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DETERMINANTS OF INDUSTRY HERDING

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ABSTRACT

This thesis provides empirical evidence on the determinants of herding in US and China using both market and industry level data. Herding is examined based on market returns, volatility, trading volume and different market conditions, using the CSAD measure on daily data from 1990 to 2016.

The findings for the US market demonstrate that herding does not exist. However, some herding becomes visible at the industry level. The results also demonstrate that there is limited evidence of herding during rising and declining markets days, which is more significant on days with low trading volatility and low trading volume. For different market conditions, the finding shows that herding is present at the market and industry level during the Dot com bubble and the Global Financial Crisis. The results for the Chinese markets provide evidence of herding at both the market and industry level, although it is more prevalent in Shenzhen stock exchange. Evidence further demonstrates that industry herding is more prevalent in the Shenzhen stock exchange when the market is declining, the trading volume is high, and volatility is low. After examining herding during the Asian crisis and Global financial crisis, the results demonstrate herding occurs during both crises at the market and industry level. Finally, the findings demonstrate that at the market level, US returns only has an impact on herding in Shanghai stock exchange.

The results have implications for financial market investors and stock market regulatory authorities in both markets. For the US, it is important that investors know the impact of industry herding on specific industries, while regulatory authorities should encourage investors to diversify their sector investments. For the Chinese markets, the findings imply that participants in the Chinese stock markets (sectors) are irrational when they make investment decisions. Therefore, regulatory authorities should consider irrationality in their rule-making processes and market reforms.

KEYWORDS: Investor herding; U.S; China; market conditions; asymmetric behavior

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List of Acronyms

AC – Asian Crisis

CSAD – Cross- Sectional Absolute Deviation

CSSD – Cross-Sectional Standard Deviation

EMH – Efficient Market Hypothesis

GFC – Global Financial Crisis

SHSE – Shanghai Stock Exchange

SZSE – Shenzhen Stock Exchange

UK – United Kingdom

US – United States

Chapter 1 Introduction to the thesis

1.1. Research background and motivation

In the behavioural finance literature, herding arises when investors inclined to buy or sell based on their private information, overturn their decision after observing the direction of the market. Consequently, investors trade in the same direction and drive asset prices away from their fundamental values, resulting in excess market volatility (Nofsinger and Sias, 1999). Although many empirical studies investigate herding in different markets and under different conditions (see, Chiang and Zheng, 2010; Gavriilidis, Kalinterakis and Leite-Ferreira, 2013; Galariotis, Rong and Spyrou, 2015 and Zheng, Li and Chiang, 2017), there is inconclusive evidence of herding at the market (sector[1]) level for the US and Chinese stock markets respectively. Therefore, the purpose of this thesis is to further investigate herding and its patterns to gain additional insight into the factors that affect herding in these markets. This investigation is motivated by a few studies which are discussed in this section.

The primary motivation of this thesis is the study by Christie and Huang (1995) that introduced the investigation of the potential impact of herding on equity returns which was then further investigated by Chang, Cheng and Khorana (2000), Hwang and Salmon (2004), Tan, Chiang, Mason and Nelling (2008) among others. Christie and Huang (1995) propose that if investors herd, then equity returns will correlate with market returns especially during periods of extreme market movements. This proposition has been tested by many authors using returns from stock markets worldwide (Chang, et al., 2000; Tan, et al., 2008, Chiang and Zheng, 2010; Economou, Kostakis and Philippas, 2011; Galariotis, Rong and Spyrou,

[1] It is important to point out that in terms of classification, industry is different from sector. On the one hand, industry is a general term that refers to a group of companies that provide similar products or services. On the other hand, sector refers to a segment of an economy. Though both terms, sector and industry are used interchangeably through this thesis, the industry definition is inferred.

2015; Bensaida, 2017). Majority of these studies provide findings that suggest that herding is more prevalent in emerging markets, which could be due to the dominance by less sophisticated investors (Demirer and Kutan, 2006). There is also evidence that herding varies across different sectors (See, Lee, Chen, and Hsieh, 2013; Gebka and Wohar, 2013, Litimi, BenSaida, and Bouraoui, 2016; Andrikopoulos, Kallinterakis, Leite-Ferreira, and Verousis, 2017 and Zheng, Li, and Chiang, 2017). More specifically, Lee, et al., (2013) find that herding in the Information Technology sector plays a role in herding in other sectors in the Chinese market. Gebka and Wohar (2013) provide evidence that herding is more significant in the Basic Materials, Consumer Services, and Oil and Gas industries. Litimi, et al., (2016) report that herding occurs during financial crisis periods in Consumer non-durables, Energy, Healthcare, Public Utilities, Technology, and Transportation. Andrikopoulos, et al., (2017) document industry effects in herding the Financials, Consumer Goods, Healthcare, Industrials, Oil and Gas, Technology, and Utilities. Zheng, et al., (2017) report that herding is prevalent in the Technology and Financial industries.

Other empirical studies examine the determinants of herding in relation to rising (declining) market returns, periods of high (low) volatility and high (low) trading volume and report evidence of herding asymmetry. Tan, et al., (2008), Lee, et al., (2013) and Economou, et al., (2015) find that herding is more significant during periods of rising market returns. Conversely, Goodfellow, et al., (2009), Demirer, et al., (2010), Economou, et al., (2011) and Gavriilidis, et al., (2013) report that herding is stronger during periods of declining returns. There is also evidence that herding is stronger when volatility is high (See, Tan, et al., 2008; Javaira and Hassan, 2011; and Blasco, et al., 2012), and when it is low (See, Economou, et al., 2011; and Homles, et al, 2013). Moreover, trading volume exhibits asymmetric properties. Evidence provided by Tan, et al., (2008) and Gavriilidis, et al., (2013) document that herding is prevalent when trading volume is high, while Tan, et al., (2008) and

Economou, et al., (2011) find significant herding when trading volume is low. Despite the persistent evidence of herding asymmetry, some studies find that it is absent (See, Chang, et al., 2000 and Chiang and Zheng, 2010) and others (Chiang, et al., 2010 and Chiang, et al., 2013) report mixed evidence of its presence. Interestingly, in view of the abovementioned studies, the industry determinants of herding in the US and Chinese stock markets have not been investigated in depth. Accordingly, this gap in the literature is addressed in this thesis to contribute to the growing literature on industry herding.

The selection of the US and Chinese stock market is motivated by several factors. US was selected because it is home to the largest stock market in the world as well as the origin of the Global Financial Crisis (GFC) in 2007-2008. Herding in the Chinese market is of interest because its unique segmented market structure which has been characterised by significant volatility (Yao, Ma and He, 2014). Another reason we select the Chinese market is because it is dominated by individual investors instead of institutional investors. In general, individual investors are deemed to less informed and inexperienced, therefore it can be argued these investors are more likely to herd than more informed institutional investors. Furthermore, we focus on industry herding because to the best of our knowledge only five studies investigate industry herding in the Chinese markets (Demirer and Kutan, 2006; Demirer, Kutan, and Chen, 2010; Lee, Chen and Hsieh, 2013; Yao, et al., 2014, and Zheng, et al., 2017).

An examination of industry herding is interesting for several reasons:

a) Choi and Sias (2009) argue that investors might be attracted by industrial characteristics when selecting their investment portfolio (for example the high level of investment in the Information Technology sector during the Dotcom bubble), b) Business managers and financial analysts make recommendations based on sector classification, and c)

Bikhchandani and Sharma (2000) suggest that herds are more likely to surface in a group of stocks in an industry sector where investors encounter similar investment decisions and are able to discern the trade of others within the group. Evidence of herding at the industry level would indicate that investors follow each other in and out of the same industry, commonly termed as ‘flight to quality’ (Gebka and Wohar, 2013).

Another source of motivation for this thesis is the mixed evidence of herding in both markets. For the US, while some studies do not find herding (see, for example, Christie and Huang, 1995, Chang et al., 2000; Chiang and Zheng, 2010; Chen, 2013; Galariotis, Krokida, and Spyrou, 2016 and Lee, 2017). In contrast, Hwang and Salmon (2004), Litimi, et al., (2016); and BenSaida, (2017) detect herding in the US. For the Chinese market, while Demirer and Kutan (2006) and Fu and Lin (2010) find no evidence of herding, Tan, et al., (2008) find herding in Chinese A-share and B-share stocks in the rising (declining) market conditions. Also, Chiang and Zheng (2010), Lao and Singh (2011) Lee, et al., (2013) and Yao, et al., (2014) find that the Chinese market herds. Research on both countries also provides mixed evidence on herding across industries. Christie and Huang (1995) find that herding is absent in the US market and industries. However, Litimi, et al., (2016) and BenSaida (2017) find evidence of herding during crisis periods in different sectors. Studies on herding in the Chinese industries find more mixed results, on the one hand, Demirer, Kutan and Chen (2010), Yao, et al., (2014), and Zheng, Li and Chiang (2017) report evidence of herd behaviour. On the other hand, Demirer and Kutan (2006) find that herding is absent. Following from these results there is an opportunity to enhance existing knowledge by investigating herding at the market and sector level in both markets.

This thesis is also motivated by the studies of Bowe and Domuta (2004), Chiang and Zheng (2010), Mobarek, Mollar and Keasey (2014), Galariotis, et al., (2015) and Zheng, et al., (2017), all of which inspired the analysis of herd behaviour during crises. This analysis facilitates the investigation of the effects of crises on herd behaviour pre, during and post crisis which has not been widely researched to date, as most of the aforementioned studies only focus on crisis periods.

1.2. Research Questions

The main research question this thesis is set out to answer is:

What are the determinants of market and industry herding in major stock markets?

The sub- research questions are:

i) What are the determinants of market and industry herding in the US market?

ii) What are the determinants of market and industry herding in the Chinese markets?

1.3. Aims and objectives

The primary goal of this thesis is to enhance the understanding of market conditions that influence herding in markets (sectors) using a developed and an emerging financial market. This goal leads to aims and objectives of this thesis which are as follows:

1. To investigate the determinants of market and industry herding in the US (for which the S&P 500 index is used as a market proxy) by:
    - Investigating the existence of herding in the market and industries.
    - Investigating whether herding is higher (lower) during periods of rising (falling) stock markets, high (low) trading volume and high (low) market volatility.
    - Investigating herding pre, during and after the Dot com bubble and the GFC.

2. To investigate the determinants of market and industry herding in the Chinese markets (Shenzhen and Shanghai stock exchanges) by:
    - Investigating the existence of herding in the stock exchanges and industries.
    - Investigating whether herding is higher (lower) during periods of rising (falling) stock markets, high (low) trading volume and high (low) market volatility.
    - Investigating herding pre, during and after the Asian crisis and the global financial crisis.
    - Comparing herding during two sub sample periods: 1996-2016 and 2011-2016, to investigate whether herding varies with time.
    - Investigating whether the US influences herd behaviour in Chinese markets.

1.4. Purpose of the thesis

The purpose of this thesis is to investigate the determinants of industry herd behaviour internationally, at both the market and the sector level. The determinants of herding in relation to market returns, trading volume and volatility will be examined in the US and Chinese stock markets. Herding will also be investigated during financial crises in both markets. Further, the impact of US returns on herding in the Chinese market will be examined. The thesis will employ daily for each market data from 1990 to 2016.

The nature of this topic dictates the use of an inductive research approach. Therefore, in this thesis, industry herding pattern is investigated using the cross-sectional absolute deviation (CSAD) measure proposed by Chang, et al., (2000). More details will be discussed in the empirical chapters. With this purpose in view, the next section discusses the research implication and contribution. .

1.5. Research implication and contribution

The investigation of herding challenges two assumptions of the Efficient market Hypothesis (EMH). First, the EMH states that informed investors trade based on the value of the stock, they buy undervalued stocks and sell overvalued stocks. Second, it also states that the stock markets are informationally efficient, securities reflect all available information. However, investors who herd differ from these assumptions by blindly copying the investment decisions of other investors[2] (Devenow and Welch, 1996). In this case, herding could be motivated by a lack of private information, possession of low-quality information or the perception that other investors have superior information (Bikhchandani, et al, 1992). If other investors also copy then an information cascade is formed, which has a potential adverse effect on the aggregation of information into stock prices. Thus, these prices may not reflect all the available information as suggested by the EMH.

The study of herding in financial markets is important for various reasons. From the investors' perspective, evidence of herding means that trades are correlated, and this increases the co-movement of stocks returns. In essence, the benefit of diversification is reduced therefore investors will require more assets in to achieve the desired reduction in systematic risk, because at high levels of correlation the risk reduction benefits of diversification might be difficult to achieve (Chang, et al., 2000; Chiang and Zheng, 2010; Vieira and Pereira, 2015). For regulators, the herding effect on stock price movement may have a negative impact on the stock market (Demirer and Kutan, 2006). Tan, et al., (2008) argue that herding can boost market volatility and create arbitrage opportunities. In addition, investigating herding can further facilitate an understanding of investors' investment trend and how it affects their investment decisions. For instance, fund managers are believed to

[2] That is, they buy stocks that others are buying and sell stocks that others are selling

mimic the behaviour of other fund managers, and thus ignore their private information to protect their reputation (Devenow and Welch, 1996). It can also provide investors with better insight on how the prices of assets are determined in financial markets.

This thesis contributes to the existing literature in the following ways. The first empirical chapter tests for the determinants of industry herding in the US under different market conditions. It adds to the growing body of literature examining the tendency of US investors to herd towards specific industries when they make investment decisions (Litimi, et al., 2016; BenSaida, 2017). Empirical evidence provided by Litimi, et al., (2016) and BenSaida (2017) have addressed herding in US sectors. However, both studies only focus on excessive market volatility. Moreover, this research investigates the effects of changing market returns, trading volume and volatility on industry herding during normal and crises periods, thus offering a more in-depth analysis.

