stock market compared to the US market. This suggests that investors get higher returns but more volatility for investing in the Chinese market.

[Insert Table 2 here]

The mean return in the US market is equal to 0.01% with a standard deviation equals 1.31%. This return/dispersion couple is lower in the US market compared to the Chinese stock market where the mean is equal to 0.02% with a standard deviation equals 1.68%. Furthermore, the maximum return in the overall period is equal to 10.96% in the US stock market and 9.03% in the Chinese stock market. In addition, the minimum return is equal to -9.47% in the US stock market and -9.26% in the Chinese stock market. We notice that the mean market return is negative for both markets in the crisis period, and that the highest and lowest returns are made in this period. The variation in returns is also high due to the financial crises.

To summarize, even though the returns are relatively close in the two markets, the return's dispersion is different, which makes it interesting to closely observe its effect on herding.

5.2. Covariates for payers vs. non-payers

We match the portfolios of dividend payers and non-payers using diverse variables. As we mention previously in the literature section, we match firms according to the variables that may affect firms' dividend policy. That is, we use the level of profitability, growth opportunities, size and leverage as covariates for matching portfolios.

We present in Table 3 some summary statistics for the matching covariates. The first column presents statistics of dividend payers, whereas the dividend non-payers statistics are in the second column. For each category, we present the statistics of the full period and the three sub-periods.Panel A is dedicated to the US market covariates, and Panel B presents statistics for the Chinese stock market.

In panel A1, we present profitability measured by earnings before interest and taxes (EBIT) scaled by total assets (TA). Profitability is a relevant factor that explains dividend policy.The life cycle theory states that firms that pay dividends are mostly mature and profitable. The statistics in Panel A1 confirms that the US dividend payers in our portfolio are largely more profitable than dividend non-payers. The mean ratios are 7% and 13% for dividend payers and non-payers respectively. In addition, the relative standard deviation is of (0.09/0.07=1.29) for the payers and (0.46/0.13=3.54) for non-payers proving that dividend non-payers are not only less profitable but the level of profitability variation is high. The dividend payer stocks' profitability reaches higher values in all periods. All those statistics confirm the higher profitability of dividend payers.

[Insert Table 3 here]

We observe the same tendency for the Chinese dividend payers. When we look into panel B1 of Table 3, the mean ratio (EBIT/TA) is higher for the payers in all of the three periods. The median value of EBIT/TA shows how half of dividend payers have a largely higher profitability compared to the non-payers. Moreover, the mean value of profitability of dividend non-payers is negative in all periods, and the minimum values are relatively lower. This confirms that the Chinese dividend payers are more profitable than the dividend non-payers.

The second variable we present in Table 3 is the growth opportunities measured by the ratio of market to book value (MTBV). The previous theoretical section suggests that dividend payers have relatively less growth opportunities because those firms start paying dividends when they reach maturity. Inversely, dividend non-payers prefer to expand by investing their cash flow rather than paying dividends.

Panel A2 of Table 3 shows a slightly superior mean MTBV in the dividend non-payers portfolio compared to the payers. The three sub-periods show the same tendency, as the ratios are barely superior in dividend non-payers. Moreover, the same observations can be made with the median values. For example, the median at the crisis period (third period) is equal to 2.17 for non-payers compared to 1.93 for payers. Even the maximum values are superior in non-payers portfolio. Similarly, the extreme values are larger, thus the standard deviation takes larger values. These characteristics suggest that the firms in the non-payers group may face some investment opportunities and retain their earnings. Inversely, the firms in the payers' group prefer to pay dividends, as they would have less investment opportunities.

We present in Panel A3 of Table 3 the variable "size" for the US stock market. The mean market value confirms that dividend payers are bigger compared to the non-payers that have smaller mean market value. The mean value is equal to 5.81 billon $ for the overall period of dividend payers, whereas the mean value for dividend non-payers is equal to 1.05 billion $. We observe some similarities in the characteristics of the Chinese portfolios in Panel B3. Firms in the dividend payers' portfolio have a mean size that approximates 2 billion $, whereas the non-payers have a mean size of 175 M$. The median values confirm this tendency. For example, more than half of the firms exceed 567 M$, unlike the Chinese non-payers 71 M$ median value. Given these points, statistics are in line with the theoretical review that supports the size variable power in explaining how dividend payers, in both the US and Chinese portfolios, are larger than dividend non-payers.

The last covariate we use to match dividend payers with dividend non-payers portfolio is leverage. We measure the leverage level using the borrowing ratio that is equal to the total loans scaled by equity capital and reserves. Panel A4 provides summary statistics for the US portfolios and panel B4 contains the Chinese market statistics. The leverage level in dividend payers portfolio is higher than the non-payers. This is in concordance with the signaling theory, which suggests that the manager would signal the good future prospect using debt and dividends. The mean borrowing ratio value for the full period of the payers' portfolio is 131.2 compared to 48.95 for non-payers.

The maximum values are close in the two portfolios but the median show superior debt level in the dividend payers portfolio. The Chinese portfolios show the same tendency as the debt is higher in payers portfolio aside with a higher median and standard deviation compared to the non-payers[9].

[9]The borrowing ratio is high because of the financial institutions' values. We have determined the statistics for the same portfolios but with a separation of financial institutions from the remaining sectors. The mean Borrowing Ratio of the US financial institutions is 173 for dividend payers and 120 for non-payers. The remaining sectors show a mean ratio of 74 for dividend payers and 48 for the non-payers. For the Chinese market, the financial institutions' mean BR equals 55 for dividend financial institutions and 41 for the non-payers, whereas the other sectors have a mean BR of 48 for dividend payers and 34 for non-payers.

5.3. Covariates for low vs. high bid-ask spread

Table 4 presents descriptive statistics for the variables we use to control for the determinants of bid-ask spread (BAS) when we match low and high BAS companies. Panel A1 describes the descriptive statistics for the share turnover. We recall that BAS is wider when trading volumes are low, because brokers require more compensation on the illiquid stocks. The descriptive statistics confirm this inverse relation between BAS and volume turnover in both the US and Chinese stock markets. For example, the three sub-periods show a high volume turnover for low BAS compared to the high BAS firms. The median value is higher too in the portfolio of low BAS companies. We observe the same tendency in the Chinese portfolios (panel B1). Volume turnover mean and median are lower in High BAS portfolio in all of the three sub-periods. The variation coefficient of high BAS is still relatively higher when it is compared to low BAS portfolios in both markets.

[Insert Table 4 here]

Price variability presents a positive relation to BAS as we discussed in the covariates literature section. This relation is confirmed by the statistics we present in Panel A2 ofTable 4. The three sub-periods show a larger price variability in high BAS portfolios. Both the mean and the median values are large in this portfolio. Even the variation coefficient of turnover is higher as it equals 1.56 for high BAS portfolio and only 0.64 for low portfolio. The extreme values confirm the same tendency. On the other hand, panel B2 of Table 4shows similar characteristics in the Chinese portfolios.

Larger variability in mean ratios are associated to high BAS portfolio. As an illustration, the full period mean variation coefficient is equal to 0.16 in low BAS portfolio while it equals 0.178 in the high BAS one. Even the median is higher, as we have a ratio of 0.14 in high BAS and 0.135 in low BAS portfolios. The statistics show essentially a lower price variability when the BAS is low, and inversely higher BAS are associated to higher price variability.

Furthermore, firms in the low BAS portfolio are relatively big compared to high BAS firms. All of the mean, median and extreme values confirm the theoretical inverse relation between BAS and firm size.

5.4. Dispersion, stock returns and correlation

Table 5 provides some descriptive statistics for the two dispersion measures we use in our empirical test. The first measure is $CSSD_t$, which stands for daily cross-sectional standard deviation of returns. The second is $CSAD_t$, the daily cross-sectional absolute deviation of returns. The table presents statistics for the matched portfolio of dividend payers and dividend non-payers[10]. Following the previous tables, Panel A provides data for the US stock market and Panel B is dedicated to Chinese stock market data. These data concerns the full period and the three sub-periods too.

[Insert Table 5 here]

[10]Given that the statistics are similar in the matched and non-matched portfolios and for dividend payers/non-payers, low/high bid-ask spread, and the size portfolios, we present the remaining statistic tables in the appendix.

Both dispersion measures show higher mean dispersion in the portfolio of dividend non-payers. We observe the same outcome in the portfolio of high BAS. Identically, we observe an inverse relation between size and return dispersion, the larger the firm, the less the dispersion is. Even though the dispersion is high for low information asymmetry portfolios, we notice lower variation coefficients compared to dividend payers, low BAS and big firms' portfolios. For example, the full period in Panel A shows a mean CSSD of 3.75 for the non-payers and 2.04 for the dividend payers' portfolio; whereas the standard deviation is 1.62 and 1.11 respectively. In that case, we can compare the variation coefficients. This coefficient is equal to (1.62/3.75)=0.43 for the group of non-payers. However, the coefficient is (1.11/2.04)=0.54 for the second portfolio.

The same observation is done for the CSAD. The mean 2.14 and 1.38 compared to the standard deviation 0.80 and 0.71 respectively gives the variation coefficients 0.37 and 0.51. This suggests that for the full period, returns' dispersion variation around the mean is greater in the portfolios of dividend payers, low BAS and big firms compared to the portfolios of dividend non-payers, high BAS and the smaller firms. Even though this distribution is slightly different among the sub-periods, the dispersion and variation are very similar among portfolios.

Mean stock returns for the US and Chinese stock markets are presented in Table 6. The mean daily stock return for the dividend non-payers of the US market is negative in the full period. However, the mean return of the payers' portfolio is positive. Both US and Chinese portfolios mean returns are greater in the payers portfolio. The same pattern is observed in the low bid ask spread for both markets.

[Insert Table 6 here]

In addition, the mean return is lower in the small firms and gets higher with the higher size. We notice a negative mean return during the crises period for all portfolios. This is the effect of the financial bubble crash and the bear market move[11].

6. Empirical findings

We present our empirical findings in this section. We start with the first information asymmetry measure; that is, the portfolio of companies that pay dividends and those who do not pay. Next, we present the low and high bid-ask spread portfolios. Finally, we provide findings for the portfolio of companies classified according to the size variable. We have

[11]Before we proceed with matching, we have checked all the matching variables for possible correlations. We used both Pearson and Spearman correlation coefficients. We recall that Pearson coefficient measures possible linear relationship among variables, while Spearman coefficient tests if a possible monotonic function can explain the relationship between variables. Most of the coefficients are not significant and show the absence of correlation among matching covariates. This result is the same for both the dividend payers/non-payers covariates (EBIT/TA; MTBV, BR, MV) and the bid-ask spread matching covariates (Turn, CV, MV). The coefficients confirm that our matching variables are free from multicollinearity issues and that regressions can be run correctly. The coefficients are available upon request.

analyzed the matched portfolios since their results are similar to those of the non-matched portfolios[12].

6.1. Matched payers and non-payers portfolios

The portfolios we treat in this section, group companies that have the same dividend policy. From the group of dividend payers and non-payers we obtain, thanks to the matching method, two new portfolios with relatively two different information asymmetry levels, but with firms that have similar characteristics. We provide findings for herding in both markets (the US stock market and the Chinese stock market) for the full period, the period pre-crisis, post-crisis and during the crisis period.

6.1.1. Christie and Huang (1995)

Table 7provides findings for the model (2). Panel A lists regression coefficients for herding test in the US stock market and Panel B shows the results on the Chinese stock market. Left column indicates findings for dividend payers' portfolio and right column gives the dividend non-payers results.

[Insert Table 7 here]

As we have seen before, the Christie and Hwang model is designed to capture the herding when market experiences extreme movements. The model focuses only on the extreme tails of market return distribution. Following (Christie and Huang, 1995), we mean by extreme movement the situation where market return lies at 5%-95% or 1%-99% extreme tails[13]. As we can see in the results fromTable 7, the positive Betas indicate the absence of herding behavior when the market reaches the extreme level both in upward and downward movements. The Christie and Hwang model fails to capture a decline in security return's dispersion in the stress periods, that is, when market return is extremely bullish or bearish. The model gives the same results for both the US and the Chinese market. All the Beta coefficients are significantly not negative[14]. These non-negative betas suggest that the investors do not replicate the market return when this latter lies in the extreme tails. We observe an absence of return convergence during those agitated periods.

On the other hand, we notice that the findings are the same for both the dividend payers and the non-payers. This means that, when the market reaches the highest or lowest level, herding does not depend on the level of market information asymmetry between the company and the investors. This difference does almost not exist even during the crisis period. The three sub-periods show the same results for both the American and the Chinese stock markets. The returns of individual securities do not get close to the average. Instead, investors may invest seeking for the fundamental value as stated by (Christie and Huang, 1995). This result

[12] Full results of the portfolios containing non-matched firms that pay or do not pay dividend, and the low/high bid-ask spread portfolios are presented in the appendix.

[13] We present in the appendix, for all portfolios, the findings of (Christie and Huang, 1995) model for 1%-99% distribution's tails.

[14] Following (Demirer and Kutan, 2006), all regressions are run using robust standard-errors. That is, we use the Newey–West standard errors to account for eventual heteroscedasticity and autocorrelation and consistent errors.

confirms the findings of previous empirical literature we present in the previous sections. They are consistent with (Christie and Huang, 1995), (Chang et al., 2000), (Demirer and Kutan, 2006), and (C.Gleason et al., 2004) findings, as they support the herding absence during extreme market stress. They suggest that investors follow the rational asset pricing models.

The results are similar regardless of the definition we chose to represent the "extreme" movement of the market. When we use 5% in the lower tail and 95% in the upper one, the results remain similar to those with the 1% and 99% values. (Chang et al., 2000) explain that this model needs more nonlinearity in the relationship between the market return and the dispersion of individual returns in order to capture herding. The model only analyzes the market at the extreme tails, it is more difficult to capture herding and to get a significant negative beta coefficients. Therefore, it is interesting to run the CCK 2000 model using the same data and portfolios, in order to get more insight about herding in the corresponding markets.

6.1.2. Chang, Cheng and Khorana (2000)

The second model we use is (Chang et al., 2000). Table 8 provides findings for this model (model 4). In the same line with the previous table, we provide regression coefficients for herding tests on the US stock market in Panel A. Panel B shows the results on the Chinese stock market. In order to measure the effect of information asymmetry on herding, we present findings for dividend payers' portfolio in the left column and we list the dividend non-payers' results in the right column. We recall that herding is captured by a significant negative β_2 that confirms the decrease of dispersion, or its increasing at a decreasing rate, when stock returns get higher or lower.

We start our analysis by observing the American stock market. By looking at the β_2 values, we notice that the CCK 2000 model does not capture any significant herding tendencies in the US stock market regardless of the information asymmetry level. This result confirms the findings obtained in the previous studies. All of (Chang et al., 2000), (C.Gleason et al., 2004) and (Chiang and Zheng, 2010) findings are consistent with the coefficients we present in Table 8.

Regarding the differences between the studied sub-periods, herding is not captured during both the pre and post crisis periods. The behavior is absent during the crisis period too. Even if the β_2 we find is negative, it isnot significant. This result suggests that the dispersion of individual security returns compared to the market return decreases or increases at a decreasing rate, but not at a significant level.On the other hand, the Chinese market shows distinct tendencies. Herding is captured in several periods. Herding does exist in the full period for dividend non-payers, as β_2 is significantly negative. The three sub-periods also confirm that herding persists among high information asymmetry firms in the Chinese stock market.

[Insert Table 8 here]

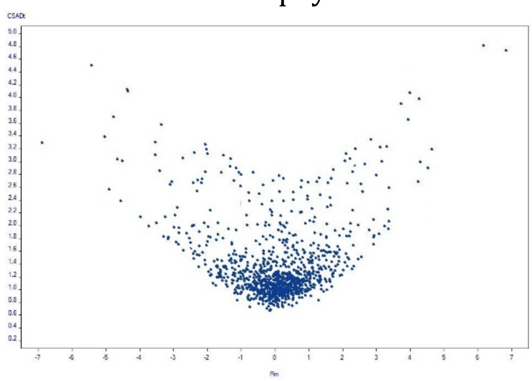
In the Chinese market, we notice some differences between the sub-periods, depending on the level of information asymmetry between firms and investors. Firms that do not pay dividends are supposed to exhibit a higher level of information asymmetry. Investors express more herding behavior when they exchange these stocks, compared to the companies that pay dividends. For the latter firms, we notice the absence of herdingwhen we test the full period. However, herding does exist during the crisis period. In fact, examining the Chinese market during the period 2004 to 2012 shows higher tendencies of herding around the 2007 and 2008 period when the financial bubble emerges.

These preliminary results suggest that, in the financial market, the reduced information asymmetry between the investors and the company may have a reducing effect on herding. For underdeveloped countries, the lack of transparency between the companies and the investors accentuates the herding behavior. On the other hand, even in the subsample of dividend payers companies, where information asymmetry is low, the information conveyed to the market is not enough to reduce the herding during the crisis period. This suggests that investors no longer trust the financial information conveyed by the market, they rather follow the market trend. (Prechter, 2001) confirms this herding tendency of investors that lack information or knowledge.

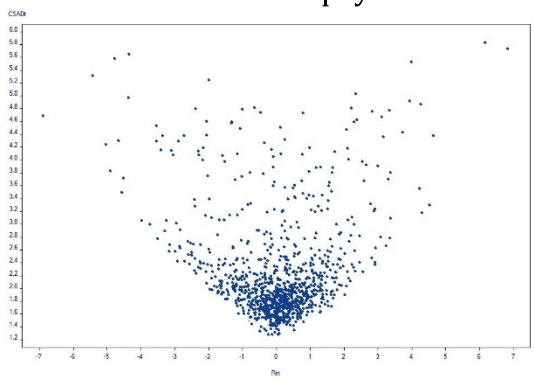
Figure 5: Plots of Market return dispersion on the $CSAD_t$

Panel A: US stock market

Dividend payers

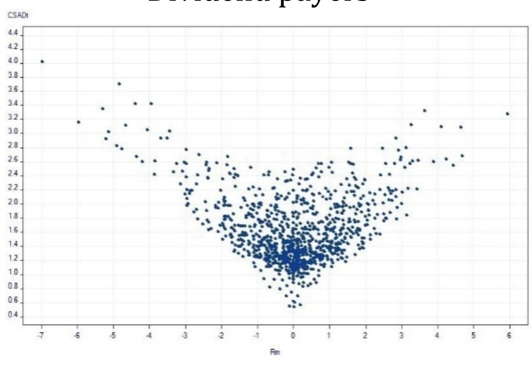


Dividend non-payers

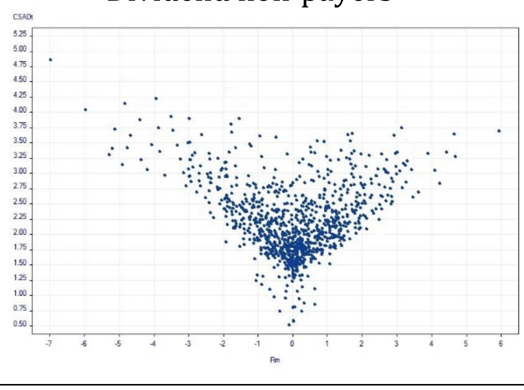


Panel B: Chinese stock market

Dividend payers



Dividend non-payers



These figures illustrate market return dispersion compared the $CSAD_t$for the US and Chinese stock market during the post crisis period. Panel A presents data for the US dividend payers and non-payers, whereas the Chinese variables are presented in Panel B. The vertical axis presents the daily dispersion ($CSSD_t$) and the horizontal axis presents the market return (R_{mt}). We can observe different cloud of dots when we compare Panel A and B. The dispersion is higher in the group of Dividend non-payers in both the US and Chinese data. Moreover, the relation between dispersion and market return is close to linearity in the US data, unlike the Chinese data where the pattern is different and almost concave in dividend-non payers group. This concavity is captured by the CCK 2000 model.

6.1.3. Additional herding analysis

In order to push further the analysis, we use two additional sophisticated models, where we use dichotomous variables, to compare the herding level on different periods and for different information asymmetry levels in the Chinese stock market. The first model, that explores differences of herding among periods, concerns the portfolio of dividend non-payer firms. We compare the three sub-periods regression coefficients to assess the differences in herding intensity. The second model aims to compare the herding between the dividend payers and non-payers portfolios during the crisis period. That is, the first additional model allows us to compare the herding periods (pre, post and during crisis) at the same level of information asymmetry. The second model measures the herding during the same period (crisis period) between two different levels of information asymmetry.

Based on the basic model of (Chang et al., 2000), we build the following model[15]:

$$CSAD_t = \beta_0 + \beta_1 D_4 + \beta_2 D_9 + \beta_3 |R_{m,t}| + \beta_4 D_4 |R_{m,t}| + \beta_5 D_9 |R_{m,t}|$$

$$+ \beta_6 R_{m,t}^2 + \beta_7 D_4 R_{m,t}^2 + \beta_8 D_9 R_{m,t}^2 + \varepsilon_t \qquad (5)$$

where

$R_{m,t}$	=	The market return at date t,
$\lvert R_{m,t} \rvert$	=	The absolute value of the market return at date t,
$CSAD_t$	=	Cross sectional absolute deviation of individual stock returns at day t,
D_4	=	Dummy variable that equals 1 if data lies in the period (2004-2006),0 otherwise,
D_9	=	Dummy variable that equals 1 if data lies in the period (2009-2012),0 otherwise.

We are interested in the coefficientsβ_6,β_7 and β_8 that allow us to compare herding relatively at the same information asymmetry level, through the three sub-periods. A significantly negative β_7 andβ_8 coefficients may capture higher herding compared to the crisis period.

The second model is again based on the model of (Chang et al., 2000). We aim to compare the herding intensity differences, between two levels of information asymmetry, during the crisis period. The model is described by the following formula:

$$CSAD_t = \beta_0 + \beta_1 D_P + \beta_2 |R_{m,t}| + \beta_3 D_P |R_{m,t}| + \beta_4 R_{m,t}^2 + \beta_5 D_P R_{m,t}^2 + \varepsilon_t \qquad (6)$$

where $R_{m,t}$ = The market return atdate t,

[15]We drop the D_7 variable to compare the periods to the crisis one, and to avoid the dummy variable trap.

$\lvert R_{m,t} \rvert$	=	The absolute value of the market return atdate t,
$CSAD_t$	=	Cross sectional absolute deviation of individual stock returns at day t,
D_P	=	Dummy variable that equals 1 if data concerns dividend payers during crisis period, 0 otherwise

This model may help capturing the herding differences in the crisis period. A significant negative β_5 may suggest higher herding tendency of investors when investing in firms that pay dividend. Otherwise, a positive or non-significant β_5 would confirm close herding level in different information asymmetry context.