The second empirical chapter contributes to the existing literature on industry herd behaviour of investors in the Chinese markets (Demirer and Kutan, 2006; Tan, et al., 2008; Yao, et al, 2014). Zheng, et al., (2017) carried out a closely related study. However, they focus on nine Asian markets and do not examine the effect of volatility on industry herding and time-varying industry herding. Therefore, we build upon this study by focusing on the unique Chinese market. Specifically, similar to the first empirical chapter we investigate the effect of changing market returns, trading volume and volatility on industry herding during normal and crises periods. We exploit the time-varying nature of herding as an opportunity to test for its effect on market returns, trading volume and market volatility using a rolling window estimate. Further, we investigate whether the US market (industry) returns play a role in herding activity in the Chinese market (industry).

1.6. Outline of thesis

The remainder of this thesis is structured as follows. Chapter two presents the theoretical framework and the literature review, it discuss behavioural finance, the evolution from the efficient market hypothesis to behavioural finance, and finally, the theoretical framework for herding is discussed. Chapter three focuses on the research methodology. This chapter presents the research philosophy, research paradigm and research approach for the study, highlighting how each analysis was selected for the thesis.

Chapter four is the first empirical chapter. This chapter examines industry herding in the US market. The chapter test for the presence of herding at the market and sector level in the US market. Further, this chapter also presents the hypotheses to be tested and the analysis of the empirical results. Chapter five is the second empirical chapter. This chapter examine industry herding in the Chinese markets. The chapter test for the presence of herding at the market and sector level in the two Chinese markets. This chapter also presents the hypotheses to be tested and the analysis of the empirical results for herding in the Chinese markets.

The final chapter presents the concluding remarks to the thesis. This chapter discusses the implication of the empirical results, the limitation of the study and possible suggestions for further studies.

Chapter 2 Review of literature

2.1 Introduction

This section is set out to survey the academic literature on herd behaviour and its determinants under different market conditions. It aims to evaluate related literature to locate this research within existing knowledge. Notably, the theoretical and empirical literature on herd behavior is vast, as a result, this chapter cannot exhaustively survey every article published on the subject. Thus, the purpose of this chapter is to give an overview of core literature on herding towards the market consensus since they facilitate a conceptualisation of the theories and methodologies. Aside from research that provide a conceptual basis for this thesis, the chapter also discusses relevant empirical evidence on herding. Preference was given to studies that considered similar questions, methodologies, and sample periods that includes major crisis periods.

The review of literature highlights the existing gaps in knowledge and demonstrates the relevance of this thesis. It also demonstrates the importance of the research questions stated in chapter 1 which informed the research hypothesis for each empirical chapter. Further, this chapter discusses core methodologies employed in this area of research and then explains the choice of the methodology employed in this thesis.

The remainder of this chapter is structured as follows:

Section 2.2 discusses EMH and the evolution of behavioural finance to provide a conceptual framework for this thesis. Based on a critical evaluation of relevant literature, the relationship between herding, EMH and behavioural finance is highlighted.

Section 2.3 provides a theoretical framework for this thesis by discussing seminal studies on herding. Specifically, this section defines key theories on herding, sources of herding and herding based on investor type.

Section 2.4 presents core methodologies and describes the methodology employed in this thesis. It also discusses empirical evidence based on the chosen methodology.

Section 2.5 highlights the gaps in literature to demonstrate the importance of this thesis and concludes the review.

2.2. Conceptual Framework: Efficient market hypothesis and behavioural finance

2.2.1. Efficient market hypothesis

The efficient market hypothesis developed by Fama (1970) is a hypothesis of how the market functions. An efficient market is defined as a market in which all security prices always reflect all available information. According to Shleifer (2000) the proposition is based on three basic arguments:

(i) Investors are rational and hence value securities based on its fundamental value. This means each security is discounted to reflect its net present value of future cash flow and risk characteristics. Therefore, security prices increase (decrease) in response to good (bad) news about the fundamental value of security prices. Prices are quickly adjusted on the arrival of new information. Consequently, security prices incorporate all available information. An implication of a fully efficient market is that it is impossible for investors to consistently earn above average risk-adjusted returns as all information is already reflected in the stock prices. Rational investors who are always logical in decision-making therefore populate an efficient market.

(ii) Not all investors may be rational; therefore, secondly, the trades of irrational investors are random and cancel out each other, maintaining the market price equilibrium. Proponents of the EMH argue that since these trades are random, they will not have a significant effect on security prices. An important condition for the trades of irrational investors to cancel out each other is that there is no correlation in trading strategies. Therefore, if investors herd, then there is a correlation and their trades will not cancel out.

(iii) If irrational investors with correlated trading strategies trade in the market, those of arbitrageurs counter this trade. Thus, eliminating the influence of irrational investors on market prices. For the EMH assumption to hold, arbitrage has to be unlimited. In broad terms, arbitrage can be defined as making a profit from price difference of a security. It involves buying and selling of the same security in different exchanges. Arbitrageurs cause price convergence by encouraging investors to buy (sell) undervalued (overvalued) assets until the increase (decrease) in demand eliminates the price difference and the price is forced to its fundamental value. Therefore, even when investors are irrational and their trades are correlated, provided close substitute securities are available, arbitrageurs will eliminate mispricing by ensuring securities are priced at their fundamental values.

Primarily, the hypothesis focuses on the informational efficiency of capital markets. Empirically, the EMH has been classified based on different kinds of information that affect market prices into three forms: weak, semi-strong and strong market efficiencies.

- Weak form EMH: asserts that current prices incorporate all information contained in past prices, therefore past prices cannot be used to predict future prices.
- Semi-strong form EMH: states all publicly available and historical information are incorporated into security prices; it concludes that investors cannot profitably exploit this information. This form is based on the assumption that current security prices instantaneously adjust to the release of all new publicly available information.

- Strong form EMH: the strong form of the market efficiency hypothesis states that all current security prices 'fully reflects' all historical, publicly available and private information. Therefore, profit cannot be generated even if the information is not publicly known. The rationale behind it is that the market already anticipates this new information and may have incorporated it into security prices.

The EMH has been widely criticised because investigations from research indicate that some of its assumptions are unrealistic. Therefore, research that challenges the EMH are reviewed in the next section.

2.2.1.1. Challenges to the Efficient Market Hypothesis

Economists and psychologists in the field of behavioural finance have posed challenges to the theoretical assumptions of the EMH in relation to investor rationality and arbitrage. Indeed, questioning the core assumption of investor rationality presents a considerable challenge for the EMH theory. This section reviews schools of thought, which challenge these assumptions.

1. *Investor rationality*

   Financial economic theories are based on the assumption that investors are fully informed and form their investment expectations following Bayesian rules. However, empirical evidence shows that investors follow the advice of financial experts, buy past winning stock and sell past losing stock as well as fail to diversify their portfolios (Kahneman and Riepe, 1998). Consequently, investors' deviation from rationality or standard decision-making has led to a hot debate in economics research. Research by Froot and Dabora (1999) provides evidence, which suggests that stock prices fluctuate due to the noise created by irrational investors. Furthermore, research provides evidence on activities by irrational investors such as confusion over ticker symbols, sentiment (over-reaction and under-reaction) and increased investment in companies as a result of an internet related Dotcom name change (See: Rashes, 2001; Barberis, Shleifer and Wurgler, 2005; Cooper, Dimitrov and Rau, 2001).

Kahneman and Tversky (1973) argue that when judgments are made under uncertainty, the estimation of expected return could deviate from Bayes' rule and other probability theories. Scholars have suggested some factors that influence rationality, most importantly bounded rationality (See, Conlisk, 1996; Dequech, 2001; Kahneman, 2003). Simon (1997) defined bounded rationality as the notion that the rationality of an individual is limited to the available information and the cognitive ability of the individual. The author suggests that risk and uncertainty, access to only incomplete information and human computing capacity can influence bounded rationality.

2. *The direction of irrational trade:*

   The second assumption of the EMH states that if irrational investors exist, they trade randomly, as these investors trade randomly with each other, their trades cancels out. Kahneman and Tversky (1973) provide psychological evidence that investors deviation from rationality does not occur randomly but in the same way. Because investors are influenced by similar beliefs; their investment decisions would be highly correlated. Thus, they would not trade randomly with each other; rather they would trade the same securities at approximately the same time (which is also known as herding). Consequently, their trades do not cancel out each other. Consequences of correlated trading strategies will be even more severe if these traders copy each other's mistakes. In this respect, investor sentiment, reflected when investors make similar errors in judgment comes into play.

Empirical studies have demonstrated that both institutional and individual investors imitate each other, which can drive security prices away from their fundamental values. Regarding institutional investors, Sias (2004) provides strong indications that they follow each other in and out of the same securities. Consequently, there is a correlation between portfolio weights of securities of one- quarter, to that of the previous quarter, which in turn affects the demand for these securities. More recently, Choi and Skiba (2015) provide evidence of institutional investor herding in international markets. They find that herding was due to these investors utilising and interpreting the same information. For individual investors, Barber, Odean and Zhu (2009a) find their trade is systematically correlated, they buy and sell the same stocks month on month. They argue that this correlation may be motivated by psychological biases such as the representativeness heuristic, limited attention which prompts purchases of popular stocks and the disposition effect[3]. Barber, Odean and Zhu (2009b) also provide evidence of individual investor herding, the direction of their trade is persistent and highly correlated. They also find that individual investors have a tendency to buy (sell) the same stocks in one month as they did in the preceding month.

3. *The effectiveness of arbitrage*:

   Market efficiency is dependent on the ability of arbitrageurs to correct prices distorted by correlated sentiment to fundamental values. For arbitrageur to achieve this, conditions supporting arbitrage must be present, i.e. the existence of close substitutes, no/minimal implementation costs and sufficiently long-time horizons for arbitrageurs to implement their strategy. However, Barberis and Thaler (2009) argue

[3] Psychological biases are discussed in detail in a later section.

that arbitrage can be risky and costly and therefore impedes the ability of arbitrageurs to correct mispricing. These risks and costs are discussed below.

a) Fundamental risk

Fundamental risk refers to the risk that the negative news about the fundamental value of the stock result in losses. Theoretically, arbitrageurs can perfectly hedge this risk by purchasing substitute securities. Substitutes are rarely perfect, therefore fundamental risk cannot be eliminated.

Barberis and Thaler (2003) argue that even if a perfect substitute exists, it may also be mispriced due to industry-wide mispricing. The authors use the the Royal Dutch and Shell shares to illustrate that shares with almost equal dividend payouts can trade at significantly different prices[4]. Two completely separate entities: Royal Dutch and Shell Transport decided to merge their interest in a 60: 40 ratio while remaining separate entities. Based on this ratio, it is therefore expected that if prices were equal to their fundamental values, the market value of the Royal Dutch shares ought to be constantly 1.5 times the value of the Shell equity. But, this was not the case, Royal Dutch shares were sometimes 35% undervalued relative to parity, and 15 % overvalued. Barberis and Thaler (2003), argue that this evidence is a clear case of mispricing due to limited arbitrage. As a result, of the mispricing, these two shares which were potentially good substitutes for each other cannot be used to create a perfect hedge against fundamental risk.

[4] The difference in prices violates the law of one price. It implies that two assets with identical cash flows should have prices equal to the theoretical parity ratio.

b) Noise Trader Risk

The noise trader risk is the risk that pessimistic traders who buy when the prices are high and sell when the prices are low cause mispricing to worsen. This risk occurs when fluctuations in investor sentiments drive prices further away from fundamental values after the arbitrageurs take their positions. From a theoretical perspective, De Long, Shleifer, Summers and Waldmann (1990) argue that noise trader risk can arise even when arbitrageurs attempt to return prices to equilibrium by maintaining positions against the price direction from correlated trades of irrational investors. Taking up such risks could potentially result in losses for arbitrageurs and the inability to maintain their positions. When this occurs, arbitrageurs have a tendency to be risk averse and unwilling to take positions against the noise traders. Campbell and Kyle (1993), who discussed the effect of noise traders on arbitrageurs' risk aversion, state that this risk aversion limits the effectiveness of arbitrage.

Noise trading can, therefore, force asset prices to deviate from their fundamental value resulting in a long-term mean reversion effect. This mean reversion occurs when arbitrageurs realise that severe mispricing exists, causing asset price to revert to their fundamental values over a long horizon (De Bondt and Thaler, 1989). De Bondt and Thaler (1989) state that there is no evidence that arbitrageurs dominate the market, and further argue that in most cases noise traders may even be more influential than arbitrageurs. The effect of arbitrage is again limited.

c) Implementation costs

Arbitrage is implemented by short selling, however, it can be expensive due to costs such as implementation costs. Implementation costs refer to costs which includes transaction costs (for example commissions), bid-ask spread, costs of resources required to find and exploit mispricing (Merton, 1987; Barberis and Thaler, 2003). There could be other monetary costs such as accounting policies and legal constraints. In some instances, these costs may exceed potential profits, which makes the exploitation of mispricing difficult for arbitrageurs.

Overall, despite the challenges to the assumption of the EMH, supporters of EMH argue that although inefficiencies exist in the market sometimes, resources should not be dedicated to exploiting them as the market will always correct irrationalities. While these arguments are logical, there are still deviations from the EMH that remain unexplained by tests based on models that support the hypothesis. Indeed, from the beginning of the 1980s, financial market academics have discovered behavioural anomalies and puzzles unexplained by traditional finance theories. For example, excess volatility in stock markets (Shiller, 1981), stock price momentum in short time horizons (Jegadeesh and Titman, 1993) and positive feedback trading (Shiller, 1990) have featured prominently in the relevant debate.
In response to these anomalies, a new approach to the financial market emerged: behavioural finance. Its concepts are examined in detail in the next section.