We run both models using the same data we use for the previous CCK 2000 tests. The coefficients of model (5) are as follows[16]:

β_0	$\beta_1 D_4$	$\beta_2 D_9$	$\beta_3 \lvert R_{m,t} \rvert$	$\beta_4 D_4 \lvert R_{m,t} \rvert$	$\beta_5 D_9 \lvert R_{m,t} \rvert$	$\beta_6 R_{m,t}^2$	$\beta_7 D_4 R_{m,t}^2$	$\beta_8 D_9 R_{m,t}^2$
2.204*** (47.71)	-0.420*** (-6.85)	-0.507*** (-9.08)	0.661*** (17.76)	-0.0006 (-0.01)	-0.153*** (-2.70)	-0.028*** (-5.18)	0.007 (0.53)	0.008 (0.72)

From the latter model, herding tendency is confirmed in the baseline category, which is the crisis period for high asymmetry portfolio (dividend non-payers). Both β_7 and β_8 are positively non-significant. These coefficients confirm that herding during the 2007 and 2008 period was close to the level of herding during the remaining periods. Consequently, even though findings of Table 8 confirm that herding exists in the high information asymmetry context in emerging markets, the impact of herding pressure is similar during the three sub-periods.

This is not in line with the work of (Borensztein and Gelos, 2000) where they test whether or not the future excess stock returns are affected by institutional herding. They used the Lakonishok at al. (1992) measure to closely examine the relation between herding behavior and the short and long-term excess stock returns. This relation is found to be positive regardless of the period used for the excess return. The excess return is greatly affected during the crisis period. These findings differ slightly depending on the investigated portfolios. In fact, herding effect on the excess return is strong and ends rapidly when the portfolio includes firms that are large, “value” or liquid. In the opposite, portfolios including small, growth or illiquid firms show a less herding effect on the excess stock returns, however this effect is more persisting. Those portfolios are analog to the portfolios we build in our study. Low information asymmetry portfolios contain firms that are large, value or liquid; whereas high information asymmetry portfolios contain small, growth or illiquid firms.

The second additional model (model 6) compares herding during the crisis period for different information asymmetry levels.We test for herding in the Chinese stock market using

[16] The model adjusted R^2 is equal to 0.6.

the same data as for the previous models. We use both the portfolio of dividend payers and dividend non-payers during the period 2007-2008 and find the following results:

β_0	$\beta_1 D_P$	$\beta_2\lvert R_{m,t}\rvert$	$\beta_3 D_P\lvert R_{m,t}\rvert$	$\beta_4 R^2_{m,t}$	$\beta_5 D_P R^2_{m,t}$
2.204*** (40.54)	-0.490*** (-6.23)	0.661*** (15.09)	-0.209*** (-3.33)	-0.028*** (-4.40)	0.015* (1.67)

Model (6) does confirm the significant herding during the crisis period in the high information asymmetry context. Moreover, even though herding was detected during crisis in the low information asymmetry portfolio, its level is similar to the level of herding in high information context. This is confirmed by the significantly positive coefficientβ_5.

The findings of this section shed some light on the hypothesis we develop in the previous theoretical section. They confirm that herding exists in a high information asymmetry context. On the other hand, findings do not confirm the higher herding among dividend non-payers and during the crisis period. Finally, our findings support the higher herding in the emerging market compared to the developed one, as herding was absent in the US stock market, but detected among the Chinese firms.

6.2. Matched Bid-Ask Spread portfolios

In this section, we discuss the herding among investors based on an alternative measure of information asymmetry. The Bid-ask spread is employed to build too portfolios: the high BAS group and low BAS. We start the section by analyzing the results of the CH 95 model for the matched Sample. We then move to analyze the findings from the CCK 2000 model.

6.2.1. Christie and Huang (1995)

We provide regression coefficients of CH 95 model in Table 9. Findings are presented for all of the three sub-periods. We assign Panel A to the US market data findings, whereas the Chinese stock market findings are in Panel B. We recall that low BAS might characterize the portfolio of low information asymmetry between investors. On the other hand, higher information asymmetry between investors may be present in high BAS according to our previous literature review. The coefficients β_1 and $\beta_2$for the three periods are positive in the US stock market. That may suggest that dispersion of stock returns do not decrease at the extreme tails of the US market return distribution. However, coefficients for low BAS are negative in the upward tail, but non-significant. This may suggest a slight decrease in the dispersion but not at a significant level to be captured by the herding model.

[Insert Table 9 here]

The high BAS shows the same aspect in the first period for both the upward and downward market moves. Table 9 suggests that herding is absent at the extreme tails in both the US and the Chinses stock market return distributions. Although we used two different levels of information asymmetry between investors, herding is always absent when we are in the extreme tails of market return distribution. The result is the same regardless of the period we use to test for herding.

For additional tests, we use the same portfolios and sub-periods and run the model of CCK 2000.

6.2.2. Chang, Cheng and Khorana (2000)

We provide the findings for the CCK 2000 model inTable 10. The left column reports coefficients for the portfolio of low BAS, while the right column gives results for the portfolio of high BAS. Following the previous tables, Panel A provides US stock market findings, and Panel B is dedicated to the Chinese stock market findings.

According to the coefficient of Panel A, herding among investors is absent in the US stock market when we test the full period. The positive coefficients of $R_{m,t}^2$ suggest the absence of herding regardless the level of asymmetry between investors. The result is the same for the three sub-periods. Despite some negative but non-significant coefficients, no investors' herding is detected in the US stock market.

Findings are different in the Chinese stock market. Panel B provides some evidence of herding among investors when trading stocks in the Chinese stock market. Furthermore, the results are slightly different from the previous information asymmetry measure (ie. dividend policy). When testing the full period, the previous measure did not show herding activities except in the portfolio of dividend non-payers, while both the low and high BAS portfolios show herding tendency in the full period. Even the sub-periods show the same difference. We recall that the portfolio of dividend payers (where information asymmetry is low) confirms that herding is present, at lower level compared to high asymmetry portfolio, only in thecrisis period. The portfolio of low BAS shows investors' tendency to herd regardless of the level of information asymmetry among investors.

[Insert Table 10 here]

We notice that the herding coefficients are less significant in the first and third sub-periods, compared to the crisis period where the coefficients are highly negatively significant. In order to assess the differences in herding level between the portfolios of low vs. high between-investors information asymmetry (ie. the portfolios of low/high BAS), and the differences among periods, we run the additional models (5) and (6) using the same data.

6.2.3. Additional herding analysis

The additional model (5) allows us to compare the herding of the high information asymmetry portfolio during the crisis, with the pre and post crisis periods. Additionally, model (6) allows herding comparison in the same period, at different levels of information asymmetry. We run the same model (5) as in the previous sections, while in model (6) we replace the dummy variable D_p by a variable D_{Low} that equals 1 if data concerns low BAS firms during the considered period, 0 otherwise.

We start our analysis with the data of high BAS portfolio. According toTable 10, herding exists during the crisis period at a highly significant level, and in the pre and post crisis at a lower level. By running model (5), we get the following results:

β_0	$\beta_1\, D_4$	$\beta_2\, D_9$	$\beta_3\lvert R_{m,t}\rvert$	$\beta_4 D_4\lvert R_{m,t}\rvert$	$\beta_5\, D_9\lvert R_{m,t}\rvert$	$\beta_6 R^2_{m,t}$	$\beta_7 D_4 R^2_{m,t}$	$\beta_8\, D_9\, R^2_{m,t}$
1.821*** (25.26)	-0.433*** (-5.05)	-0.114 (-1.35)	0.786*** (13.89)	-0.105 (-1.28)	-0.287*** (-3.60)	-0.038*** (-4.80)	0.017 (1.08)	0.018 (1.19)

The model confirms the tendency of investors to herd during the crisis period. Both coefficients $\beta_7$and β_8 are positive and non-significant. This suggests that herding, during the crisis, when the between-investors information asymmetry is high, is similar to the level of herding in the remaining periods.

(Jiang et al., 2010) argues that noise traders coulddrive a crash in a stock market. Given that herding was also captured in low BAS portfolio, we run the same model and get those results[17]:

β_0	$\beta_1\, D_4$	$\beta_2\, D_9$	$\beta_3\lvert R_{m,t}\rvert$	$\beta_4 D_4\lvert R_{m,t}\rvert$	$\beta_5\, D_9\lvert R_{m,t}\rvert$	$\beta_6 R^2_{m,t}$	$\beta_7 D_4 R^2_{m,t}$	$\beta_8\, D_9\, R^2_{m,t}$
1.703*** (25.78)	-0.372*** (-4.94)	-0.132 (-1.46)	0.470*** (9.24)	-0.179*** (-2.60)	-0.175** (-2.04)	-0.049*** (-6.86)	0.031** (2.38)	0.025 (1.56)

The coefficients show the same tendency as for the previous test. Herding during the crisis period is comparable to the remaining periods when we keep the level of information asymmetry unchanged.

Following the same procedure, we run the model (6) in order to compare herding for each sub-period at different levels of information asymmetry. In other words, we test the difference in herding between two levels of information asymmetry but at the same period. The model gives the following results:

- **Low vs high BAS for the crisis period:**

β_0	$\beta_1\, D_{Low}$	$\beta_2\lvert R_{m,t}\rvert$	$\beta_3 D_{Low}\lvert R_{m,t}\rvert$	$\beta_4 R^2_{m,t}$	$\beta_5 D_{Low} R^2_{m,t}$	Adj R^2
1.821*** (19.39)	-0.117 (-0.86)	0.786*** (10.66)	-0.315*** (-2.98)	-0.038*** (-3.69)	-0.010 (-0.69)	0.45

- **Low vs high BAS for the pre-crisis period:**

β_0	$\beta_1\, D_{Low}$	$\beta_2\lvert R_{m,t}\rvert$	$\beta_3 D_{Low}\lvert R_{m,t}\rvert$	$\beta_4 R^2_{m,t}$	$\beta_5 D_{Low} R^2_{m,t}$	Adj R^2
1.388*** (38.18)	-0.056 (-1.16)	0.681*** (14.71)	-0.389*** (-6.25)	-0.021* (-1.92)	0.003(0.01494)	0.41

[17] The adjusted R^2 for the previous test is equal to 0.47, and to 0.40 for this model.

- **Low vs high BAS for the post-crisis period:**

β_0	$\beta_1 D_{Low}$	$\beta_2\lvert R_{m,t}\rvert$	$\beta_3 D_{Low}\lvert R_{m,t}\rvert$	$\beta_4 R^2_{m,t}$	$\beta_5 D_{Low} R^2_{m,t}$	Adj R^2
1.707***	-0.136*	0.498***	-0.203**	-0.020*	-0.003	0.39
(43.86)	(-1.84)	(10.06)	(-2.38)	(-1.85)	(-0.18)	

The three sub-periods confirm the similar tendency of investors to herd when they invest in higher information asymmetry stocks compared to low information asymmetry. The portfolio of high BAS is affected by herding similarly compared to low BAS as the coefficient β_5 is non negatively significant in all of the three sub-periods. These findings are not in line with the hypotheses we develop in the previous sections. Investors do express similar herding when they trade stocks that are characterized by high information asymmetry between investors (ie. High BAS stocks). Even though investors do herd in low "between-investors information asymmetry", the level of herding stay similar compared to the herding when the asymmetry is high. The findings are the same whatever the period we use to test for herding.

6.3. Firm size portfolios

The last measure of information asymmetry we use in our study is the firm size. The literature review we present in the former section agrees on the investors' tendency to herd while trading smaller stocks. This section allows us to test if this hypothesis is confirmed in both the US and the Chinese stock markets.

6.3.1. Christie and Huang (1995)

We provide findings for CH 95 model in Table 10. We retain the same presentation as in the previous tables: Panel A lists coefficients of CH 95 model for the US stock market and Panel B is dedicated to the Chinese stock market[18].

[Insert Table 11 here]

Panel A ofTable 10 does not show evidence in support of herding in the extreme up and down tails of US market return distribution. No coefficients for D^{up} and D^{down} are significantly negative. The result is the same regardless of the portfolio size we use and for all of the three sub-periods. The Chinese stock market shows the same findings. Panel B confirms the non-existence of herding when market is at the extreme upward or downward moves. When market return is at the extreme distribution tails, herding cannot be spotted by CH 95 model. This result is the same for all periods, and for all portfolio sizes. This is in line with the findings of the previous empirical studies we present in the empirical literature review section.(Venezia et al., 2011) states that herding is greater in lower size firms. They explain this behavior by the noise investors' information need. They explain how large firms' financial information is more available to investors.

[18] We list findings for Total assets' size variable in the appendix.

6.3.2. Chang, Cheng and Khorana (2000)

The model of CCK 2000 allows us to detect herding more easily as it does not focus on only the extreme tails of market return distribution. It rather tests for the linearity between market return and individual stock returns dispersion. Table 11, Panel A shows no investors' herding tendency in the US market except for the small firms. Those companies are characterized by a high information asymmetry level. During the crisis period, the coefficient of $R^2_{m,t}$is significantly negative. This is the only situation where we spot herding in the US stock market. These findings confirm that herding could exist at high information asymmetry context during the crisis period even in a developed market. This is in line with the work of (Chiang and Zheng, 2010) where they detect herding in the US sectors during the crisis period. This is also in line with the findings of (Wermers, 1999), where he explains herding by the US portfolio managers' lack of financial information about small firms.

Except for the largest firms in the Chinese stock market, Panel B shows the herding tendency of investors in medium and small firms. During the crisis period, even the big firms are affected by herding. This may suggest that emerging markets are affected byherding during the crisis period, regardless the firm size. Herding does exist whatever the level of information asymmetry[19].

In order to test if herding is stronger in small firms compared to large firms in the Chinese stock market, we run an additional model where we compare the crisis period at different levels of information asymmetry. The model is built as follows:

$$CSAD_t = \beta_0 + \beta_1 D_H + \beta_2 D_{MH} + \beta_3 D_{ML} + \beta_4 |R_{m,t}| + \beta_5 D_H |R_{m,t}| + \beta_6 D_{MH} |R_{m,t}|$$

$$+ \beta_7 D_{ML} |R_{m,t}| + \beta_8 R^2_{m,t} + \beta_9 D_H R^2_{m,t} + \beta_{10} D_{MH} R^2_{m,t} + \beta_{11} D_{ML} R^2_{m,t} + \varepsilon_t$$

where $R_{m,t}$ = The market return during the date t.

$|R_{m,t}|$ = The absolute value of the market return during the date t.

$CSAD_t$ = Cross sectional absolute deviation of individual stock returns at day t.

D_H = Dummy variable that equals 1 if data concerns big firms, 0 otherwise.

D_{MH} = Dummy variable that equals 1 if data concerns medium big firms, 0 otherwise.

D_{ML} = Dummy variable that equals 1 if data concerns medium small firms, 0 otherwise.

Running the model for the crisis period gives the following results:

[19] It is challenging to compare firm size across markets, as long as the biggest Chinese companies are smaller than large firms in the US stock market, and this is alike for the other sizes.

β_0	$\beta_1\ D_H$	$\beta_2\ D_{MH}$	$\beta_3\ D_{ML}$	$\beta_4\lvert R_{m,t}\rvert$	$\beta_5 D_H\lvert R_{m,t}\rvert$	$\beta_6\ D_{MH}\lvert R_{m,t}\rvert$
1.715*** (12.86)	0.332** (2.32)	0.106* (0.67)	0.017 (0.11)	0.883*** (9.96)	-0.570*** (-5.78)	-0.371*** (-3.44)

$\beta_7\ D_{ML}\lvert R_{m,t}\rvert$	$\beta_8 R^2_{m,t}$	$\beta_9 D_H R^2_{m,t}$	$\beta_{10}\ D_{MH}\ R^2_{m,t}$	$\beta_{11}\ D_{ML}\ R^2_{m,t}$	Adj R^2
-0.292*** (-2.66)	-0.039*** (-3.49)	0.028** (2.17)	0.0007*** (0.06)	0.001*** (0.07)	0.52

All the coefficients of $R^2_{m,t}$ are significant and non-negative except for small firms, suggesting that herding in the Chinese stock market is similar in small firms during the sub-periods. The information asymmetry of smaller firms has been largely documented in the previous studies. These findings are not in line with (Zhou and Lai, 2009) study that confirms higher herding of institutional investors on smaller firms. The need for information is often claimed as an explanation for investors' herding on smaller firms.

7. Conclusion

In contrast to the existing literature, we employ several information asymmetry proxies in order to measure the effect of information availability on herding behavior. Unlike the growing literature that principally examines the existence of herding behavior, we choose a different point of view by focusing on the relation between herding and the financial information availability. We examine both the American and Chinese stock markets. The level of investors' abilities might be different in the developed (American) and emerging (Chinese) markets, thus we might detect different herding levels. That is, in stock markets, it is challenging to consider investors to be completely independent, so herding might be detected in both stock markets.

According to the model of CH 95, when the market move is at the highest or lowest level, herding cannot be explained by the level of information asymmetry between firms and investors. Findings show no difference between a high or low information asymmetry context even during the crisis period. In fact, herding is absent at the extreme tails in both the US and the Chinese stock market return distributions. Even though we employ different proxies to assess information asymmetry between firm and investors or among investors, herding is always absent when we are in the extreme tails of market return distributions. The results are the same for the developed and emerging markets.

CCK 2000 model does not capture any significant herding tendencies in the US stock market regardless of the "firm-investor" information asymmetry level. Investors' herding tendency is observed in the US market only on small firms. Investors exhibit herding when trading those companies during the crisis period. These findings confirm that herding could exist in a high information asymmetry context during the crisis period even in a developed market.

Chinese investors herding tendency was spotted by the CCK 2000 model using different information asymmetry proxies. Herding exists when investors trade medium and small firms. During the crisis period, even big firms are affected by herding. These findings suggest that emerging markets are affected by herding during the crisis period, regardless of the firm size. Herding does exist whatever the level of information asymmetry is. On the other hand, the Chinese market shows distinct tendencies if we focus on dividend policy. Herding does exist when investors trade firms that omit paying dividends. These results suggest that, in the financial market, the reduced information asymmetry between the investors and the company may have a reducing effect on herding. For underdeveloped countries, the lack of transparency between companies and investors accentuates herding behavior. On the other hand, even in the subSample, where information asymmetry is low, information conveyed to the market is not enough to reduce herding during the crisis period. This may suggest that investors no longer trust the financial information conveyed by the market, they rather follow the market trend. Even if the level of herding starts diminishing as a result of the set of regulations made by the China Securities Regulatory Commission, herding is yet significant during the crisis period.

These findings are in line with the existing literature. (Chang et al., 2000) indicate that in emerging markets, the difference in herding is due to investors' inability to get firm-specific information. (Chang and Lin, 2015) show an investors' tendency to herd in less sophisticated markets. They also point out the existence of some cultural features that affect herding appearance. According to (Voronkova and Bohl, 2005), herding is more prominent in emerging markets than in developed markets, because of the poor information quality and inferior market transparency. (Bikhchandani et al., 1992) mention how an investor who notices a considerable number of trading operations, is uncertain about the asset's value and got a weak signal, will be disposed to follow the market trend. (Ni et al., 2015) explain how the difference between the American and the Chinese findings could be due to the distortion in market characteristics. The Chinese individual investors represent over 80% of the overall Chinese market participants. In addition, Chinese companies often exhibit a high level of state ownership and information asymmetry. In the Chinese market, the dominant investors are Chinese, and their investing knowledge is generally limited. The Chinese investors and market characteristics give rise to the ideal environment for herding appearance. It will be interesting for future research to use a different model of herding to compare our findings, and to better understand the incentives behind herding tendency.

References

Agrawal, V., Kothare, M., Rao, R.K.S., Wadhwa, P., 2004. **Bid-ask spreads, informed investors, and the firm's financial condition**. Quarterly Review of Economics and Finance, 44, 58–76.

Aharony, J., Swary, I., 1980. **Quarterly Dividend and Earnings Announcements and Stockholders' Returns: An Empirical Analysis.** The Journal of Finance, 35, 1–12.

Ali, I., 2013. **Dividend payment behavior of European listed firms : Three essays**. University of Grenoble.

Arouri, M., Jawadi, F., 2010. **Nonlinear Stock Market Links between Mexico and the World, Nonlinear**. International Symposia in Economic Theory and Econometrics.

Atiase, R.K., 1985. **Predisclosure Information , Firm Capitalization , and Security Price Behavior Around Earnings Announcements.** Journal of Accounting Research, 23, 21–36.

Atiase, R.K., 1980. **Predisclosure informational asymmetries, firm capitalization, earnings reports, and security price behavior**. University of California, Berkeley.

Austin, P.C., 2011. **An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies.** Multivariate behavioral research, 46, 399–424.

Bagehot, W., 1971. **The Only Game in Town.** Financial Analysts Journal, 22, 12–14.

Baker, H., 1989. **Why companies pay no dividends**. Akron Business and Economic Review, 20, 48–61.

Bamber, L.S., 1987. **Unexpected Earnings , Volume Around Firm Size , Quarterly and Trading Earnings Announcements**. The Accounting Review, 62, 510–532.

Benartzi, S., Michaely, R., Thaler, R., 1997. **Do changes in dividends signal the future or the past?** The Journal of Finance, 52, 1007–1034.

Bhattacharya, S., 1979. **Imperfect Information , Dividend Policy , and " The Bird in the Hand " Fallacy**. The Bell Journal of Economics, 10, 259–270.

Biais, B., 1993. **Price Formation and Equilibrium Liquidity in Fragmented and Centralized Markets.** The Journal of Finance, 48, 157–185.

Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. **A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades.** Journal of Political Economy, 100, 992–1026.

Bikhchandani, S., Sharma, S., 2001. **Herd Behavior in Financial Markets**. International Business Research, 47, 279–310.

Black, F., 1986. **Noise**. The Journal of Finance 41, 529–543.

Block, F.E., 1995. **A Study of the Price to Book Relationship**. Financial Analysts Journal, 51, 63–73.

Borensztein, R., Gelos, R. gaston, 2000. **A panic-prone pack? The behavior of emerging market mutual funds** (No. WP/00/198). International Monetary Fund (IMF) Working Paper.

Brav, A., Graham, J.R., Harvey, C.R., Michaely, R., 2005. **Payout policy in the 21st century**. Journal of Financial Economics, 77, 483–527.

Brunnermeier, M.K., 2001. **Asset pricing under asymmetric information: bubbles, crashes, technical analysis and herding**, Library of Congress Cataloging in Publication Data - Oxford University Press.

Burdekin, R.C.K., Siklos, P.L., 2012. **Enter the dragon: Interactions between Chinese, US and Asia-Pacific equity markets, 1995-2010**. Pacific Basin Finance Journal, 20, 521–541.

C.Gleason, K., Mathur, I., A.Peterson, M., 2004. **Analysis of intraday herding behavior among the sector ETFs**. Journal of Empirical Finance, 11, 681–694.

Chae, J., 2005. **Trading volume, information asymmetry, and timing information**. Journal of Finance, 60, 413–442.

Chang, C.-H., Lin, S.-J., 2015. **The effects of national culture and behavioral pitfalls on investors' decision-making: Herding behavior in international stock markets**. International Review of Economics and Finance, 37, 380–392.

Chang, E.. ., Cheng, J.., Khorana, A., 2000. **An examination of herd behavior in equity markets: An international perspective**. Journal of Banking & Finance, 24, 1651–1679.