2.2.2. Behavioural finance

Traditional finance theories like the EMH and modern portfolio theory have failed to explain some puzzles and anomalies in the financial market. In response to these challenges, theories based on individual and social psychology have emerged to examine factors that influence asset-pricing models. Behavioural finance is one of the major theories that have provided an alternative approach to traditional finance. It studies the influence of psychology on human decision-making and argues that emotions and sentiment explain the mispricing of securities.

Behavioural finance has its roots in behavioural economics, a field that combines psychology and economics. The link between economics and psychology was established during the classical period of economics, with pioneering research from authors like Adam Smith, which suggested that behaviour such as self-interest could be explained by psychology. During the 1960s, cognitive psychology provided more insight on how individuals process information. In 1979, two psychologists Daniel Kahneman and Amos Tversky proposed a widely accepted model in behavioural economics: Prospect Theory. Prospect theory presents a deviation of decision -making from the expected utility function when decision makers are faced with uncertainty (Shefrin, 2000). The theory has been widely applied in behavioural finance for investigating deviations from rational thinking.

One of the major successes of behavioural finance is the demonstration of the significant effects that the interaction of rational and irrational investors can have a long-term impact on asset prices. This success resulted from theoretical literature on the building blocks of behavioural finance: investor psychology and limits of arbitrage (Barberis and Thaler, 2003). Specifically, this section discusses an important aspect of behavioural finance: investor psychology, which is directly relevant to this thesis.

2.2.2.1. Investor Psychology

The objective of this section is to shed light on the influence of psychology on finance as a building block of behavioural finance. Investor psychology can help to explain investor financial decision-making and its influence on irrational behaviour. Psychology is a scientific field of study that examines the impact of an individual's physical, mental and external environment on their behaviour (Rabin, 1998).

Most often, in decision-making individuals base their judgment on heuristics due to limited knowledge of the particular probability that would lead to the best outcome (Gigerenzer, and Gaissmaier, 2011). From a behavioural finance perspective, heuristics is referred to as a simple means of making complex decisions using the rule of the thumb. In other words, mental shortcuts taken by an investor confronted with different choices in uncertain conditions. Although heuristics aids decision-making, it could result in biases (Khaneman and Tversky, 1973). Biases are intuitive thinking patterns originating from observation and generalisations that may lead to inaccurate judgment (Khaneman and Tversky, 1973). Biases, in turn, stem from beliefs and preferences (Barbeis and Thaler, 2003). Relevant beliefs and preferences are discussed in the proceeding section.

2.2.2.2. Beliefs

Beliefs have been considered by many studies, thus, there exists a vast amount of literature that discusses it. As a result, this section focuses on beliefs that are more directly linked to herding.

Representativeness

Kahneman and Tversky (1972), define representativeness as a heuristic that formulates probability around uncertain events of a general population. Essentially, decisions are made based on stereotypes rather than a detailed evaluation of probabilities (Shefrin and Staman 2000). Representativeness can result in two major biases: base rate neglect and sample size neglect. Base rate neglect results from putting too little weight on background information when estimating the likelihood of an event. An example of ignoring base rate is when the luck of fund managers in picking investment is equated to skill. Indeed, a study by Wermers (2000) found that the US actively managed mutual funds, only outperformed the market benchmark index on a net return level. The second bias: sample size neglect sometimes also referred to as the law of small numbers occurs when an individual makes a judgement based on a sample without taking the sample size into consideration (Rabin, 2002). This means that they incorrectly assume that few data points are representative of the entire data set. For example, an investor might think that a financial analyst with three good stock picks in the previous month is skilled, whereas, this assessment is the only representative of a small sample size (Barberis and Thaler, 2003).

Representativeness is also associated with two other biases: the gambler's fallacy and the 'hot hand'. Gambler's fallacy is a mistaken belief that two events are statistically dependent whereas, the occurrence of one is independent of the occurrence of the other. For example, when observing the toss of a fair coin, people erroneously believe that after a consecutive outcome of heads, the next toss is likely to be a tail. The gambler's fallacy stems from the belief in the law of small numbers, where people believe that a small sample must be representative of a larger population. Hence, an event like the toss of a coin is a self-correcting process, a deviation in the direction of tails is required to restore equilibrium for it to be representative of the population (Rabin, 2002). In contrast, sometimes people mistakenly believe that previous success generated by a 'hot hand' is more likely to be replicated rather than reversed when, however, the successes are entirely random. Using the example of tossing a fair coin, people who believe that consecutive heads are generated by a 'hot hand' expect that heads will persist. These biases are applicable in finance. Research by Shefrin and Statman (1985) and Odean (1998) show that investors prone to gambler's fallacy are likely to sell stocks past winning stocks because they believe that the performance will reverse. Other researchers (see, Cahart, 1997 and Sirri and Tufanno, 1998) show that fund managers buy fund shares with prior superior performance. These findings suggest that investors base their purchase decision on the belief that certain fund managers have 'hot hands'.

Overconfidence

Psychologists argue that people are generally overconfident and overestimate their abilities (see Lichtenstein, Fischhoff, and Phillips, 1982). Barber and Odean (2001) state that overconfidence drives individuals to be overly optimistic resulting in two major illusions: the illusion of knowledge and the illusion of control. First, the illusion of knowledge is the tendency of individuals to believe that their ability to make accurate decisions increases with the amount of information that they possess. For instance, the illusion of knowledge could come from the internet, tips from colleagues or friends and financial analysts' reports or opinions, however, it is difficult to ascertain if the information is true and complete. Indeed, research by Tumarkin and Whitlaw (2001) provides evidence that for the internet service sector, information embedded in user ratings did not predict trading volume or exhibit abnormal industry-adjusted returns, and consequently had no effect on stock prices.

Second, the illusion of control is defined as "An expectancy of a personal success probability inappropriately higher than the objective probability would warrant" (Langer, 1975, pp. 313). Consequently, individuals behave as though an event were based on skill and they can control the outcomes of chance events, especially when it entails factors relating to skill, such as competition, choice, and familiarity (Taylor and Brown, 1988). Hence, the presence of these factors increases confidence and risk taking. In a seminal experiment, Langer (1975) provides evidence that people valued lottery tickets they selected by themselves more highly than randomly selected ones. In reality, the sale of lottery tickets in Massachusetts increased significantly when people could choose their lucky number instead of being given a random number as in the old system (Perlmuter and Monty, 1977). The illusion of control is widespread and influences investment decisions, many new investors prefer to trade by themselves rather than through a broker as it gives them an inflated sense of control over the performance of their trades (Barber and Odean, 2001).

Barber and Odean (2002) analysed investors who changed from phone-based to online trading and find that they made more profit before than after the switch. They also find that these investors traded more actively, aggressively and speculatively after going online because they become overconfident and tend to overestimate the control they have over their successes. In addition, they propose that this overconfidence is partly due to the illusion of knowledge and illusion of control as they had access to large quantities of information, mostly manage their portfolios and could trade with ease. However, the resultant overtrading violates the traditional finance paradigm assumption of rationality. If investors were indeed rational, they would know that overtrading would rarely lead to greater profits as excessive transaction costs are also incurred with a corresponding increase in risk. Research by Barber and Odean (2000) of over 66,000 households demonstrate that the most active traders underperformed the market benchmark. Thus, despite the compelling evidence not to overtrade, it is apparent that investors execute trades beyond what they should if they were indeed rational.

Psychologists and behavioural economists have identified that self-attribution bias is a common source of overconfidence (Kahneman and Tversky, 1996). Self- attribution bias is an individuals' tendency to give themselves credit for positive outcomes and credit external factors or bad luck for negative outcomes. Hirshleifer (2001) argues that self-attribution makes people overconfident rather than accurately evaluate themselves, as a result, those who become wealthy through successful investment decisions tend to become more overconfident.

Overconfidence can also be expressed in the hindsight bias. Hindsight bias or 'The knew it all along effect" refers to an inflated certainty in predicting the probability of occurrence of a past event prior to its occurrence (Fischhoff, 1975). In essence, in hindsight, individuals inflate the accuracy of their foresight, thus they believe an outcome is predictable even before it occurs. For example, an individual who is told to guess the outcome of a fair coin toss before it is tossed guesses a head and a tail is obtained. If after the toss, the individual states that he/she knew that it would be a tail, then he/she has expressed the hindsight bias.

The hindsight bias is a robust phenomenon evident in many fields including finance. Biais and Weber (2008), report that hindsight biased investment bankers were unable to remember the extent of their uncertainty when asked to select initial estimates before observing outcomes, and therefore made lower volatility estimates than their unbiased peer. Also, these bankers earned far less than their peers, hence the bias created a discrepancy between their actual performance and perceived performance.

The effect of overconfidence becomes more severe, especially in bull market conditions. Bull markets are characterised by rising security prices and investors tend to become overconfident that the prevailing conditions will persist. However, this collective overconfidence may contribute to a subsequent economic crisis. In an analysis of the recent global financial crisis, Avgouleas (2009) argues that the enormous credit expansion led to the crisis. Moreover, the author suggests the credit expanded because market regulators became increasingly overconfident that the market would continue to be liquid for the foreseeable future.

Optimism (and wishful thinking)

Optimism (and wishful thinking) stems from overconfidence. Most people tend to hold optimistic albeit unrealistic views about their abilities and the future (Thaler, 2000). Another belief related to this bias is systemic planning fallacy: individuals often have a tendency to underestimate the completion time for a task (Barberis and Thaler, 2003).

Many economic phenomena originate from optimism; it can lead to under-reaction of stock prices to public news, over-reaction to good or bad news (Barberis, Shleifer and Vishny, 1998), an inflation of asset prices in the presence of short-sales restrictions (Chen, Hong, and Stein, 2002) and agents overestimating the return on their investment in portfolio selection (Brunnermeier and Parker, 2005).

Cognitive Dissonance

Cognitive dissonance theory posits that people like to act in a way that is in line with their beliefs and values and as such may be uncomfortable in maintaining inconsistencies (Festinger, 1957). Consequently, individuals have a tendency to either alter their past values or beliefs or attempt to rationalize their choice. In the financial investment context, this theory can apply when investors seek to justify contradictory behaviours so that they flow from personal beliefs. For instance, recently more investors have altered their beliefs from traditional forms of investing to ethical investment strategies. Goetzmann and Peles (1997) examined the empirical implication of cognitive dissonance on mutual fund investors. They find that these investors may be subject to psychological influences like cognitive dissonance specifically in making buy or sell decisions and portfolio selection.

2.2.2.2. Preferences

Preferences are a vital part of decision-making. In behavioural finance, preferences are analysed based on how investors make decisions regarding the future under conditions of uncertainty, or how they evaluate risky gambles (Barberis and Thaler, 2003). The traditional utility framework, the Expected Utility Theory (EUT) posits that when faced with risk, decision makers are rational and choose the prospect that maximizes their expected utility. Under the EUT theory investors' risk preferences are captured by the shape of the utility function; whereby, the shape is concave if the investor is risk-averse and convex if risk seeking. In addition, decisions are made based on outcomes of wealth and probabilities under risky conditions. An argument against EUT is that it focuses on how decisions should be made under uncertainty and not how they are actually made.

2.2.2.2.1. Prospect Theory

Challenges to the EUT were highlighted by paradoxes such as the Ellsberg (1961) paradox[5] and Allais (1953)[6] paradox which, represented deviations from the EUT and thus led to the postulation of an alternative framework for decision under risk; the Prospect Theory (PT) postulated by Tversky and Kahneman (1991). Tversky and Kahneman (1991) argue that the EUT did not properly describe how individuals make decisions in risky conditions, thus failed to predict the decision-makers' choice. PT posits that individuals are not always rational; and thus, (i) evaluate outcomes such as gains and losses relative to a reference point (ii) are loss averse; more sensitive to losses than equivalent gains, (iii) are risk averse for gains and risk-loving for losses. PT attempts to represent how individuals evaluate risky gambles (Barberis and Thaler, 2003). It suggests that when individuals are presented with choices between two or three alternatives, they behave in a way that mirrors maximising an s-shaped function as illustrated in Figure 1 below.

[5] This is a paradox in decision making under conditions of uncertainty which states that in situations of ambiguous probability, agents prefer to bet on known probabilities rather than unknown probabilities (Ellsberg, 1961). Thus, agents seek (avoid) ambiguous probability in the domains of losses (gains).

[6] According to this paradox, agents tend to irrationally change their decisions among a set of outcomes when the probability of the reward in each option is reduced by a common ratio. This change may be motivated by the fear of regret, i.e. they anticipate that their choice can potentially lead to regret.

Although similar to the value function in the EUT, the value function in the PT is defined based on gains and losses instead of final wealth. Therefore, it predicts that people value utility based on gains and losses differently when the expected final wealth is the reference point, regardless of whether or not the reference point is updated (Grinblatt and Han, 2001). This means that losses in relation to the reference point (usually the purchase price), have a greater emotional impact than equivalent gains cause satisfaction which implies loss aversion.

Mental accounting pioneered by Thaler (1983), explains how decision-makers use a cognitive process to set reference points for the accounts that determine gains and losses. Thaler (1983) further states that mental accounting enables decision-makers to record, summarise, and analyse their financial transactions.