Chen, J., Xiao, X., Cheng, P., 2007. **Herd Behaviour of Chinese mutual funds**, in: Suk-Joong Kim, M.D.M. (Ed.), Asia -Pacific Financial Markets: Integration, Innovation, and Challenges, International Finance Review. pp. 373–391.

Chen, Y.-F., Yang, S.-Y., Lin, F.-L., 2012. **Foreign institutional industrial herding in Taiwan stock market**. Managerial Finance, 38, 325–340.

Chiang, T.C., Nelling, E., Tan, L., 2008. **The speed of adjustment to information: Evidence from the Chinese stock market**. International Review of Economics & Finance, 17, 216–229.

Chiang, T.C., Zheng, D., 2010. **An empirical analysis of herd behavior in global stock markets**. Journal of Banking & Finance, 34, 1911–1921.

Choi, N., Sias, R.W., 2009. **Institutional industry herding**. Journal of Financial Economics, 94, 469–491.

Christie, G., Huang, R.D., 1995. **Following the Pied Piper : Do Individual the Returns Herd around the Market?** Financial Analysts Journal, 51, 31–37.

Christoffersen, S., Tang, Y., 2009. **Institutional Herding and Information Cascades: Evidence from Daily Trades**. Social Science Research Network March, 1–55.

Chung, K.H., McInish, T.H., Wood, R.A., Wyhowski, D.J., 1995. **Production of information, information asymmetry, and the bid-ask spread: Empirical evidence from analysts' forecasts**. Journal of Banking and Finance, 19, 1025–1046.

Collins, D.W., Kothari, S.P., Rayburn, J.D., 1987. **Firm size and the information content of prices with respect to earnings**. Journal of Accounting and Economics, 9, 111–138.

Conroy, R.M., Harris, R.S., Benet, B.A., 1990. **The Effects of Stock Splits on Bid-Ask Spreads**. The Journal of Finance, 45, 1285–1295.

Copeland, T.E., Galai, D., 1983. **Information Effects on the Bid-Ask Spread**. The Journal of Finance, 38, 1457–1469.

Damodaran, A., 2011. **Applied Corporate Finance**, 3rd Editio. ed. New York University.

Dasilas, A., Lyroudi, K., Ginoglou, D., 2009. **The impact of dividend initiations on Greek listed firms' wealth and volatility across information environments**. Managerial Finance, 35, 531–543.

Dass, N., Massa, M., Patgiri, R., 2008. **Mutual Funds and Bubbles : The Surprising Role of Contractual Incentives.** Review of Financial Studies, 21, 51–99.

Deangelo, H., Deangelo, L., 2006. **Dividend policy and the earned/contributed capital mix: a test of the life-cycle theory**. Journal of Financial Economics, 81, 227–254.

Demirer, R., Kutan, A., 2006. **Does herding behavior exist in Chinese stock markets?** Journal of International Financial Markets, Institutions and Money, 16, 123–142.

Demsetz, H., 1968. **The Cost of Transacting.** The Quarterly Journal of Economics 82, 33–53.

Denis, D.J., Osobov, I., 2008. **Why Do Firms Pay Dividends? International Evidence on the Determinants of Dividend Policy**. Journal of Financial Economics, 89, 62–82.

Devenow, A., Welch, I., 1996. **Rational herding in financial economics**. European Economic Review, 40, 603–615.

Diamond, D.W., Verrecchia, R.E., 1991. **Disclosure, liquidity, and the cost of capital.** The Journal of Finance, 46, 1325–1359.

Dornbusch, R., Park, Y.C., Claessens, S., 2000. **Contagion: Understanding How It Spreads**. The World Bank Research Observer, 15, 177–197.

Economou, F., Kostakis, A., Philippas, N., 2011. **Cross-country effects in herding behaviour: Evidence from four south European markets**. Journal of International Financial Markets, Institutions and Money, 21, 443–460.

Fama, E.F., French, K.R., 2001. **Disappearing dividends: changing firm characteristics or lower propensity to pay?** Journal of Financial Economics, 60, 3–43.

Fernández, B., Garcia-Merino, T., Mayoral, R., Santos, V., Vallelado, E., 2011. **Herding, information uncertainty and investors' cognitive profile**. Qualitative Research in Financial Markets, 3, 7–33.

George, T.J., Kaul, G., Nimalendran, M., 1991. **Estimation of the Bid-Ask Spread and Its Components : A New Approach**. The Review of Financial Studies, 4, 623–656.

Glosten, L.R., Milgrom, P.R., 1985. **Bid, Ask and transaction prices in a specialist market with heterogeneously informed traders**. Journal of Financial Economics, 14, 71–100.

Grant, E.B., 1980. **Market Implications of Differential Amounts of Interim Information**. Journal of Accounting Research, 18, 255–268.

Hanousek, J., Podpiera, R., 2003. **Informed trading and the bid-ask spread: Evidence from an emerging market**. Journal of Comparative Economics, 31, 275–296.

Heckman, J.J., Ichimura, H., Todd, P.E., 1997. **Matching as an Econometric Evaluation Estimator : Evidence from Evaluating a Job Training Programme**. The review of Economic Studies, 64, 605–654.

Hilliard, J., Zhang, H., 2015. **Size and price-to-book effects: Evidence from the Chinese stock markets.** Pacific-Basin Finance Journal, 32, 40–55.

Huang, T.C., Lin, B.H., Yang, T.H., 2015. **Herd behavior and idiosyncratic volatility**. Journal of Business Research, 68, 763–770.

Hussain, S.M., 2011. **The Intraday Behaviour of Bid-Ask Spreads , Trading Volume and Return Volatility : Evidence from DAX30**. International Journal of Economics and Finance, 3, 23–34.

Hwang, S., Salmon, M., 2004. **Market stress and herding.** Journal of Empirical Finance, 11, 585–616.

Jensen, C., Meckling, H., 1976. **Theory of the Firm : Managerial Behavior , Agency Costs and Ownership Structure**. Journal of Financial Economics, 3, 305–360.

Jiang, Z.Q., Zhou, W.X., Sornette, D., Woodard, R., Bastiaensen, K., Cauwels, P., 2010. **Bubble diagnosis and prediction of the 2005-2007 and 2008-2009 Chinese stock market bubbles**. Journal of Economic Behavior and Organization, 74, 149–162.

John, K., Williams, J., 1985. **Dividends , Dilution , and Taxes : A Signalling Equilibrium**. The Journal of Finance, 40, 1053–1070.

Kang, J., Liu, M.H., Ni, S.X., 2002. **Contrarian and momentum strategies in the China stock market: 1993-2000**. Pacific Basin Finance Journal, 10, 243–265.

Khang, K., King, T.D., 2002. **Is Dividend Policy related to Information Asymmetry? Evidence from Insider Trading Gains**., in: AFA 2003 Washington, DC Meetings. pp. 1–46.

Khanna, N., Mathews, R.D., 2011. **Can herding improve investment decisions ?** Rand Journal of Economics, 42, 150–174.

Kim, O., Verrecchia, R.E., 2001. **The relation among disclosure, returns, and trading volume information.** The Accounting Review, 76, 633–654.

Kim, O., Verrecchia, R.E., 1994. **Market liquidity and volume around earningsannouncements**. Journal of Accounting and Economics, 17, 41–67.

Kim, W., Wei, S.-J., 2002. **Offshore Investment Funds: Monsters in Emerging Markets?** Journal of Development Economics, 68, 205–224.

Klein, L.S., O'Brien, T.J., Peters, S.R., 2002. **Debt vs. Equity and Asymmetric Information: A Review**. The Financial Review 37, 317–349.

Kremer, S., Nautz, D., 2013. **Causes and consequences of short-term institutional herding**. Journal of Banking and Finance, 37, 1676–1686.

Kyle, A.S., 1985. **Continuous Auctions and Insider Trading**. Econometrica 53, 1315–1335.

Lakonishok, J., Shleifer, A., Vishny, R.W., 1992. **The impact of institutional trading on stock prices**. Journal of Financial Economics, 32, 23–43.

Lee, H., Ryan, P., 2000. **The information content of dividend initiations and omissions: the free cash flow and dividend signaling hypotheses**. The Journal of Research in Finance, 3, 196–277.

Lin, J.-C., Sanger, G.C., Booth, G.G., 1995. **Trade size and components of the bid-ask spread**. Review of Financial Studies, 8, 1153–1183.

Lin, M., Fu, T., 2010. **Herding in China Equity Market**. International Journal of Economics and Finance, 2, 148–156.

Lintner, J., 1956. **Distribution of Incomes of Corporations Among Dividends , Retained Earnings , and Taxes**. The American Economic Review, 46, 97–113.

Liu, C., Chen, A.S., 2015. **Do firms use dividend changes to signal future profitability? A simultaneous equation analysis**. International Review of Financial Analysis, 37, 194–207.

Luo, Z., Schinckus, C., 2015. **The influence of the US market on herding behaviour in China**. Applied Economics Letters, 22, 1055–1058.

Lux, T., 1995. **Herd Behaviour, Bubbles and Crashes**. The Economic Journal, 105, 881–896.

McInish, T.H., Wood, R.A., 1992. **An Analysis of Intraday Patterns in Bid/Ask Spreads for**

NYSE Stocks. The Journal of Finance, 47, 753–764.

Michaely, R., Thaler, R.H., Womack, K.L., 1995. **Price Reactions to Dividend Initiations and Omissions : Overreaction or Drift?** The Journal of Finance, 50, 573–608.

Miller, M.H., Modigliani, F., 1961. **Dividend Policy , Growth , and the Valuation of Shares** The Journal of Business, Vol . 34 , No . 4 , pp . 411-433.

Miller, M.H., Rock, K., 1985. **Dividend Policy under Asymmetric Information**. The Journal of Finance, 40, 1031–1051.

Mueller, D.C., 1972. **A Life Cycle Theory of the Firm**. The Journal of Industrial Economics, 20, 199–219.

Ni, Y., Liao, Y., Huang, P., 2015. **MA trading rules , herding behaviors , and stock market overreaction**. International Review of Economics and Finance, 39, 253–265.

Park, B.-J., 2011. **Asymmetric herding as a source of asymmetric return volatility**. Journal of Banking & Finance, 35, 2657–2665.

Payne, B., 2011. **On the financial characteristics of firms that initiated new dividends during a period of economic recession and financial market turmoil**. Journal of Economics & Finance, 35, 149–163.

Payne, B., 2011. **On the financial characteristics of firms that initiated new dividends during a period of economic recession and financial market turmoil**. Journal of Economics and Finance, 35, 149–163.

Pettit, R.R., 1976. **The Impact of Dividend and Earnings Announcements : A Reconciliation**. The Journal of Business, 49, 86–96.

Poon, S.H., Rockinger, M., Stathopoulos, K., 2013. **Market liquidity and institutional trading during the 2007-8 financial crisis**. International Review of Financial Analysis, 30, 86–97.

Prechter, R.R., 2001. **Unconscious Herding Behavior as the Psychological Basis of Financial Market Trends and Patterns**. Journal of Psychology, 2, 37–41.

Ravi, R., Hong, Y., 2014. **Firm opacity and financial market information asymmetry**. Journal of Empirical Finance, 25, 83–94.

Rhee, S.G., Chang, R.P., 1990. **The Impact of Personal Taxes on Corporate Dividend Policy and Capital Structure Decisions**. Financial Management, 19, 21–31.

Roll, R., 1984. **A simple measure of the implicit bid-ask spread in an efficient market**. Journal of Finance, 39, 1127.

Rosenbaum, P.R., Rubin, D.B., 1983. **The central role of the propensity score in observational studies for causal effects**. Biometrika, 70, 41–55.

Seyhun, H.N., 1992. **The Effectiveness of the Insider-Trading Sanctions**. The Journal of Law & Economics, 35, 149–182.

Shiller, R.J., Konya, F., Tsutsui, Y., 1987. **Investor Behaviour in the October 1987 Stock Market Crash: Survey Evidence** (No. Working paper n° 2684), National Bureau of Economic Research.

Stoll, H.R., 1978. **The Supply of Dealer Services in Securities Markets**. The Journal of Finance , 33, 1133–1151.

Subrahmanyam, A., 1991. **Risk Aversion , Market Liquidity , and Price Efficiency**. The review of Economic Studies, 4, 417–441.

Suominen, M., 2001. **Trading Volume and Information Revelation in Stock Markets**. The Journal of Financial and Quantitative Analysis, 36, 545–565.

Tinic, S.M., 1972. **The Economics of Liquidity Services**. The Quarterly Journal of Economics, 86, 79–93.

Van Eaton, R.D., 1999. **Stock Price Adjustment to the Information in Dividend Changes**. Review of Quantitative Finance and Accounting, 12, 113–134.

Venezia, I., Nashikkar, A., Shapira, Z., 2011. **Firm specific and macro herding by professional and amateur investors and their effects on market volatility**. Journal of Banking and Finance, 35, 1599–1609.

Von Eije, J., Megginson, W., 2006. **Dividend policy in the European Union**.Available at SSRN 891035.

Voronkova, S., Bohl, M.T., 2005. **Institutional Traders' Behavior in an Emerging Stock Market: Empirical Evidence on Polish Pension Fund Investors**. Journal of Business Finance & Accounting, 32, 1537–1560.

Wang, M.-H., Ke, M.-C., Liu, D.-Y., Huang, Y.-S., 2011. **Dividend Policy and the Life Cycle Hypothesis: Evidence from Taiwan**. International Journal of Business and Finance Research, 5, 33–52.

Wärneryd, K.-E., 2001.**The Chinese stock market: Efficiency, predictability and profitability**. Cheltenham (UK): Edward Elgar ISBN 1-840, 69–95.

Wermers, R., 1999. **Mutual Fund Herding and the Impact on Stock Prices**. The Journal of Finance, 54, 581–622.

Xie, T., Xu, Y., Zhang, X., 2015. **A new method of measuring herding in stock market and its empirical results in Chinese A-share market**. International Review of Economics and Finance, 37, 324–339.

Yamamoto, R., 2011. **Volatility clustering and herding agents: Does it matter what they observe?** Journal of Economic Interaction and Coordination, 6, 41–59.

Yook, S.H., Kim, Y., 2008. **Herd behavior in weight-driven information spreading models for financial market**. Physica A: Statistical Mechanics and its Applications, 387, 6605–6612.

Zhang, M.Y., Russell, J.R., Tsay, R.S., 2008. **Determinants of bid and ask quotes and implications for the cost of trading.** Journal of Empirical Finance, 15, 656–678.

Zhou, R.T., Lai, R.N., 2009. **Herding and information based trading.** Journal of Empirical Finance, 16, 388–393.

Appendix

Table 1: Number of firms by portfolio

	US stock market			Chinese stock market		
	Period I	Period II	Period III	Period I	Period II	Period III
Payers	1796	2098	2243	411	615	655
Non-payers	2873	3412	3596	519	718	787
Matched Sample	1473	1685	1715	396	598	627
High BAS	2522	3061	3179	1596	1635	2386
Low BAS	2590	3158	3357	1706	1967	2462
Matched Sample	2169	2282	3063	1533	1631	2315
Big firms	1475	1373	1412	546	526	840
Mid big	1767	1536	1735	789	691	1181
Mid small	1837	1556	1872	653	607	1112
Small firms	1596	1400	1592	264	277	391

This tablelists the number of firms by stock market and period. Left column provides data for the US stock market, while right column gives data for the Chinese stock market. Periods I, II, III stand for (2004-2006), (2007-2008) and (2009-2012) respectively. Payers are firms who pay dividends; non-payers do not pay any dividends. Low/high BAS firms have respectively narrow/wide BAS compared to the quarter median %BAS. Matched Sample stands for the portfolio of matched payers/non-payers or low/high BAS. Big firms have capitalization greater than 75% of the year distribution. Mid big are medium big firms (<75%,>50%). Mid small are medium small firms (<50%,>25%). Small are the smallest stocks (<25%). Number of firms is a "total" and fluctuates during the considered period.

Table 2: Market daily return summary statistics

Panel A: US stock market

Sample period	Mean	Standard deviation	Max	Median	Min
Full period	0.01	1.31	10.96	0.04	-9.47
Period I	0.03	0.66	2.13	0.07	-1.85
Period II	-0.09	1.97	10.96	0.06	-9.47
Period III	0.05	1.33	6.84	0.08	-6.90

Panel B: Chinese stock market

Sample period	Mean	Standard deviation	Max	Median	Min
Full period	0.02	1.68	9.03	0.02	-9.26
Period I	0.08	1.36	7.89	0.04	-5.48
Period II	-0.08	2.59	9.03	0.03	-9.26
Period III	0.02	1.44	5.94	0.07	-6.98

This table provides summary statistics for market returns. Panel A lists summary statistics for the US stock market and Panel B is dedicated to Chinese stock market statistics. Periods I, II, III stand for (2004-2006), (2007-2008) and (2009-2012) respectively. Values are in percentage (%).

Table 3: Summary statistics for covariate variables of matching dividend payers vs. non-payers

Panel A: US Stock Market

Panel A1: EBIT/TA	**Payers**					**Non payers**				
Sample period	**Mean**	**Standard deviation**	**Max**	**Median**	**Min**	**Mean**	**Standard deviation**	**Max**	**Median**	**Min**
Full period	0.07	0.09	0.55	0.05	-0.21	-0.13	0.46	0.39	0.03	-1.80
Period I	0.07	0.09	0.55	0.05	-0.06	-0.13	0.48	0.34	0.04	-1.67
Period II	0.08	0.09	0.53	0.06	-0.06	-0.11	0.45	0.39	0.04	-1.62
Period III	0.06	0.10	0.51	0.05	-0.21	-0.14	0.46	0.34	0.02	-1.80
Panel A2: MTBV										
Full period	2.76	3.17	23.75	1.97	-1.74	2.85	5.48	35.66	2.09	-17.31
Period I	2.83	3.07	23.71	2.17	0.65	2.86	6.14	35.66	2.26	-17.31
Period II	2.76	3.09	21.96	1.93	-1.74	3.07	5.55	34.32	2.17	-16.24
Period III	2.61	3.34	23.75	1.77	-1.74	2.64	4.82	28.59	1.90	-16.41
Panel A3: MV[20]										
Full period	5 815	17 071	145 312	761	17	1 053	2 500	21 082	251	0.3
Period I	5 862	16 889	125 474	813	29	933	2 331	17 333	227	1
Period II	6 394	19 091	145 312	776	23	1 236	2 945	21 082	293	2
Period III	5 222	15 034	113 698	731	17	976	2 135	14 260	239	0.3
Panel A4: BR										
Full period	131.32	186.99	1326.85	78.97	-348.70	48.95	184.76	1043.36	13.37	-826.30
Period I	136.52	175.65	1078.05	81.04	0.00	44.27	171.25	976.61	11.62	-478.14
Period II	131.23	182.55	1164.66	79.59	-173.42	52.77	168.98	937.39	14.16	-550.38
Period III	126.93	200.28	1326.85	76.07	-348.70	49.08	208.02	1043.36	14.25	-826.30

[20] We present statistics for the Market value to better asses the size; however, we use the logarithmic Market value in the regression model. Market values are in Millions.

Panel B: Chinese Stock Market										
Panel B1:EBIT/TA	**Payers**					**Non payers**				
Sample period	**Mean**	**Standard deviation**	**Max**	**Median**	**Min**	**Mean**	**Standard deviation**	**Max**	**Median**	**Min**
Full period	0.08	0.08	0.34	0.07	-0.23	-0.20	0.92	0.25	0.01	-3.68
Period I	0.08	0.06	0.28	0.07	-0.05	-0.11	0.69	0.19	0.00	-2.84
Period II	0.10	0.07	0.34	0.08	-0.04	-0.07	0.54	0.25	0.02	-2.33
Period III	0.07	0.09	0.31	0.07	-0.23	-0.37	1.25	0.16	0.00	-3.68
Panel B2:MTBV										
Full period	2.84	2.84	20.00	2.00	0.14	3.80	6.34	33.35	1.91	-18.39
Period I	1.75	1.14	6.28	1.62	0.29	1.86	6.47	33.35	1.45	-18.39
Period II	3.97	3.78	20.00	2.89	0.38	4.33	6.26	21.11	2.74	-5.97
Period III	2.80	2.49	12.73	2.18	0.14	3.50	6.05	20.01	2.21	-8.82
Panel B3:MV										
Full period	2 296	5 461	39 838	567	10	175	265	1 786	71	1
Period I	1 127	3 016	22 293	291	10	63	101	690	28	1
Period II	2 782	6 193	39 838	703	19	213	299	1 786	98	2
Period III	2 576	5 811	37 537	647	15	215	287	1 552	113	3
Panel B4: BR										
Full period	50.82	51.21	192.32	35.38	0.00	39.14	100.37	330.56	20.10	-192.88
Period I	47.84	46.29	152.62	32.14	0.00	47.02	97.26	298.21	26.85	-164.35
Period II	52.27	52.26	189.16	38.77	0.00	36.77	92.95	264.77	20.34	-175.27
Period III	51.34	53.13	192.32	34.57	0.00	36.09	108.42	330.56	14.85	-192.88

This table lists the summary statistics for covariates of payers vs. non payers. Left column provides data for the dividend payers, while right column gives data for the dividend non-payers. Payers are firms who pay dividends; non-payers do not pay any dividends. Periods I, II, III stand for (2004-2006), (2007-2008) and (2009-2012) respectively. Panel A provides statistics for the US stock market, while Panel B lists statistics for the Chinese stock market. EBIT/TA stands for Earnings before interests and taxes scaled by Total assets. MTBV stands for market value scale by book value of equities. MV is the market value (number of outstanding shares times stock price). BR is the Borrowing ratio (total loans scaled by equity capital and reserves). All variables are winsorized at 1%-99%.