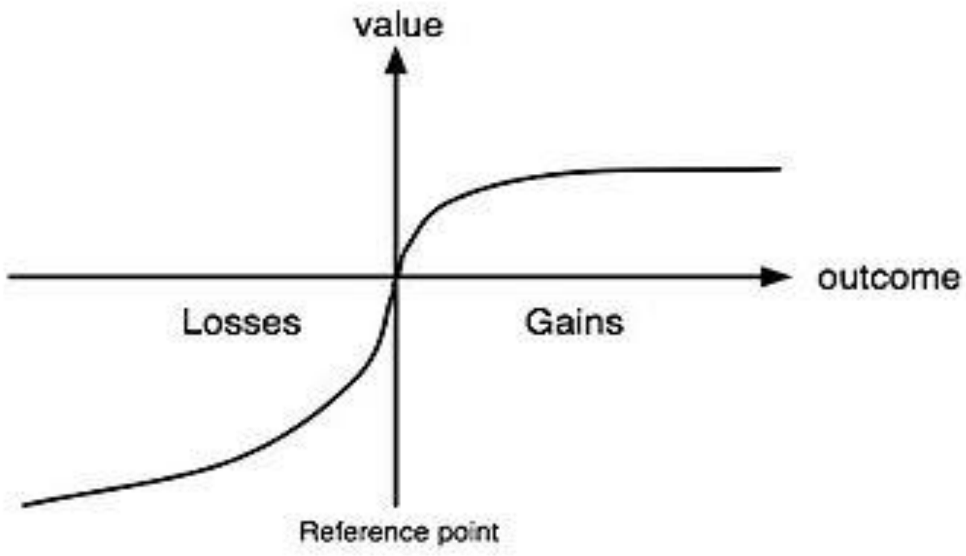

Figure 2.1 The value function proposed Tversky and Kahneman (1991).

Source: Tversky and Kahneman (1991).

Framing of the monetary outcomes obtained from these transactions is an important aspect of mental accounting. Framing, which can be either narrow (based a single transaction) or broad (based on a spending category) influences the reference point. However, Grinblatt and Han (2005), argue that decision-makers have a tendency to engage in narrow framing and ignore the relationship between these mental accounts.Consequently, motivated by the need for gains, their evaluation of new investments is only focused on individual accounts rather than a broad consideration their overall position. Indeed, Barberis and Huang (2001) suggest that investors are either concerned about whole portfolio or the value of each stock in their portfolio and therefore disregard correlations.

Further, the PT explains how decision-making is influenced by the context in which options are presented: framing. Framing is a cognitive bias that is observed when individuals' decisions are dependent upon how the options are presented. Specifically, the PT predicts that individuals are likely to be risk averse when faced with a decision that is framed positively (for instance as a gain) and risk seeking when a decision is negatively framed (for instance as a loss).

Studies by Shefrin and Statman (1985) and Odean (1998a) show that the PT has direct implications on a cognitive bias: the disposition effect. The disposition effect refers to a tendency that people would rather avoid losses and seek to realise gains in decision-making situations. Shefrin and Statman (1985) find evidence that investors are more likely to sell winner stocks and hold loser stocks. Consequently, people avoid actions that can result in regret or losses in favour of actions that can result in gains or pride. Consistent with the disposition effect, Odean (1998a) and Barber and Odean (1999) find that US investors were more willing to sell winners while holding on to losing investment. Grinblatt and Han (2002) argue that the disposition effect has implications for the equilibrium of stock prices, past winner stocks may subsequently outperform past losers due to under-reaction to public information when there is a higher demand for losing stock.

In order to illustrate how the PT is applied in investor decision-making, Barber and Odean (1999), give an example of an investor who purchases a stock in anticipation that the expected return will exceed the risk. If the investor uses the purchase price of the stock as the reference point and the value of the stock appreciates, the shape of the value function will become more concave. This shows that s (he) is more risk averse. Conversely, if the stock price declines, the value function becomes convex in the risk-seeking region. At this point, the investor will still hold the stock regardless of if its expected return is below expectation. Therefore, s (he) would rather only sell the stock when the expected return in their own expectation is lowered despite the decline in prices. In essence, the investor has an irrational tendency to sell quickly when the stock appreciates but do not sell when the prices decline.

Overall, the PT demonstrates how people make decisions under risk by using practices that deviate from rational behaviour. People make decisions under risk by based on loss aversion, losses have greater emotional impact than gain, and thus people select options where gains are probable. Moreover, they set up mental accounts for evaluating options narrowly, without considering the relationship between different accounts. Furthermore, in many situations, people exhibit framing; they tend to be risk averse when faced with a decision that is framed positively and risk seeking when a decision is negatively framed. Finally, the PT explains the disposition effect: people prefer gains to losses and become more risk-averse after they have made gains and more risk loving after they have made losses.

2.2.2.4. Collective behaviour

The biases discussed so far have focused on individual decision-making. An important question, however, is how these biases affect collective behaviour. Collective behaviour can potentially affect asset prices and even create new biases (De Long, et al., 1990). According to Le Bon (1947) the fact that heterogeneous individuals have been formed into groups creates in them a collective mind that makes them think and act similar to members of the group than they would in isolation. Galbraith (1993) documents the effects of collective behaviour in recent episodes in the financial market. Nofsinger (2001) demonstrates how the limited knowledge of investors prompts searches for investment financial advice in investment decision-making. This information makes them overly optimistic and in turn attracts other investors. The popular consensus drives prices away from their fundamental values, the prices further rise until it returns to the market equilibrium. The Dot com bubble is a clear example of how collective behaviour drives prices.

2.2.3. Behavioural finance versus efficient market hypothesis

The purpose of this section is to compare the three basic assumptions of the EMH to the assumptions of behavioural finance. The rationality assumption is compared to behavioural finance and heuristics. Thereafter, the random walk of prices is compared to observed price patterns.

2.2.3.1. Investor rationality versus biases and heuristics

The EMH assumes that individuals are rational, meaning they make optimal decisions that maximise their expected utility. Grossman and Stiglitz (1980) argue that a direct implication of this is that, prices reflect all available information; so private information cannot be exploited to earn excess returns above the market portfolio. In contrast, behavioural finance argues that individuals' decisions under uncertainty are influenced by biases and heuristics. Some biases and heuristics were discussed in detail in the previous section, as such, only a brief summary is carried out here. Heuristics are mental shortcuts for making complex decisions, which may involve on focusing on a specific aspect as the expense of others. It could result in errors such as biases (Kahneman and Tversky, 1973). Biases are intuitive thinking patterns originating from observation and generalisations that may lead to inaccurate judgment.

2.2.3.2. Random walk of prices versus observed price patterns

The rationality assumption is associated with the random walk hypothesis. It posits that stock prices follow a random walk and implies that successive price movement is independent. Thus, these prices are unpredictable, and no patterns can be observed. Empirical evidence from Fama (1965) and Seiler and Rom (1997) to determine whether stock prices followed random walks showed strong support for the model.

More recent evidence discovered some price patterns in both the short and long run that violates the random walk hypothesis and asset pricing models. These patterns are referred to as anomalies, defined as empirical evidence that present deviations from standard asset pricing behaviour (Schwert, 2003). Interestingly, some anomalies happen only once, while others vanish, reverse or persist. Evidence of anomalies raises issues of whether anomalies are merely random or represent profitable opportunities, which have not been eliminated by arbitrage (Schwert, 2003).

Short-run price patterns have been tested by measuring short-run serial correlations between successive price changes (for example see Fama, 1965 and Seiler and Rom, 1997). These studies found zero correlation between these price movements, implying that future prices cannot be predicted from past prices. However, Lo and MacKinlay (1988) provide empirical evidence of positive short-run serial correlation for weekly US stock returns examined, implying the predictability of stock price from past returns and thus reject the random walk hypothesis. Besides, studies by Allen and Karjalainen (1999) and Lo, Mamaysky and Wang (2000) find that price movement follows technical patterns. Indeed, Jegadeesh (1990), Jegadeesh and Titman (1993), Rouwenhorst (1998) and more recent evidence by Jegadeesh and Titman (2001) have documented evidence of excess returns earned using this strategy, which poses a strong challenge to the EMH. The weak form of the EMH posits that all stock prices incorporate all past information. However, according to behavioural finance, evidence of under-reaction of stock prices to news over short time horizons violates this form of market efficiency. Therefore, this slow reaction to news results in stock prices exhibiting a positive serial correlation.

Some studies document long-run price reversal whereby past long-run losers outperform past-long run winners. One of the pioneering studies in this respect is DeBondt and Thaler (1985), who find evidence of negative serial correlation of stock returns over long horizons. Notably, they find that over a five-year period stocks with poor prior performance exhibit subsequent superior performance and vice versa. Similarly, Fama and French (1988) and Poterba and Summers (1988) find mean reversion in stock returns and predictability over long horizons. A behavioural explanation for this predictability is based on investors over-reacting to news. De Bondt and Thaler (1985), proposed the over-reaction hypothesis where investors tend to over-respond to the earnings-related news. This hypothesis suggests that asset prices temporarily deviate from fundamental values due to waves of optimism and pessimism. As a result, investors irrationally make decisions based on recent news announcement instead of updating their beliefs in conformity to Bayes' law.

The review of empirical literature thus far clearly demonstrates the relevance of behavioural finance in providing insights on market anomalies and puzzles. It can be concluded that it plays an importance role in modern finance as indicated by the findings of the above studies.

2.3. Theoretical Literature

2.3.1. Theories on herding: Why do investors herd?

The tendency of people to herd may seem to be apparently irrational, such as a desire to act in conformity to a group. This tendency has led to questions on whether people who engage in herd behaviour act on purpose or are completely unaware of their behaviour, a question that is difficult to answer in reality. In an attempt to answer this question, academic researchers (see, Bikhchandani and Sharma (2000)) explain the motives behind herding in two dimensions – intentional and spurious. This section examines the relevant literature on these two dimensions.

2.3.1.1. Intentional herding

Intentional herding involves a deliberate intent by investors[7] to mimic the investment decisions of each other regardless of their private information (Bikhchandani and Sharma, 2001). Kremer and Nautz (2013), state that this type of herding leads to excess the volatility of asset prices[8], destabilise financial markets and therefore potentially create/contribute to bubbles and crashes. Thus, intentional herding can lead to market inefficiency by driving assets away from their fundamental values. To understand intentional herding, it is important to know the factors that motivate such strategy. Using theoretical literature, these factors are examined in subsequent the sub-sections below.

2.3.1.1.1. Sources of intentional herding

Informational cascade

Bikhchandani, Hirshleifer and Welch (1992), demonstrate that when an individual investor observes the trade patterns of predecessors, s /he can make a decision to mimic the choice

[7] These investors may deem themselves as lesser informed or have lower ability than their peers.
[8] See, for example empirical evidences provided by Morris and Shin (1999) and Persaud (2000)

of these investors even if it conflicts with his/her own information. An informational cascade occurs when investors ignore their private information signals. The central idea is that individuals can glean important information by observing others trade.

Banerjee (1992) argues that if the information signal is incorrect, then the wrong information will filter through the market and might sway other investors to invest. Banerjee (1992) gives an example of how herding takes place. If a hundred people set out to eat at two restaurants A and B next to each other with known probabilities of 51 percent that A is better than B, 49 percent that B is better than A. In addition, they have information that restaurant A is better than B. People arrive in the restaurant in sequence and make their decisions based on their predecessors. Assuming 100 out of the 99 people had information that restaurant B was better than A, then only one person would go to A. However, if the second person sees the choice that the first person made and goes to A instead of B, then s (he) has ignored his/her information. If the third person follows him/her then everyone would end up at restaurant A even when he had information that restaurant B was better. In essence, the second person's decision to ignore his/her personal information and follow the herd led others to make the wrong choice. This wrong choice made by ignoring one's information and imitating others is described as "herd externality". Bikhchandani, et al., (1992) contend that regardless of the social appeal of the result, the cognition behind it might be rational.

Moreover, Hirshleifer, David and Teoh (2003) state that this kind of herding impedes information aggregation because it is difficult to detect the source of information that the herd is acting on. In stock markets, asset returns are determined by the information that can be deduced from market variables such as prices and volumes. However, in the presence of cascades, either the private information may not be reflected in prices or individuals may decide to imitate others possibly decreasing the amount of both private and public information (Hirshleifer, et al., 2003).

In an experimental research, Avery and Zemsky (1998) demonstrate that informational cascade as a source of herding is impossible if simple information structures and trade settings are assumed. Conversely, herding is only possible in complex information structures and in uncertainty which may affect security prices and lead to the formation of price bubbles. Cipriani and Guarino (2005) obtained similar results in a laboratory experiment where they find that herding rarely occurs in a frictionless market where participants' trade based on information. They observe that sometimes subjects may ignore their private information or pursue a contrarian trading strategy. Furthermore, they suggest that herd behaviour maybe better understood by examining other possible explanations such as reputational concerns (Scharfstein and Stein, 1990).

Reputational-based herding

The agent-principal relationship can also lead to herd behaviour in investment decisions. The performance assessment of fund managers (agents) by their clients (principals) is often measured in relation to other managers (See for example Lakonishok, Shleifer, and Vishny 1992). As a result, these agents are interested in what other traders do, hence inclined to ignore their own private information and make investment decisions based on imitation. Keynes (1936, p.158) argues that this might be motivated by the conventional wisdom that 'It is better for reputation to fail conventionally that to succeed unconventionally'.

The study of Scharfstein and Stein (1990) was seminal in demonstrating that reputational concerns can result in herd behaviour. They assume that the economy consists of two managers faced with investment decisions. They may have a high or low ability that is unknown to themselves or observers. Observers may infer the ability of the managers in relation to their investment decisions, which in turn determines their remuneration. As a result, the high ability managers will observe correlated trade signals about investments, whereas the low ability managers observe noise. With this type of information structure, in herding equilibrium, reputation depends on the action of others, which, creates an incentive to herd. Therefore, it is assumed that the first manager trades on their own signal and the second manager imitates him/her. If both managers invest based on their own signal, observers would accurately infer that both managers had different signals, and thus infer that they both have low ability. Conversely, if the second manager makes the same decisions as the first manager and the outcome is poor, then observers would infer that both managers are probably high quality and the poor outcome occurred by chance. Therefore, they conclude that it is better for reputation to fail as part of the herd than to succeed as an individual.

While Scharfstein and Stein (1990) describe a setting where agents follow the trade of high ability agents, Zwiebel (1995) takes an alternative approach that explores a setting where the agent with superior information has to decide whether to be a leader in deviating from the herd. In Zwiebel's model, the manager's ability is measured relative to the market benchmark; therefore, reputation depends on outperforming the market rather than other managers. As a result, managers may become loss averse and shun superior projects that would result in a greater discrepancy between their performances relative to others in the industry. This approach suggests that herding might occur where some managers reduce the risk of their portfolios relative to the market benchmark, whereas others intentionally deviate from the benchmark.

In some principal-agent models, managerial incentives such as compensation schemes can also lead to herd behaviour in managers.

Compensation-based herding

Compensation schemes dependent on the absolute or relative performance of managers have been designed to align the interests of principals and agents. However, some investment managers have a tendency to herd when their compensation is depends on their performance relative to the performance of other managers, this may result in a distortion of incentive and inefficient portfolio allocation (Maug and Naik, 1995).

In their model, Maug and Naik (1995) consider a risk-averse fund manager whose compensation is dependent on his/her own performance relative to a performance benchmark. The benchmark may be the performance of other investors or the market portfolio. In a situation where the fund manager and the benchmark both have imperfect private information about asset returns, informational efficiency can motivate the agent to imitate the benchmark such that his/her investment portfolio is similar to the benchmark's portfolio. Moreover, the compensation contract also provides an additional incentive for the agent to ignore his or her own information and herd towards the benchmark. As the compensation of the fund manager decreases, if he/she underperforms, his/her portfolio will be correlated to the benchmark's portfolio. In addition, benchmarking can also drive the manager to trade during periods where s/he would not have traded if he/she were managing their personal portfolio.

2.3.1.2. Spurious Herding

Spurious herding occurs when investors make similar decisions because they share the same fundamental-driven information or stock preferences (Devenow and Welch, 1996). In other words, correlated trade occurs without investors imitating each other. Spurious herding is consistent with market efficiency because it is driven by changes in asset fundamentals (Caparrelli, D'Arcangelis and Cassuto, 2004). There are two sources of spurious herding:

relative homogeneity and characteristic trading. These sources are discussed in the sub-sections below.

Relative Homogeneity

Relative homogeneity refers to common factors among fund managers which can result in similar investment decisions (De Bondt and Teh, 1997). For example, most fund managers have similar educational background and professional qualifications (Kremer and Nautz, 2013). Further, their investment decisions may be made based on similar sources of information [9] or by using similar indicators (Hirshleifer, Subrahmanyam, and Titman, 1994; Wermer, 1999). Market risk is another factor that can induce homogeneity, fund managers are exposed to the same market risk and tend to trade in similar directions (Broeders, Chen, Minderhoud and Schudel, 2016). In addition, these managers are also subject to similar regulatory frameworks. For example, Olivares (2008) provides evidence that the regulation on Chilean pension funds which requires managers to yield a minimum guaranteed return resulted in funds holding the same portfolios. They argue that the regulation significantly increased the correlation of asset allocation among fund managers because they were motivated reputational reasons. Studies have also found that fund managers also react to endogenous shocks in the same way. For example, Broeders, et al., (2016) find that Dutch pension funds react similarly to endogenous shocks such as changes in pension fund regulation. They also find that pension funds have similar portfolio rebalancing strategies, a finding further confirmed by Blake, Sarno and Zinna (2017). More specifically, Blake, et al., (2017), report that pension funds in the U.K. rebalance their portfolios in line with asset weight restrictions in the short term.

[9] For example, financial ratios

Characteristic Trading

Characteristic trading also known as style investing occurs when investors base their selection of stocks or portfolios on certain characteristics or styles (Andrikopoulos, et al., 2017). Institutional investors use characteristics such as size, value/growth, sector and past performance to formulate their views and investment strategies (Kalinterakis and Gregoriou, 2017). Indeed, empirical research provides evidence of the manifestations of these characteristics. Gompers, and Metrick (2001) find that institutional investors have a preference for larger stocks, however later studies by Bennett, Sias and Stark (2003) and Sias (2004) report that institutional investors have shifted their preference to smaller stocks. Further, Froot and Teo (2008), report that institutional investors reallocate their portfolios across size, value/growth and sector styles. Choi and Sias (2009) document that institutional investors herd across industries, they buy/sell stocks from the same industries which is consistent with style investing.

There is also evidence of investing based on past performance which can be either momentum or contrarian. The former refers to buying (selling) past winning (losing) stocks while the latter refers to buying (selling) past losing (winning) stocks. Numerous studies show that institutional investors utilise both strategies (Grinblatt, et al., 1995; Sias, 2004; Choi and Sias, 2009; Jegadeesh, and Titman, 1995; Baytas and Cakiki, 1999; Kaniel, Saar and Titman, 2008). According to Falkenstein (1996), mutual funds also share a preference for stocks with other characteristics such as high liquidity, highly visible stocks amongst analysts and low transaction costs. Ultimately, the implication of forming investment strategies using specific characteristics is a correlation in trading strategy which is not based on the copying decisions of other investors (i.e. intentional herding).

Rational versus Irrational Herding

There are two opposing views on herding: rational and irrational herding (Devenow and Welch, 1996). The rational view suggests that herding can be driven by principal-agent concerns or the ability to infer information from prior trades of other investors. Principal-agent concerns, observed in agents (for example fund managers, stock market traders and investment analysts) stems from their need to protect their reputation or compensation because their performance is evaluated comparatively. Therefore, they prefer to ignore their information and either copy a higher ability manager to prove quality or copy to avoid being exposed as being incompetent (Devenow and Welch, 1996). The irrational view is based on investor psychology, it suggests that investors ignore their information and follow each other like lemmings (Devenow and Welch, 1996).

Psychological biases and heuristics[10] have been found to influence herding (Barber, Odean and Zhu, 2009b). There is evidence that investors tend to have a preference for investing in domestic as opposed to foreign securities, this preference is known as home bias (See, Feng and Seasholes ,2004; Seasholes and Zhu, 2010) Ivkovic and Weisbenner (2005) and Zhu (2003) provide evidence that US investors invest approximately 30% of their portfolios in companies with headquarters close to their homes, Feng and Seasholes (2004) report a similar pattern for investors in mainland China, they invest more in firms in their province. If agents/investors in a locality are home biased in selecting stock for their portfolios, their counterparts will herd mimicking this home bias.

Seasholes and Zhu (2010) contend that home bias is motivated by advantageous information asymmetry, investors can exploit undisclosed information for domestic securities.

[10] Recall that a detailed discussion of heuristics and biases has been conducted in section 2.2.2. Therefore, the discussion here focuses on those that relate to irrational herding.

Alternatively, the home bias may be driven by other psychological biases such as familiarity bias, recognition heuristics and conformity. Regarding familiarity bias[11] Huberman (2001) finds that investors tend to invest in their local Regional Bell Operating Company (RBOC) than any others and argue that this bias is induced by familiarity. In a study that investigates the use of recognition heuristics[12] for portfolio selection, Boyd (2001) reports that participants tended to select stocks with highly recognisable names as potential winning stocks. Hirshleifer, (2001), states that people tend to conform to the behaviour of others. In relation to home bias, when a community dominated by inherently home biased agents/investors, there is an increased tendency of others to follow the group norm.

Conservatism bias which refers to slow response to new information is also a key characteristic of irrational herd behaviour. Hirshleifer, (2001), highlights that a possible explanation for conservatism bias is the cost of processing new information. As such, information that is difficult to process is weighed less in decision-making. Investors also make decisions using the representative heuristic, which can cause them to chase trends or perceive non-existent patterns. Barber, et al., (2009a) suggest that investors motivated by this heuristic focus on buying past winning stocks and selling past losing stocks. Rabin (1998) contend that the hot hand and gambler’s fallacies are linked to the representative heuristics.

Investors who are driven by the former are encouraged to herd because after observing purchases (sales) trades of other participants, they think that the trend will persist and thus mimic the purchases (sales) of their predecessors. Conversely, investors motivated by the

[11] Familiarity bias occurs when investors prefer securities that they are more familiar with
[12] Recognition heuristics is a decision-making strategy in which investors choose stocks based on recognition retrieved from memory.

latter are inhibited from herding and trade in the opposite direction because they believe that the recent trend will reverse (Rabin and Vayanos, 2009).

Irrational herding can also be driven by the illusion of control, individuals think that they have control of random events (Kahneman and Riepe, 1998). Moreover, Quiamzade and L'Huillier, (2009), suggest that individuals influenced by the illusion of control interpret the actions of others in a way that is predictable. In a market setting, investors influenced by this illusion tend to believe that other investors are similarly influenced. Consequently, these investors deduce information from the trades of other investors since they assume that the latter's trades are based on relevant information rather than random information. Therefore, this illusion of control motivates herding. According to Prast (2000), there are two concepts that may explain irrational herding: cognitive dissonance and congruity. Cognitive dissonance makes individuals seek information that confirms of the belief that they have made the right choice (Festinger, 1957). In a financial market setting, cognitive dissonance may explain herding, whereby investors who encounter dissonance make themselves feel more comfortable by assuming that preceding investors made similar decisions consequently, these investors engage in sequential herd behaviour. Congruity is a cognitive consistency which indicates that people have a biased attitude towards information and neglect any information that is inconsistent with their existing belief. Prast (2000), suggests that investment analysts and fund managers affected by congruity are biased in the way they gather and interpret information and are further encouraged to make decisions that align with their earlier beliefs even disregard new information that could alter this belief. Lastly, limited attention (being able to process a limited amount of information at a given point in time) can also contribute to irrational herd behaviour.

When faced with vast amounts of information concerning stocks, investors with limited attention tend to limit their search to stocks which have recently attracted their attention (Barber, et al., 2009a). According to Hirshleifer and Teoh (2003) investors even focus their attention on popular but incompetent analysts because they wrongly associate popularity with ability. In particular, limited attention is pronounced in periods of market stress (e.g. during a crisis), as such conditions can prompt investors to focus their attention on market-level information rather than asset-level information. Peng (2005) shows that in periods of uncertainty investors have limited information processing capacity, thus they allocate this information capacity across various sources to minimise the overall uncertainty of their portfolio. Therefore, limited attention can induce irrational herding when investors neglect how their predecessors make their information preferences and herd with them.

2.3.2. Herding: Institutional investors versus individual investors

Empirical literature examines herding in two strands. One strand examines herding in institutional investors, while the other considers herding in individual investors. According to Chang (2010), herding is more prevalent among institutional investors because they have financial information/trading information advantage. Wermers (1999) posed two questions concerning these investors: first, do institutional investors herd when they trade assets? Second, do individual investors follow the investment pattern of other investors? These questions provide more insight into herding behaviour of investors. Hence, Wermers (1999) proposed four theories in herding literature, which provide explanations for the herding behaviour of institutional investors. First, managers may neglect information gained from private research and herd in order to protect reputation (See Scharfstein and Stein, 1990). Second, managers may invest based on the same information, resulting in informational cascades (see Banerjee, 1992). Third, managers may trade in the same direction by utilising private information before that of market analysts (See Hirshleifer, et al., 1994). Fourth, institutional investors may exhibit similar aversions based on, for example, liquidity or analyst coverage and momentum trading (See Falkenstein, 1996). The first two theories are based on intentional herding while the subsequent two are based on spurious herding.

Concerning the herding behaviour of individual investors Shiller (2003) indicates that recommendations from market analysts, brokerage houses, and arrival of fundamental information may influence their investment decisions.

2.4. Empirical Evidence for herding

For over two decades, herding has attracted increasing attention from finance academics (Galariotis, et al., 2015), with empirical evidence focusing on one of two strands. The first strand pioneered by Christie and Huang (1995) tests for herd behaviour by measuring the cross-sectional dispersion of individual equity returns relative to the overall market return. The second examines the herd behaviour among institutional investors using transaction data (Lakonishok, et al., 1992; Nofsinger and Sias, 1999).

Starting with the first strand, Christie and Huang (1995) conducted a seminal study which investigates the presence of herd behaviour during periods of market stress. The authors developed a Cross-Sectional Standard Deviation (CSSD) of returns[13] model, a linear model that measures the cross-sectional dispersion of returns towards the aggregate average market return. It is based on the rationale that investors have a tendency to ignore their information in favour of the market consensus during periods of market stress. Thus, these investors have a propensity to herd during such periods. The CSSD model was tested using daily and monthly data for the US market; it provides evidence of the absence of herding at the market and industry levels during periods of extreme price movement. Interestingly, when the

[13] Returns here refers to the logged equity excess return

authors investigate herding asymmetry during periods of market stress, they find herding increases when the market is rising relative to when it is declining.

The methodology developed by Christie and Huang (1995) was criticised by Chang, et al., (2000) because it does not incorporate deviations from a linear relationship in the market.

(Gebka and Wohar, 2013). They argue that the linear relationship will be eliminated in the presence of herding and thus become nonlinear or even decrease in certain market conditions. Based on this intuition, Chang, et al., (2000), developed an alternative measure for herding using the Cross-Sectional Absolute Deviation (CSAD). They examine herding in developed (US, Hong Kong, Japan) and developing countries (South Korea, Taiwan) and only find herding in developing markets. Chang, et al., (2000) also examine possible asymmetric effects, consistent with Christie and Huang (1995) they find that for all markets examined, herding is more prevalent in up market conditions than in down market conditions.