Table 4: Summary statistics for covariate variables of matching low vs. high BAS

Panel A: US STOCK MARKET

Panel A1: V.Turn	**Low BAS**					**High BAS**				
Sample period	**Mean**	**Standard deviation**	**Max**	**Median**	**Min**	**Mean**	**Standard deviation**	**Max**	**Median**	**Min**
Full period	0.011	0.010	0.054	0.009	0.001	0.005	0.008	0.057	0.003	0.000
Period I	0.011	0.010	0.032	0.008	0.000	0.005	0.008	0.050	0.003	0.000
Period II	0.012	0.010	0.031	0.010	0.001	0.006	0.009	0.057	0.003	0.000
Period III	0.011	0.009	0.054	0.008	0.001	0.005	0.007	0.034	0.003	0.000
Panel A2:CV										
Full period	0.118	0.075	0.410	0.102	0.004	0.191	0.298	0.814	0.131	0.009
Period I	0.091	0.052	0.283	0.082	0.004	0.107	0.096	0.542	0.080	0.009
Period II	0.131	0.085	0.410	0.114	0.004	0.264	0.504	0.538	0.161	0.016
Period III	0.118	0.072	0.372	0.102	0.007	0.174	0.147	0.814	0.130	0.016
Panel A3:MV										
Full period	4 178	11 076	93 044	904	40	349	680	5 729	134	3
Period I	5 028	12 271	88 823	1 298	111	427	792	5 729	182	5
Period II	3 867	9 864	71 242	857	40	433	822	5 446	154	3
Period III	4 142	11 328	93 044	853	105	291	563	3 911	112	4

Panel B: Chinese stock market

Panel B1:V.Turn	Low BAS					High BAS				
Sample period	Mean	Standard deviation	Max	Median	Min	Mean	Standard deviation	Max	Median	Min
Full period	0.021	0.020	0.100	0.015	0.005	0.009	0.013	0.071	0.003	0.000
Period I	0.015	0.017	0.097	0.009	0.005	0.006	0.009	0.041	0.003	0.000
Period II	0.026	0.020	0.100	0.020	0.000	0.012	0.016	0.071	0.005	0.000
Period III	0.023	0.021	0.096	0.017	0.000	0.009	0.014	0.067	0.003	0.000
Panel B2:CV										
Full period	0.160	0.096	0.596	0.135	0.028	0.178	0.125	0.719	0.140	0.022
Period I	0.138	0.071	0.385	0.126	0.028	0.150	0.109	0.608	0.125	0.022
Period II	0.255	0.125	0.596	0.253	0.043	0.265	0.143	0.719	0.222	0.049
Period III	0.135	0.066	0.376	0.121	0.034	0.164	0.114	0.624	0.129	0.030
Panel B3:MV										
Full period	1 018	2 786	30 594	326	3	698	2 063	19 609	146	2
Period I	535	1 462	10 689	159	3	303	768	5 622	88	2
Period II	1 474	3 966	30 594	401	10	688	1 754	12 935	184	5
Period III	1 077	2 723	23 121	410	16	873	2 485	19 609	190	10

This table reports the summary statistics for covariates of low vs. high BAS. Left column provides data for the low BAS portfolio, while right column gives data for the high BAS portfolio. Low/high BAS firms have respectively narrow/wide BAS compared to the quarter median %BAS.Full period refers to (2004-2012) whereas periods I, II, III stand for (2004-2006), (2007-2008) and (2009-2012) respectively. Panel A provides statistics for the US stock market, while Panel B lists statistics for the Chinese stock market. V.turn is share turnover (liquidity measure that equals to the number of traded shares scaled by shares outstanding for a year). CV is the variation coefficient (price variability measure that equals the annual coefficient of variation of the daily mid-point of the quoted spreads). MV is the market value (number of outstanding shares times stock price). All variables are winsorized at 1%-99%.

Table 5: Dispersion for dividend payers' matched portfolio vs. non-payers

Panel A: US stock market		Payers					Non payers				
Sample period	Variable	Mean	Standard deviation	Max	Median	Min	Mean	Standard deviation	Max	Median	Min
Full period	CSSDt	2.04	1.11	9.92	1.74	0.84	3.75	1.62	13.54	3.45	1.91
	CSADt	1.38	0.71	7.09	1.15	0.60	2.14	0.80	7.65	1.91	1.11
Period I	CSSDt	1.59	0.31	6.51	1.56	0.84	3.49	1.40	13.54	3.17	2.13
	CSADt	1.05	0.17	1.68	1.03	0.60	1.82	0.25	2.56	1.79	1.11
Period II	CSSDt	2.72	1.51	9.92	2.27	1.10	4.20	1.72	11.13	3.72	1.91
	CSADt	1.82	1.04	7.09	1.51	0.73	2.45	1.17	7.65	2.15	1.22
Period III	CSSDt	2.20	0.97	8.06	1.87	1.06	4.03	1.34	10.60	3.66	2.21
	CSADt	1.41	0.62	4.82	1.20	0.67	2.22	0.77	5.83	1.97	1.28

Panel B: Chinese Stock market		Payers					Non payers				
Sample period	Variable	Mean	Standard deviation	Max	Median	Min	Mean	Standard deviation	Max	Median	Min
Full period	CSSDt	2.49	0.93	7.70	2.31	0.98	4.53	1.65	17.40	4.42	0.75
	CSADt	1.83	0.69	6.18	1.66	0.52	2.57	0.87	7.12	2.41	0.48
Period I	CSSDt	2.27	0.61	6.81	2.15	0.98	4.85	1.47	17.40	4.63	0.75
	CSADt	1.59	0.50	4.68	1.47	0.53	2.46	0.66	6.32	2.41	0.48
Period II	CSSDt	3.46	0.98	7.70	3.25	1.52	5.42	1.58	12.97	5.22	1.50
	CSADt	2.54	0.79	6.18	2.36	0.83	3.38	1.00	7.12	3.25	0.80
Period III	CSSDt	2.37	0.61	5.12	2.21	1.04	4.14	1.31	12.45	3.98	1.20
	CSADt	1.65	0.49	4.03	1.52	0.52	2.21	0.59	4.86	2.11	0.56

This table reports summary statistics for dispersion variables of dividend payers vs. non-payers portfolios. Left column provides data for the dividend payers, while right column gives data for the dividend non-payers. Payers are firms who pay dividends; non-payers do not pay any dividends. Full period refers to (2004-2012) whereas periods I, II, III stand for (2004-2006), (2007-2008) and (2009-2012) respectively. Panel A provides statistics for the US stock market, while Panel B lists statistics for the Chinese stock market. CSSD stands for Cross sectional standard deviation of stock returns. CSAD stands for Cross sectional absolute deviation of stock returns.

Table 6: Returns for dividend payers' matched portfolio vs. non-payers

Firms' return		Payers					Non payers				
Sample period	**US vs. CN**	**Mean**	**Standard deviation**	**Max**	**Median**	**Min**	**Mean**	**Standard deviation**	**Max**	**Median**	**Min**
Full period	**US**	0.018	1.698	8.380	0.009	-10.839	-0.016	1.721	8.969	0.010	-9.894
	CN	0.025	1.258	7.210	0.123	-9.315	0.001	1.160	6.459	0.099	-8.878
Period I	**US**	0.036	0.642	2.184	0.054	-1.984	0.052	0.761	2.724	0.081	-2.250
	CN	0.040	0.802	3.579	0.086	-3.657	-0.013	0.738	2.351	0.008	-2.573
Period II	**US**	-0.112	1.860	8.380	-0.001	-10.839	-0.156	1.844	8.969	0.001	-9.894
	CN	-0.062	1.891	7.210	0.250	-9.315	-0.042	1.739	6.459	0.196	-8.878
Period III	**US**	0.034	1.447	7.607	0.029	-7.594	0.041	1.527	6.612	0.079	-8.474
	CN	0.059	1.135	3.636	0.124	-4.768	0.034	1.052	2.856	0.168	-4.571

This table reports summary statistics for returns of stocks in dividend payers vs. non-payers portfolios. Left column provides data for the dividend payers, while right column gives data for the dividend non-payers. Payers are firms who pay dividends; non-payers do not pay any dividends. Full period refers to (2004-2012) whereas periods I, II, III stand for (2004-2006), (2007-2008) and (2009-2012) respectively. US provides summary statistics for stock returns in the US stock market, while CN lists statistics for the stock returns in the Chinese stock market.

Table 7:findings of CH 95 model – matched portfolio of dividend payers vs. non-payers

Panel A: US stock market (5% - 95% criterion)

	Payers			Non payers		
	α	**β_1**	**β_2**	**α**	**β_1**	**β_2**
Period I	1.509*** (98.77)	0.327*** (4.97)	0.267*** (4.06)	3.325*** (58.33)	0.327 (1.33)	0.524** (2.14)
Period II	2.407*** (36.33)	2.022*** (7.26)	2.070*** (7.43)	3.818*** (47.62)	2.120*** (6.29)	2.219*** (6.58)
Period III	2.015*** (62.82)	1.076*** (7.92)	0.956*** (7.04)	3.771*** (78.26)	1.156*** (5.66)	1.086*** (5.32)

Panel B: Chinese stock market(5% - 95% criterion)

	Payers			Non payers		
	α	**β_1**	**β_2**	**α**	**β_1**	**β_2**
Period I	2.101*** (90.28)	1.076*** (10.74)	0.793*** (7.91)	4.694*** (79.49)	0.666*** (2.62)	0.140 (0.55)
Period II	3.181*** (66.72)	1.082*** (5.40)	1.600*** (7.98)	5.112*** (64.33)	1.134*** (3.40)	1.754*** (5.25)
Period III	2.223*** (98.18)	0.513*** (5.35)	0.804*** (8.38)	3.946*** (83.42)	0.441** (2.20)	0.782*** (3.90)

This table provides findings of model (2) for the portfolio of matched payers vs. non-payers. Model (2) represents the CH95 model: $CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t$. $CSSD_t$stands for cross-sectional dispersion of stock returns. D_t^Lequals1 if the market return on day "t" is lying in the lower tail of the market return distribution, and 0 otherwise. D_t^Uequals1 if the market return on day "t" is lying in the upper tail of the market return distribution, and 0 otherwise. $\beta_1$is the coefficient for the variable D_t^L, and β_2 is the coefficient for the variable D_t^U. αis the intercept. Left column provides data for the dividend payers, while right column gives data for the dividend non-payers. Payers are firms who pay dividends; non-payers do not pay any dividends Full period refers to (2004-2012), whereas periods I, II, III stand for (2004-2006), (2007-2008) and (2009-2012) respectively. Panel A provides coefficients for the US stock market, while Panel B lists coefficients for the Chinese stock market.

Table 8: findings of CCK 200 model – matched portfolio of dividend payers vs. non-payers

Panel A: US market Sample

	Payers				**Non payers**			
	α	**β_1**	**β_2**	**R^2 Adj**	**α**	**β_1**	**β_2**	**R^2 Adj**
Full period	0.975*** (63.46)	0.449*** (23.68)	0.011*** (3.65)	0.552	1.681*** (93.45)	0.515*** (23.20)	0.009*** (2.61)	0.526
Period I	0.936*** (95.26)	0.168*** (5.14)	0.059*** (2.83)	0.421	1.690*** (101.89)	0.192*** (3.48)	0.067* (1.89)	0.446
Period II	1.135*** (24.54)	0.572*** (12.90)	- 0.006 (- 1.10)	0.602	1.699*** (32.09)	0.629*** (12.40)	- 0.005 (- 0.88)	0.590
Period III	1.078*** (43.54)	0.288*** (8.20)	0.036*** (4.37)	0.447	1.803*** (57.36)	0.391*** (8.78)	0.032*** (3.08)	0.420

Panel B: Chinese market Sample

	Payers				**Non payers**			
	α	**β_1**	**β_2**	**R^2 Adj**	**α**	**β_1**	**β_2**	**R^2 Adj**
Full period	1.267*** (77.75)	0.450*** (25.85)	-0.003 (-1.07)	0.569	1.786*** (76.92)	0.634*** (25.78)	-0.018*** (-4.23)	0.534
Period I	1.147*** (58.31)	0.393*** (15.32)	0.015** (2.41)	0.617	1.783*** (46.36)	0.660*** (13.54)	- 0.021* (- 1.80)	0.478
Period II	1.713*** (37.20)	0.452*** (12.38)	- 0.013** (- 2.46)	0.574	2.204*** (35.08)	0.661*** (13.06)	- 0.028*** (- 3.81)	0.537
Period III	1.304*** (63.00)	0.296*** (10.55)	0.011* (1.76)	0.446	1.696*** (68.96)	0.508*** (15.25)	- 0.020** (- 2.50)	0.480

This table provides findings of model (4) for the portfolio of matched payers vs. non-payers. Model (4) represents the CCK 2000 model: $CSAD_t = \alpha + \beta_1 |R_{m,t}| + \beta_2 R^2_{m,t} + \varepsilon_t$. CSADt stands for cross-sectional absolute deviation of stock returns in day t. |Rm,t| is the absolute value of market return during the date t.$R^2_{m,t}$is the square market return of date "t". $\beta_1$is the coefficient for the variable |Rm,t |, and β_2 is the coefficient for the variable $R^2_{m,t}$. αis the intercept. Left column provides data for the dividend payers, while right column gives data for the dividend non-payers. Payers are firms who pay dividends; non-payers do not pay any dividends. Full period refers to (2004-2012), whereas periods I, II, III stand for (2004-2006), (2007-2008) and (2009-2012) respectively. Panel A provides coefficients for the US stock market, while Panel B lists coefficients for the Chinese stock market.