Gleason, Lee and Mathur (2003), employ the CSSD model to investigate herding in thirteen commodity futures contracts traded on three European exchanges[14]. Like Christie and Huang (1995), they report that herding is absent. However, in contrast to Christie and Huang (1995) and Chang, et al., (2000), they report that the cross-sectional return dispersion increases rather than decreases during up and down-market periods.

Using tick data for Exchange Traded Funds from the S&P 500 index from 1999 - 2002, Gleason, Mathur and Peterson (2004), utilise the CSSD and the CSAD models, as well as modified versions of both models. They provide evidence that cross-sectional returns increased during rising and declining markets, which implies the absence of herding. Interestingly, they find that investors in ETFs herd away from the market consensus during

[14] The study was carried out using data from the following exchanges: London Futures and Options Exchange, International French Futures and Options Exchange, Agricultural Futures Market Amsterdam.

periods of market stress. They also investigate the reaction to news and report a weak asymmetric reaction to news during rising and declining markets.

Hwang and Salmon (2004) criticised the CSSD model. They argued that herding could also occur without significant movement in the return of the overall market, therefore, using this assumption could result in misleading conclusions. Furthermore, they contend that it is difficult to define ‘extreme’ price. Consequently, Hwang and Salmon (2004) developed an alternative measure for herding based on the movement in fundamentals that focuses on the cross-sectional dispersion of beta rather than market returns. The authors document evidence of herding in US and South Korea, which is more pronounced prior to and after crises periods examined. However, a major drawback of this method is that it only focuses on factor sensitivities of stocks and would only be of interest to investors with diversified portfolios, who are concerned about reducing their exposure to specific risk.

Caparrelli, et al., (2004) examine herding in the Italian market during the period between 1988 and 2001. Employing the CSSD, CSAD and Hwang and Salmon (2004) models, they find mixed evidence of herding. More specifically, results for the CSSD model are inconsistent with herding, both in normal and extreme market states. For the overall sample, the CSAD model yields results inconsistent with herding, the cross-sectional dispersion of returns is stronger during up market periods. Lastly, for the Hwang and Salmon (2004) model, they document evidence of herding, which more significant prior to a market crash.

For the Chinese market, Demirer and Kutan (2006) examine herd behaviour under different market conditions. They employ the CSSD model on stocks listed on the SZSE and SHSE between 1993[15] and 2001 at the firm and sector levels and find no evidence of herd behaviour at both levels. Further empirical results suggest that equity return dispersions are more

[15] 1994 for Shenzhen

significant during periods of market stress, with these dispersions lower when the market is declining than when it is rising, indicating more correlation in returns when the market is declining. They find consistent results when they test for robustness using the 1997 Asian crisis.

Henker, Henker and Mitsios (2006) argue that most studies produce evidence that herding is absent because of the use of inadequate data frequencies, hence, they propose testing herding using high frequency intraday data. Applying adapted versions of the CSSD and CSAD models, they examine herding at the market and industry level for a sample of 200 largest Australian stocks for the years 2000-2002 and find general evidence that is inconsistent with intraday herding for both models. However, they report that herding exists in the Property Trust sector and explain that it may be ascribed to the sector being perceived as a 'safe haven' during the Dotcom bubble. In addition, Henker, et al., (2006) document mixed evidence for herding asymmetry, the level of cross-sectional return dispersion increases and is more significant in down market conditions.

Tan et al., (2008) investigate herd behaviour in dual-listed Chinese A-share and B-share stocks using the CSAD model and find evidence of herding. They also investigate herding asymmetry and report herding in both A and B shares within both stock exchanges and find that investors tend to herd more when the market is rising, the trading volume is high and return volatility is high. In relation to the different data frequencies, they find lower levels of herding for weekly and monthly data compared to daily data, which is consistent with Christie and Huang's (1995) point that herding is a short-lived phenomenon[16]. Like Demirer and Kutan (2006), their robustness test using the 1997 Asian crisis shows that it did not influence herd behaviour.

[16] Christie and Huang (1995) report higher level of dispersion for monthly data and explain that with monthly data, investors have a longer period to deviate from the mean

Using daily data for 10 most traded stocks on different international markets from 1998 to 2004,[17] Blasco and Ferreruela (2008) report significant evidence of herding only for Spain, this herding persists during both periods of crises and tranquil periods. They employ a variant of the CSSD model which is compared to the CSSD of a notional stock market devoid of intentional herding. Moreover, they only find limited evidence of herding in the other markets.

Caporale, Economou and Philippas (2008) investigate herding in the Greek market before and after the 1999[18] stock market crash using the CSSD and CSAD models and find significant herding for the period between 1998 and 2007. When they test for herding asymmetry, they find that it is more significant during up market. Further, consistent with the proposition that herding is a short-lived phenomenon, they find more significant levels of herding for daily data compared to lower data frequencies. Besides, the authors discover that herding diminishes after 2002 due to the regulatory reforms in the Greek market.

Goodfellow, Bohl and Gebka (2009) test for herding in the Polish market. This market is particularly interesting because it has two parallel trading platforms, one dominated by institutional investors and the other dominated by individual investors, enabling the authors to determine the investor type that is more prone to herding. Their findings indicate that individual investors herd more significantly during down-markets than during up-markets, which they attribute to investor sentiment when returns decline. Moreover, institutional investors do not herd regardless of the market condition.

[17] France, Germany, Japan, Mexico, Spain, the U.S. and the U.K.
[18] They use daily, weekly and monthly data frequencies

Cajueiro and Tabak (2009) utilise the CSAD model to investigate herding in the Japanese stock market over the period 2000 through to 2006 and herding is observed during periods of market stress.

By employing daily market and industry data for 18 countries[19] for the 1988-2009 period, Chiang and Zheng (2010) use the original version of the CSSD model and a modified version of the CSAD model[20] and find evidence of herd behaviour in all markets except the U.S. and Latin American markets. Notably, they find that US returns have an impact on the returns of other markets which is more significant in Brazil, Chile, Mexico, China and Hong Kong, indicating that these markets herd around the US market. When they examine herding in up and down-market days, they report that herding is more prevalent in up markets than in down markets specifically in China, Japan and Hong Kong. In addition, the authors investigate herding during tranquil and crisis (1994 Mexican crisis, 1997 Asian crisis, the 1999 Argentine turmoil and 2008 credit crisis) periods, they document that the crisis triggers herding in the country it originates and then it spreads to neighbouring markets. Furthermore, they find that herding surfaces in the Latin American and US markets during crisis periods.

Demirer, Kutan, and Chen, (2010), investigate herding in the Taiwanese market using daily return for 689 stocks categorised into sectors, from 1995 through to 2006. Using the CSSD, CSAD and Hwang and Salmon (2004) models they find mixed evidence of herding. For the first model, herding was absent in all sectors except Electronics. However, the other two models provide significant evidence of herding in all sectors examined. It's important to note that these results further support the view that models based on the assumption of a non-

[19] They are as follows: the developed markets: Australia, France, Germany, Hong Kong, Japan, the U.K., and the U.S.; Latin American markets: Argentina, Brazil, Chile, and Mexico; Asian markets: China, Indonesia, Malaysia, Singapore, South Korea, Taiwan, and Thailand.
[20] Modified to account for herding asymmetry under different market conditions

linear relationship between the return dispersion and the market return are for reliable for detecting herding. They also find that herding is stronger when the market is declining.

Fu and Lin (2010) investigate herd behaviour and investors' reaction to news in the Shanghai and Shenzhen composite indexes using monthly data from 2004 – 2009. They employ both the CSSD and CSAD models and find no evidence of herding. Although they do not find evidence of herding, consistent with previous studies, their results reveal an asymmetric relationship where investors tend to engage in herd behaviour when the market is declining. Based on previous studies demonstrating that herding is a short-lived phenomenon, it can be argued that a possible explanation for the absence of herding found in Fu and Lin (2010)'s study may be due to the monthly frequency of the data explored (Christie and Huang, 1995; Tan, et al., 2008).

Chiang, et al., (2010) employ a quantile regression analysis[21] and a least squares method to test for herding using daily returns and turnover ratios for all firms listed on the SZSE and SHSE over the period 1996-2007. Both tests were conducted using the CSAD model. For the least squares method, they only report herd behaviour in Shanghai and Shenzhen A-share markets, with no evidence of herding in the aggregate market. Further, they investigate herding asymmetry based on and document evidence of herd behaviour in A-share markets during rising and declining conditions, while B-share market investors herd only in declining conditions. Their results for the quantile regression analysis provides supporting evidence of herding for both A and B share investors conditional on the return dispersion in the lower quantile regions[22].

[21] Quantile regression separates the data into quantiles with the aim of testing for co-movements between return dispersions and the market return in different quantiles. The authors argue that this method reduces common issues such as statistical errors and outlier sensitivity.
[22] The authors use 5 quantiles: 10%, 25%, 50%, 70%, and 90%

Lao and Singh (2011) examine herd behaviour in Chinese and Indian[23] stock markets using Tan, et al.,'s (2008) version of the CSAD model. They find evidence that herding is present in both markets and is more significant during periods of extreme price movement. However, they find that both markets show distinct herding trends. Herding is greater in the Chinese market when the market is declining, and the trading volume is high[24]. In contrast they find that herding occurs during up market periods in the Indian market. In addition, they find that different from China there is no relationship between herding and trading volume in the Indian market. Moreover, they report that herd behaviour is more prevalent in the Chinese market during the GFC[25], whereas they failed to find evidence of herding in the Indian market during the crisis. They explain that the dominance of institutional investors in the Indian market results in a decrease in speculative investment and thus contributes less to herding during the crisis.

By applying daily returns data for the Portuguese, Italian, Spanish and Greek market from 1998-2008, Economou, et al., (2011) document mixed evidence of herding using the CSAD model. More specifically, they find that herding is present mainly in the Greek and Italian markets, but absent in the Spanish market, while the Portuguese market presents mixed evidence. As part of their study, the authors investigate herding asymmetries in relation to market returns, trading volume and the volatility of market returns. They find evidence of significant herding asymmetry in high and low market returns, high and low trading volume and volatility. Further, Economou et al., (2011) examine whether it is stronger during the GFC and fail to find evidence that it is stronger during this period. Finally, following Chiang

[23] For China they apply daily data from top 300 firms listed on the Shanghai A-share index and for India they apply daily data from the top 300 firms listed on the Bombay Stock Exchange for the period 1999 to 2009.
[24] The authors explain that the observed asymmetry may be due to the dominance of inexperienced individual investors in the market who try to avoid losses during extreme periods by herding with the market.
[25] The authors suggest that the observed herding may be due to the contagion effect stated by Chiang and Zheng (2010).

and Zheng (2010), they investigate the impact of US returns on herding for the four markets in their study and did not find supportive evidence of its impact.

Chiang, Tan, Li and Nelling (2013) propose a time-varying approach which uses a Kalman-filter-based model to measure dynamic herding. When they employ the conventional static regression approach on daily individual stock returns for 10 Pacific-Basin markets (Australia, China, Hong Kong, Indonesia, Malaysia, Japan, Singapore, South Korea Thailand, Taiwan and the U.S.) from 1997-2009, they find evidence of herding in all the markets. Interestingly, the finding for the time-varying approach is consistent with the static approach, herding is present in all the markets except the US market. Thus, the authors argue that herding is time varying. In addition, they report an interdependence of herding in the markets examined.

Using daily market and sector data for 32 international stock markets[26], Gebka and Wohar (2013), employ the CSSD and CSAD models for 1998-2012 period and fail to find evidence of herding internationally[27]. Instead, they discover ‘negative herding’, whereby the cross-sectional dispersion of returns is significantly higher, which implies that market participants largely ignore the market consensus and follow the investment pattern of dominant investors. Further, they explain that this behaviour can be associated with three phenomena localised herding, excessive ‘flight to quality’ and overconfidence. Localised herding occurs when market participants simultaneously move in and out of markets, excessive ‘flight to quality’ refers to when market participants move their investments from risky assets to more secure ones during times periods of excessive volatility, and overconfidence makes investors rely on their stock-picking skills rather than the market consensus. At the sector level, the authors

[26] Argentina, Australia, Austria, Brazil, Canada, Chile, China, Colombia, Czech Republic, France, Greece, Hong Kong, India, Ireland, Israel, Italy, Japan. Korea, Luxemburg, Malaysia, Netherlands, New Zealand, Norway, Pakistan, Philippines, Singapore, South Africa, Spain, Thailand, Turkey, U.K. and U.S.
[27] They obtained similar results when the employ the quantile regression method.

observe that herding is significant in Basic Materials, Consumer Services and Oil and Gas. When they investigate herding asymmetry, they find that cross-country return dispersion is more significant in up market conditions. Lastly, they find that herd is not more significant during crisis periods.

Similar to Demirer, et al., (2010), when Chen (2013) applied the CSSD, CSAD and state space model (proposed by Hwang and Salmon, 2004) to stocks traded in 69 countries, they report herding for the CSAD and state space model. The authors argue that the inconsistent results for the CSAD model compared to other studies might be due to the larger number of countries in their sample.

Philippas, Economou, Babalos and Kostakis (2013) investigate herding in US Real Estate Investment Trusts (REIT) for the period 2004-2011, using the CSAD model. Their empirical evidence show that herding occurred during the 2004-2009 period, which they attribute to investor sentiment and adverse macro conditions related to the conditions of the real estate market.

Using a modified version of the CSAD model [28]Luo and Schinckus (2015) examine herding asymmetry in rising, declining and extreme market conditions using daily data from Shanghai and Shenzhen stock exchanges from 2006 to 2012. In line with Chiang and Zheng (2010), Lao, and Singh (2011), they find that herding is more prevalent in declining market conditions. The authors observe that herding is more significant in B- shares when the market is rising. In contrast, herding is prevalent in declining market conditions for A-shares. They obtained similar results for extreme market conditions.