Table 9: findings of CH 95 model – matched portfolio of low vs. high BAS

Panel A: US market Sample (5% - 95% criterion)

	Low BAS			High BAS		
	α	**β1**	**β2**	**α**	**β1**	**β2**
Period I	2.194***	0.278	0.657***	2.904***	0.925***	0.491*
	(41.02)	(1.19)	(2.85)	(45.62)	(3.38)	(1.79)
Period II	2.457***	1.306***	1.426***	3.840***	2.592***	2.203***
	(46.55)	(5.88)	(6.42)	(44.05)	(7.07)	(6.01)
Period III	1.993***	0.822***	0.785***	3.854***	1.251***	1.109***
	(81.51)	(7.93)	(7.57)	(87.00)	(6.66)	(5.90)

Panel B: Chinese market Sample (5% - 95% criterion)

	Low BAS			High BAS		
	α	**β1**	**β2**	**α**	**β1**	**β2**
Period I	2.007***	- 0.049	0.002	3.742***	- 0.276	- 0.078
	(61.94)	(- 0.35)	(0.01)	(80.96)	(- 1.37)	(- 0.39)
Period II	3.040***	- 0.279	0.982	4.758***	1.355***	1.593***
	(58.05)	(- 1.27)	(4.46)	(66.16)	(4.48)	(5.27)
Period III	2.123***	- 0.020	0.831***	3.462***	0.653***	0.693***
	(81.45)	(- 0.19)	(7.53)	(95.94)	(4.28)	(4.53)

This table provides findings of model (2) for the portfolio of low vs. high BAS. Model (2) represents the CH95 model: $CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t$. $CSSD_t$ stands for cross-sectional dispersion of stock returns. D_t^L equals1 if the market return on day "t" is lying in the lower tail of the market return distribution, and 0 otherwise. D_t^U equals1 if the market return on day "t" is lying in the upper tail of the market return distribution, and 0 otherwise. β_1 is the coefficient for the variable D_t^L, and β_2 is the coefficient for the variable D_t^U. αis the intercept. Left column provides data for the low BAS, while right column gives data for the high BAS. Low/high BAS firms have respectively narrow/wide BAS compared to the quarter median %BAS. Full period refers to (2004-2012), whereas periods I, II, III stand for (2004-2006), (2007-2008) and (2009-2012) respectively. Panel A provides coefficients for the US stock market, while Panel B lists coefficients for the Chinese stock market.

Table 10: findings of CH 95 model – Market value size portfolios

Panel A: US stock market (5% - 95% criterion)

	Big			Mid big		
	α	**β1**	**β2**	**α**	**β1**	**β2**
Period I	1.550***	0.307***	0.208***	2.071***	0.412***	0.359***
	(103.23)	(4.75)	(3.23)	(106.62)	(4.92)	(4.30)
Period II	2.156***	1.331***	1.479***	2.696***	1.585***	1.590***
	(43.34)	(6.36)	(7.07)	(47.86)	(6.69)	(6.71)
Period III	1.765***	0.742***	0.744***	2.319***	0.852***	0.786***
	(77.44)	(7.68)	(7.71)	(86.93)	(7.54)	(6.96)

	Mid small			Small		
	α	**β1**	**β2**	**α**	**β1**	**β2**
Period I	2.542***	0.463***	0.398***	4.635***	0.111	0.398
	(106.49)	(4.50)	(3.87)	(59.85)	(0.33)	(1.20)
Period II	3.206***	1.945***	1.794***	5.039***	2.537***	2.187***
	(47.82)	(6.91)	(6.37)	(44.97)	(5.38)	(4.64)
Period III	2.923***	1.073***	1.022***	5.066***	1.330***	1.006***
	(77.45)	(6.71)	(6.39)	(82.75)	(5.13)	(3.88)

Panel B: Chinese stock market (5% - 95% criterion)

	Big			Mid big		
	α	**β1**	**β2**	**α**	**β1**	**β2**
Period I	2.241***	0.787***	0.699***	2.399***	0.368***	0.804***
	(81.77)	(6.67)	(5.93)	(84.27)	(3.01)	(6.56)
Period II	3.237***	0.535**	1.444***	3.333***	0.326	1.397***
	(65.10)	(2.56)	(6.91)	(64.34)	(1.50)	(6.41)
Period III	2.279***	0.241**	0.624***	2.379***	0.062***	0.764***
	(86.96)	(2.17)	(5.62)	(90.78)	(0.56)	(6.88)

	Mid small			Small		
	α	**β1**	**β2**	**α**	**β1**	**β2**
Period I	2.672***	0.520***	0.882***	4.395***	0.938***	0.373*
	(77.30)	(3.50)	(5.92)	(88.48)	(4.39)	(1.75)
Period II	3.627***	0.642***	1.474***	5.005***	1.588***	1.658***
	(68.34)	(2.88)	(6.61)	(52.10)	(3.93)	(4.11)
Period III	2.555***	0.041	0.901***	3.802***	0.838***	0.863***
	(90.50)	(0.35)	(7.53)	(90.87)	(4.73)	(4.87)

This table provides findings of model (2) for the portfolio of firms' Size. Model (2) represents the CH95 model: $CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t$. $CSSD_t$stands for cross-sectional dispersion of stock returns. D_t^Lequals1 if the market return on day "t" is lying in the lower tail of the market return distribution, and 0 otherwise. D_t^Uequals1 if the market return on day "t" is lying in the upper tail of the market return distribution, and 0 otherwise.$\beta_1$is the coefficient for the variable D_t^L, and β_2 is the coefficient for the variable D_t^U. αis the intercept. The columns provides data respectively for Big, Mid big, Mid small and small firms. Big firms have capitalization greater than 75% of the year distribution. Mid big are medium big firms (<75%,>50%). Mid small are medium small firms (<50%,>25%). Small are the smallest stocks (<25%). Periods I, II, III stand for (2004-2006), (2007-2008) and (2009-2012) respectively. Panel A provides coefficients for the US stock market, while Panel B lists coefficients for the Chinese stock market.

Table 11: findings of CCK 2000 model – Market value size portfolios

Panel A: US market Sample

	Big				Mid big			
	α	**Rm,t**	**R^2m,t**	**R^2 Adj**	**α**	**Rm,t**	**R^2m,t**	**R^2 Adj**
Full period	0.978*** (80.62)	0.329*** (21.96)	0.009*** (3.81)	0.523	1.273*** (92.34)	0.397*** (22.96)	0.006** (1.98)	0.510
Period I	0.992*** (81.16)	0.089** (2.20)	0.064** (2.47)	0.397	1.259*** (83.10)	0.239*** (4.73)	0.029 (0.93)	0.369
Period II	1.107*** (29.80)	0.431*** (12.11)	- 0.005 (- 1.06)	0.570	1.402*** (32.52)	0.482*** (11.66)	- 0.008 (- 1.39)	0.537
Period III	1.007*** (53.64)	0.231*** (8.69)	0.023*** (3.69)	0.440	1.308*** (61.04)	0.288*** (9.27)	0.022*** (3.07)	0.443

	Mid small				Small			
	α	**Rm,t**	**R^2m,t**	**R^2 Adj**	**α**	**Rm,t**	**R^2m,t**	**R^2 Adj**
Full period	1.481*** (90.90)	0.509*** (25.31)	0.006* (1.69)	0.505	2.052*** (92.23)	0.678*** (24.67)	0.015*** (3.29)	0.528
Period I	1.496*** (96.83)	0.221*** (4.28)	0.082*** (2.47)	0.341	1.994*** (107.06)	0.283*** (4.56)	0.094*** (2.35)	0.352
Period II	1.574*** (32.53)	0.613*** (13.22)	- 0.009 (- 1.57)	0.568	1.990*** (31.33)	0.857*** (14.08)	- 0.006*** (- 0.78)	0.567
Period III	1.550*** (55.43)	0.376*** (9.50)	0.031*** (3.28)	0.457	2.299*** (59.09)	0.511*** (9.27)	0.034*** (2.63)	0.422

Panel B: Chinese Sample

	Big				Mid big			
	α	**Rm,t**	**R^2m,t**	**R^2 Adj**	**α**	**Rm,t**	**R^2m,t**	**R^2 Adj**
Full period	1.476*** (77.59)	0.343*** (17.31)	- 0.003 (- 0.96)	0.385	1.446*** (50.29)	0.524*** (18.51)	- 0.035*** (- 7.30)	0.352
Period I	1.378*** (56.21)	0.239*** (7.73)	0.024*** (3.32)	0.401	1.276*** (40.02)	0.429*** (10.42)	- 0.02488** (- 2.52)	0.395
Period II	2.047*** (38.87)	0.312*** (7.70)	- 0.011** (- 1.97)	0.396	1.821*** (30.53)	0.511*** (10.77)	- 0.039*** (- 5.61)	0.417
Period III	1.496*** (66.73)	0.175*** (5.91)	0.014** (2.04)	0.464	1.616*** (27.81)	0.382*** (5.86)	- 0.035*** (- 2.55)	0.370

	Mid small				Small			
	α	**Rm,t**	**R^2m,t**	**R^2 Adj**	**α**	**Rm,t**	**R^2m,t**	**R^2 Adj**
Full period	1.346*** (64.95)	0.558*** (24.82)	- 0.029*** (- 7.16)	0.417	1.462*** (63.40)	0.862*** (34.46)	- 0.036*** (- 7.86)	0.411
Period I	1.293*** (45.10)	0.528*** (13.95)	- 0.033*** (- 3.56)	0.384	1.458*** (35.27)	0.903*** (18.09)	- 0.049*** (- 4.15)	0.455
Period II	1.733*** (30.00)	0.591*** (12.69)	- 0.038*** (- 5.63)	0.431	1.715*** (25.97)	0.883*** (16.60)	- 0.039*** (- 5.06)	0.545
Period III	1.300*** (45.66)	0.494*** (12.58)	- 0.041*** (- 4.30)	0.391	1.386*** (42.67)	0.838*** (18.73)	- 0.058*** (- 5.33)	0.408

This table provides findings of model (4) for the portfolio ranked according to firms' Size. Model (4) represents the CCK 2000 model: $CSAD_t = \alpha + \beta_1|R_{m,t}| + \beta_2 R^2_{m,t} + \varepsilon_t$.$CSAD_t$ stands for cross-sectional absolute deviation of stock returns. $|R_{m,t}|$ is the absolute value of market return during the date t.$R^2_{m,t}$is the square market return of date "t". $\beta_1$is the coefficient for the variable $|R_{m,t}|$, and β_2 is the coefficient for the variable $R^2_{m,t}$. αis the intercept.The columns provides data respectively for Big, Mid big, Mid small and small firms. Big firms have capitalization greater than 75% of the year distribution. Mid big are medium big firms (<75%,>50%). Mid small are medium small firms (<50%,>25%). Small are the smallest stocks (<25%). Periods I, II, III stand for (2004-2006), (2007-2008) and (2009-2012) respectively. Panel A provides statistics for the US stock market, while Panel B lists statistics for the Chinese stock market.