Empirical evidence on industry herding in the Chinese market indicates that it varies across industries. Lee, et al., (2013) conducted an analysis of industry herd behaviour and market

[28] They combine the original version of the model with Tan et al's., (2008) methodology

states, applying Chiang and Zheng's (2010) CSAD specification on daily returns for 1,863 A-shares listed on Shanghai stock exchange. Different from Demirer and Kutan (2006), they report strong evidence of herding at the firm level and obtain similar results for the 22 sectors in both exchanges[29]. They show that all sectors except Agriculture, Chemicals, Machinery, Metals & non-metals, Petrochemicals, Pharmaceuticals, Textiles, Social services, and Wholesale & Retail trade herd with the IT sector[30]. Further, they find that the Shenzhen market herds more than the Shanghai market, which supports the argument that the Shanghai market is more sophisticated and thus demonstrates the characteristic differences between both exchanges.

Yao, et al., (2014) investigate herding in Shanghai and Shenzhen A and B shares at the market and industry level and find that herding occurs in both exchanges but is more significant in the B-share market with no evidence of herding in the all industries portfolio[31]. However, they document that herding is prevalent at the individual industry level, with the strongest level of herding reported in Social Services and Media industries. Their results also show positive herding in Agriculture and Mining industries with no evidence of herding in Financial Services (possibly due to heavy regulation). Yao, et al., (2014) also test for herding asymmetry under different market conditions and find that consistent with Demirer and Kutan (2006) herding is persistent when market returns decline.

In an investigation of herding in European markets (France, Germany, Denmark, Norway, Finland, Sweden, Portugal, Italy, Ireland, Greece, Spain (also known as the PIIGS), Mobarek, et al., (2014), only report strong evidence of herding during crises and asymmetric market conditions. More specifically, they find herding variation during crises. Continental

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[29] This may be due to the difference in time span and sample size in both studies

[30] That is the dispersion of the returns in the IT sector plays a role in herding in these sectors

[31] They used a modified version of the CSAD model, which includes the arithmetic mean of the market return to eliminate multi collinearity between the explanatory variables.

countries herd more during the GFC, Nordic countries during the Eurozone crisis and PIIGS herd during both. In relation to asymmetry, they find that Germany, Greece, Portugal and Sweden have a greater tendency to herd when market returns are negative, Ireland and Norway during low volume periods and Denmark, Greece and Sweden during both high and low volatility periods. They conclude that markets with similarities herd in similar ways.

Galariotis, et al., (2015) used both the CSSD and CSAD methods to examine herding and find that it is absent from the S&P 100 index. Interestingly, they find that herd formation in the US market takes place after the release of important macroeconomic news. Similarly, Galariotis, et al., (2016) employ the CSSD and CSAD model and find no evidence of herding.

As part of their study, Hillard and Zhang (2015) investigate the presence of herding in the SZSE and SHSE during different periods from 2002 to 2012. They find herding in both exchanges for the whole period. However, herding is stronger in the 2002 to 2005 period compared to the 2007 to 2012 period. The authors point out that their results suggest that the reforms[32] carried out by the China Securities Commission improved informational efficiency in the market.

Herding has also been investigated in frontier markets. Using data from the Mongolia stock market between the period 1999-2012, Erdenetsogt and Kallinterakis (2016), find significant evidence of herding which is persistent regardless of the direction of the market's returns, the level of trading volume and the US market's returns. Additionally, they find evidence of herding before and after but not during the GFC. Similarly, Guney, Kallinterakis and Komba

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[32] Four major reforms which have been carried out recently are: 1) the 1996 reform: a market stabilisation measure was introduced that imposed a price limit on stock price movements; 2) the 1999 reform: the securities law was implemented to strength corporate governance; 3) the 2001 reform: the trade restriction which prevented Chinese residents from investing in B shares was removed; 4) the 2002 reform: a Qualified Foreign Institutional Investors System was created to allow foreign investors to invest in A-shares.

(2017) investigate herding in 8 African frontier markets (BRVM[33], Botswana, Ghana, Kenya, Namibia, Nigeria, Tanzania, Zambia) over the period 2002-2015 and document evidence of herding. They contend that the evidence of herding can be attributed to low levels of transparency which in turn reduces the quality of information and thus increases investors' propensity to mimic their peers. They also investigate herding asymmetry with respect to market return and volatility, and only report evidence of asymmetry for market volatility which is more significant during periods of low volatility. Furthermore, they find evidence of herding before, during and after the GFC for all markets expect Botswana (only herded before the crisis). Lastly, they find limited evidence that US and South African returns induce herding across all the 8 markets.

It is important to point out that majority of the studies based on modified versions of the CSSD and CSAD model or other models find evidence of herding. Some studies have modified the CSSD and CSAD model by adding explanatory variables such as volume and volatility to examine whether they trigger herding.

Litimi, et al., (2016) modify the CSSD and CSAD to include potential triggers of herding such as volatility, volume and sentiment. They test these models using market and sector data for all firms listed on NYSE, AMEX and NASDAQ and find evidence of herding for the modified CSAD[34]. For the sectors, the modified version of the CSSD model provided evidence of herding in the Basic industries, Healthcare and Utilities sectors. For the CSAD model, herding is only reported in the Public utilities and Transportation sectors, while for the modified version they find herding in Public utilities, Transportation, Energy, and Healthcare sectors. They also provide evidence that while volatility affects herding in all

[33] BRVM is an abbreviation for Bourse Régionale des Valeurs Mobilières a cross border exchange consisting of Benin, Burkina Faso, Guinea Bissau, Ivory Coast, Mali, Niger, Senegal and Togo.
[34] There is not sufficient evidence of market level herding using the modified CSSD model

sectors, volume affects herding in only 5 sectors (Basic industries, Energy, Health care, Public utilities and Transportation). In addition, they provide empirical evidence that the presence of herding in the US market has contributed to the bubbles and financial crises from the 1987 Black Monday till the recent GFC.

BenSaida (2017) conducted a study using similar data as Litimi, et al., (2016), they modify CSAD model by including variables to capture trading volume and investor sentiment. They only find herding in the Healthcare and Public utility sectors. Interestingly, during crisis periods they find herding in 10 out of the 12 sectors examined and argue that US investors blindly mimic other investors in such periods.

Vo and Phan (2017), investigate herding in the Vietnamese market using daily, weekly and monthly data for 299 companies over the period 2005-2015. They utilise the CSSD and CSAD models and find evidence of herding for daily and weekly data, which supports the proposition of Christie and Huang (1995) that herding is a short-lived phenomenon. They also report evidence of herding during up and down-market conditions. The authors suggest that investors in the Vietnamese market herd during up-markets because of the market's limited information transparency regarding its institutional investors, while herding during down-markets is prompted by the poor quality of the information in published accounts. Additionally, they find herding in both high and low trading volume states. Evidence of herding is also reported before and after but not during the GFC crisis.

By employing a modified version of the CSAD model[35] on data from the US market, Bekiros, Jlassi, Lucey, Naoui, and Uddin (2017), document time-varying dynamic herding which is significant in extreme market conditions. Notably, they find that herding is mainly significant before the crisis rather than during or after it. They point out that this evidence is

[35] The model is modified to include volatility as a metric for agents' risk assessment

inconsistent with previous studies and may be due to the use of the quantile regression approach.

Zheng, et al., (2017) examine industry herding in nine Asian markets (China, Korea, Hong Kong, Singapore and Taiwan) using daily data for the period 1993 to 2013. They test for herding using the CSAD model and the model developed by Chiang and Zheng (2010) and report herding in major industries across all the markets. For the Chinese market, they find herding in all industries except Utilities, with herding more significant in the Technology industry consistent with Lee, et al., (2013). Similar results were also obtained for the Japanese, Korean and Hong Kong markets. Zheng et al., (2017) also investigate the influence of the U.S. market on herding and find evidence that implies that Japan and Korea herd more with the U.S than the other markets. When they investigate herding asymmetry in relation to market return and trading volume, they find that Japan, Korea and Taiwan herd when the market is declining and is prevalent during days with low trading volume. They conclude that herding is more likely to occur in concentrated industries such as Industrial Goods. The authors obtain mixed evidence of herding during crisis and tranquil periods, however, the Japanese, Korean and Taiwanese markets herd more during crises.

Andrikopoulos, Kallinterakis, Ferreira, and Verousis (2017), test for intraday herding on the Euronext for the 2002-2010 period at the market and industry levels, using the CSAD model, they document evidence of herding for the group. Specifically, they find that herding is prevalent in all the countries (Belgium, France and Portugal) except Netherlands. The authors attribute the lack of herding in the market to the dominance of sophisticated foreign investors who base their investment decisions on international market conditions as opposed to domestic conditions. Moreover, they report evidence of industry herding in sectors (Financials, Healthcare, Oil and Gas and Utilities) with the largest market capitalisation, indicating a size effect. Lastly, they observe herding before, during and after the GFC, though it is less significant during the crisis.

Li, Liu and Park (2017) develop time-varying models based on the CSAD model to test for herding in the Chinese market. Using daily price returns from the CSI 300 index[36] stocks, they find weak evidence of herding with the static model. However, the coefficient of the time-varying model show that herding is present between 2006 and 2010 and the second half of 2014. Relating to herding in market conditions, they document evidence that investors only herd during turbulent periods, particularly during the GFC.

Utilising the CSAD and enhanced CSAD models, Kabir (2018) investigates herd behaviour of investors in the US financial industry[37] during the 2008 financial crisis to identify whether investors herd towards the financial sector/ its sub-sectors/ the market. For the CSAD model they provide evidence that investors herd towards the financial sector, with higher levels of herding in Savings and Loans Institutions. The findings for the enhanced model show significant levels of herding, which implies that herding is affected by market conditions and volatility. Further, Kabir (2018) reports that the financial crisis did not increase the level of herding.

Recently, researchers have focused on investigating herding in the excessively volatile cryptocurrency market (Bouri, Gupta, Roubaud, 2018), and have found mixed evidences on its existence. For example, Vidal-Tomas, Ibanez and Farinos (2018) investigate herding in the cryptocurrency market using the CSSD and CSAD models and fail to detect herding. Nevertheless, when they investigate herding asymmetry, they find that herding is significant when the market is declining. Similarly, Bouri, et al., (2018), fail to find herding using these

[36] The index consists of the 300 most liquid A shares on the Shanghai and Shenzhen stock Exchanges
[37] Specifically, commercial banks, savings and loans institutions, and investment and insurance companies.

models, however, when they use a rolling window regression approach, they find evidence of dynamic herding. They argue that due to the nonlinearities, static models are unsuitable for investigating herding in cryptocurrencies. Kaiser and Stockl (2019), provide contrasting evidence, they find herding in the cryptocurrency market when they employ the CSSD and CSAD models. They explain that their contrasting results is due to the survivorship bias and small data sample used previous studies. In the same spirit, Kallinterakis and Wang (2019) find significant evidence of herding which is asymmetric especially during rising markets, high trading volume and low volatility days.

Some important issues arise from the review of empirical evidence on herding at the aggregate level. First, the examined evidence reveals that models which account for non-linearities between return dispersions and market returns are more reliable for explaining herding than models that are based on a linear relationship. The characteristics of the market microstructure may result in non-linear behaviour of returns due to the difficulties in executing arbitrage transactions (e.g. restrictions on short selling, differences between stock markets and derivative markets) [Antoniou, Ergul and Holmes (1997)]. Non-linearities could also occur because of market imperfections, for example transactions costs which may prevent investors from trading. Hence, they only trade when it is profitable, resulting in a clustering of return which may impact herding. Antoniou, et al., (1997) point out that investor irrationality could also lead to non-linearity. Investor irrationality is at odds with the finance theory that assumes investors are rational, risk averse and capable of processing relevant information relating to assets in an unbiased manner. Yet, as earlier discussed investors may exhibit biases such as overconfidence and take on excessive risk. Thus, linear models may be inadequate for explaining the relationship between returns. These reasons for nonlinearities buttresses why linear models fail to adequately explain herding, hence nonlinear models such as the CSAD provide more reliable evidence of herding as opposed to the CSSD model.

Second, empirical research has revealed that emerging markets are more prone to herding than developed markets (see for example Chiang and Zheng (2010)). Thus, some studies have cited factors that provide possible explanations for the prevalence of herding in these markets. According to Chang et al., (2000), the existence of herding might be due to a high degree of government intervention in issues relating to monetary policy. In addition, they suggest that scarcity of accurate information disclosure can also explain herding whereby scarcity of fundamental firm specific information may cause investors in these markets concentrate more on macroeconomic information. Another possible explanation could be the impact of the dissemination of global investment information. For example, Chiang and Zheng (2010) argue that investors in Asian markets tend herd because they track international news and make investment decision informed by those of U.S. institutional investors. Lee et al., (2013) contend that herding may due to inherent characteristics of emerging markets such as inadequate corporate governance, dominance of less-educated investors, insider trading and weak financial market regulation. Yao et al., (2014) argue that it may be attributed to low transparency of emerging markets whereby financial reporting is relatively less stringent and information is costly to acquire, thus increasing investors' propensity to mimic the actions of each other. Finally, the studies have shown that the presence of thin trading[38] in emerging markets conceals the degree of herding. Kallinterakis, Kratunova (2007) and Andronikidi, Kallinterakis (2008) report that thin trading induces bias in the estimation of trading models for the Bulgarian and Israeli market respectively. Both

[38] Thin trading occurs when there is low trading volume because of lack of buy (sell) orders. It can induce serial correlation of market returns and biased estimators (Antoniou, et al., 1997).

authors adjusted the returns to account for thin trading and report it caused herding to be more persistent.

Lastly, relevant research reveals that herding is affected by the occurrence of financial crises (Hwang and Salmon, 2004). For example, some studies (Hwang and Salmon, 2004; Bowe and Domuta; Economou, Katsikas and Vickers, 2016) report that herding dissipates during crises, while other studies find that herding increases during crises (Chiang and Zheng, 2010; Lao and Singh, 2011, Mobarek, et al., 2014; Economou, et al., 2015; Zheng, et al., 2017). There are possible explanations for the effect financial crises have on herding. Kallinterakis and Gregoriou (2017) explain that crises expose fundamentals, which changes the consensus on which market participants herded on pre-crisis and consequently results in a new consensus that informs the herding of these participants. The authors further explain that the change in the consensus prior to the crisis is a possible explanation for the dissipation of herding post crisis, in contrast the new consensus results in an increase in herding tendency post crisis. Another possible explanation for the increase in herding post crisis could be due to investors who enter the market in anticipation of its recovery. But the market might still be risky due to post crisis excess volatility, hence investors who are risk-averse are prone to herding with other investors (Vo and Phan, 2017). Interestingly, contrary to prior literature (see and Tan, et al., 2008 and Economou, et al, 2011) that suggests that herding should be more pronounced during crises, some studies report that (see Demirer and Kutan, 2006, Philippas, et al., 2013; Yao, et al., 2014) herding is absent during financial crises. These studies may have failed to find herding because high market volatility during crises makes it difficult for investors to view the direction of the market hence, they are unable to herd towards the market consensus (Gavriilidis, et al., 2013). In contrast, Gavriilidis, et al., (2013) point out that in tranquil market conditions, investors can clearly view the market consensus and herd towards it.

Besides the research based on aggregate data, there has also been extensive amount of research based on transaction data of markets investigating herding. Lakonishok et al. (1992) conducted a seminal study using the LSV measure they developed to examine herding in 769 U.S. tax-exempt funds[39] from 1985-1989. They find weak evidence of herding for stocks with smaller market capitalization, while they find insignificant evidence of herding for larger capitalization stock. In the same spirit, Grinblatt, et al., (1995) find weak evidence of herding for 155 U.S. mutual funds from 1974-1984. Wermers (1999) investigates the relationship between mutual fund herding and stock prices using data for U.S. mutual funds from 1974 to 1994 and finds that smaller stocks exhibit higher level of herding whereas average stocks showed slight herding behavior. In a study of all NYSE companies from 1977-1996, Nofsinger and Sias (1999) provide evidence of herding; however, institutional investor herding had more impact on returns than individual investor herding. Similarly, Jones, et al., (1999) report evidence of herding for U.S. institutional investors over the period from 1984 to 1993.

Evidence from studies that examine institutional investor herding in emerging markets indicate mixed evidence of herding in these markets especially in the aftermath of the Asian Crisis. Using data of foreign investors from 1996-1997, Choe, Kho and Stulz (1999), report that they herded more before the 1997 Asian crisis compared to during it. Kim and Wei (2002a) also investigate the herd behavior of offshore and onshore institutional and individual investors in the Korean market and document that onshore funds herd more compared to foreign institutional investors during the Asian crisis. These results are corroborated by Kim and Wei (2002b) who investigate herding of foreign investors in Korea

[39] These funds were predominantly pension funds. All the funds in the sample were managed by 341 fund managers.

before and during the Asian crisis, they find that offshore foreign investors are more likely to herd than their domestic counterparts.

Sias (2004) develop a new measure to detect herding using U.S. data for the period 1983-1997 and find that institutional investors herd. Other studies in different countries and markets also provide evidence of institutional herding: Indonesia (Bowe and Domuta, 2004); Chile (Olivares 2008); U.K. (Wylie, 2005; Blake, Sarno and Zinna, 2017[40]); Poland (Voronkova and Bohl, 2005), Japan (Chang and Dong, 2006), Taiwan (Chen and Hung, 2006, Hung, Lu and Lee, 2010; Lu, Fan and Nieh, 2012); Germany (Walter and Weber, 2006, Oehler, and Wendt, 2009[41], Kremer and Nautz, 2013), Spain (Blasco and Ferreruela, 2008[42], Agudo, Sarto and Vicente, 2008; Gavriilidis, et al., 2013); Portugal (Lobao and Serra, 2007; Homles et al., 2013); U.S. (Choi and Sias, 2009); Hong Kong (Zhou and Lai, 2009), India (Lakshman, Basu and Vaidyanathan, 2013).

There are two interesting findings from the reviewed empirical evidence. First, a size effect is evident in institutional herding. Some studies (e.g. Lakonishok, et al., 1992; Grinblatt, et al., 1995) report that herd behaviour is more significant in small market capitalisation stocks. This finding can be attributed to the information risk (due to the low analyst coverage of these stocks) which characterises to these stocks, and consequently results in low trading volume (Kallinterakis and Gregoriou, 2017). Low trading volume increases investors' tendency to herd as they are likely to mimic the trading decisions of their peers. Contrastingly, other studies (e.g. Wylie, 2005; Kremer and Nautz, 2013) find that herding is more significant among large capitalisation stocks, this could be due to market regulations that require institutional investors to invest in companies with specific characteristics (See

[40] They investigate herding in U.K. pension funds

[41] They investigate herding in bond markets, the evidence of herding is weaker than stock markets.

[42] Other countries examined were Germany, United Kingdom, United States, Mexico, Japan, Spain and France. However, they only find significant evidence of herding in Spain.

Voronkova and Bohl, 2005; Olivares 2008). Some of these characteristics include investing in larger stocks, this can lead to herding because these investors investing in similar stocks. In like manner, the performance of institutional investors is often linked to benchmarks such as indices, which increases their tendency to mimic the portfolio composition of these indexes (Walter and Weber, 2006).

Lastly, herding has been found to be more significant in emerging markets compared to developed markets. A possible explanation for this is information asymmetry, whereby as earlier stated, emerging markets often have low quality information about fundamentals, which prompts institutional investors to neglect the market information and mimic their peers (Kallinterakis and Gregoriou, 2017).

Table 2.1 Related evidence on herding in the US market

Author	Data	Sample	Purpose	Method	Result
Christie and Huang (1995)	Daily from 1962-1988 monthly from 1925-1988	NYSE and Amex firms, 12 industries	Tests for herding by investigating whether dispersions are significantly lower than average during periods of market stress.	CSSD	No herding is reported at the firm and sector level. During declining markets, when herding is expected to be significant, return dispersion is consistent with the predictions of rational asset pricing models.
Chang, et al., (2000)	Daily returns from 1963-1997	NYSE and Amex firms	Herding behaviour in US, Hong Kong, Japan, South Korea, and Taiwan	CSAD	Herding is absent, during periods of extreme price movements. Return dispersion is higher when the market is rising than when it is declining.
Hwang and Salmon (2004)	Daily returns from 1993-2002	US (S&P500) and Korea (KOSPI)	Measures and detects herding during market stress.	State-space model	Herd formation exists both when the market is rising and when it is declining. The Russian crisis helped to reduce herding and returned the market to equilibrium.
Chiang and Zheng (2010)	Daily returns from 1998-2009	Stock exchanges in 18 countries	Herding in international stock markets	CSAD	No evidence of herding in the US market. No evidence of herding asymmetry in up and down market conditions. US market herds during crisis periods.
Chen (2013)	Daily returns from 200-2009	35,328 stocks traded in 69 countries.	Herd behaviour in international stock markets	CSSD, CSAD, Hwang and Salmon's state-space model.	No evidence of herd formation using the CSSD model but finds herding using the CSAD and state-space models.

Galariotis, et al., (2015)	Daily returns from 1989 2011.	S&P100 and FTSE100	Does the release of macroeconomic news affect investor herd behaviour?	CSAD estimated using a rolling regression method	US market herds when macroeconomic news is released. US investors herd due to fundamental and non-fundamentals in different crises conditions.
Galariotis, et al., (2016)	Daily returns from 1997 to 2009.	France, Germany, Japan, UK, and US.	The effect of liquidity of herd behaviour	CSAD and Amihud (2002) illiquidity measure.	No evidence of herding in the US market, but it becomes visible when liquidity is controlled for.
Litimi, et al., (2016)	Daily returns from 1985-2013.	All firms in the on NYSE/AMEX/NASDAQ (4,183)	Does herding play a role in excess volatility in US sectors?	CSSD, CSAD, Vector Autoregressive model (VAR), modified CSAD.	No evidence of herding using in CSSD model, but the modified CSAD provides evidence of herding. It is prevalent in 8 out of 10 sectors. Only two sectors herd using the modified CSAD. Herding and trading volume affect market volatility.
BenSaida (2017)	Daily and returns from 1985-2015	All firms in the on NYSE/AMEX/NASDAQ (4,183) divided into 12 sectors.	Examines the effect of herding on excessive idiosyncratic volatility in US industries.	CSAD, modified CSAD	According to the CSAD model, herding is absent in all US sectors, however the modified version shows that herding is present in 10 out of 12 sectors. Trading volume does not trigger industry herding but reduces the conditional volatility at the market level and in some sectors. Herding in only present in the whole market during crises and bubbles.
BenMabrouk and Litimi (2018)	Daily firm level and sector level returns from 2000-2017	All listed stocks in the US market.	Examines sectorial herding during extreme oil market movement.	CSAD	No evidence of industry herding, but herding occurs during downward extreme oil market movements. The market herds based on information from the oil market.
Kabir (2018)	Daily data from 2003-2012	US commercial banks, savings and loan (S&Ls) institutions, investment, and insurance banks.	Did investors in the US financial industry herd during the financial crisis?	CSAD	Investors in commercial and investment banks spuriously herd during the crisis. S&Ls and investment banks intentionally herd when volatility is high.

Table 2.2 Related evidence on herding in the Chinese markets

Author	Data	Sample	Purpose	Method	Result
Demirer and Kutan (2006)	Daily firm and industry returns from 1999-2002	375 stocks listed on Shanghai and Shenzhen	Does herding exist in the Chinese markets?	CSSD	Herding does not exist in the Chinese market at the firm and sector level. No herding during the Asian crisis.
Tan, et., (2008)	Daily, weekly and monthly returns from 1994-2003	87 dual-listed firms A- and B-share stocks	Herding in dual-listed A and B-share stocks	CSAD	Evidence of herding in rising and declining market conditions. A-share investors in SHSE herd more under rising markets, high trading volume and high volatility conditions. No evidence of asymmetry in B share markets. No herding during the Asian crisis.
Fu and Lin (2010)	Monthly returns from 2004-2009	Shanghai and Shenzhen composite indexes	Herd behaviour and investors' asymmetric reaction to good and bad news	CSSD and CSAD	No evidence of herding. Asymmetric rherding is more prevalent during declining market conditions.
Chiang and Zheng (2010)	Daily returns from 1998-2009	18 countries	Herding in international stock markets	CSAD	Evidence of herding in the Chinese market. Return dispersions of the US markets provide more insights on the observed herding. No evidence of herding in the Chinese market during GFC.
Chiang et al. (2010)	Daily returns from 1996-2007	SHSE and SZSE A- and B-share stocks	Herd behaviour in Chinese stock markets	CSAD, quantile regression	Evidence of herd behaviour in both A-share and B-share groups which is conditional on the dispersions of returns in the lower quantile region.
Lao and Singh (2011)	Daily and Weekly 1999-2009	Shanghai A-Share	Herd behaviour in Chinese and Indian stock markets	CSAD	Herding is more significant when the market is declining, and the trading volume is high. No evidence of herd formation using weekly data. Significant herding during GFC.

Chiang, et al., (2012)	Daily industry and market price returns from 1996 to December 2008.	China, Hong Kong, Japan, and the United States.	Does herding behaviour in Chinese markets react to global markets?	CSAD estimated using a rolling regression method	Chinese markets exhibit herding behaviour at both firm data and industry level. They employ a rolling regression method to estimate the herding equation, and report that the herding coefficient displays a time-varying property.
Chiang, et al., (2013)	Daily from 1997 to 2009.	Australia, Hong Kong, Japan, Singapore and the United States, China, Indonesia, Malaysia, South Korea, Thailand, and Taiwan.	Does investor herding behaviour in Pacific-Basin equity markets?	Kalman-filter-based model	Herding is present using the CSAD model, but it is absent using the time-varying approach and present in both rising and falling markets.
Lee, et al., (2013)	Daily returns from 2001-2011	A-share market	Do investors follow each other in and out of the same industries in Chinese A-share markets?	CSAD	Strong evidence of herding which is significantly influenced by the stock return dispersion of the Information Technology sector. Industry herding is more significant in the SZSE, and it is more significant in some sectors in the SHSE in bull market conditions.
Yao, et al., (2014)	Daily and weekly returns from 1999-2008	All listed firms A and B shares in SZSE and SHSE	Examines the existence and prevalence of herding in a segmented market setting	CSSD, CSAD	Herding is only reported in the B-share markets, and it is more prevalent at the industry level. Herd behaviour is more pronounced in declining market conditions for the A-share markets and the Shanghai B-share market. Herding is absent during the GFC.
Luo and Schinckus (2015)	Daily data from 2006-2012	SZSE and SHSE	Investigates herding asymmetry in bull, bear and extreme market conditions	CSAD	Herding is prevalent in bullish states for B-shares while a bearish situation generates herding for A-shares.
Hillard and Zhang (2015)	Daily data from different time periods between 2007 -2012	SZSE and SHSE	Examines the size, price-to-book effects and herding in Chinese markets.	CSAD	Provides evidence of strong size effects but not price- to-book effect. Herding behaviour is prevalent between 2002 and 2012 but decreases after 2006.

Zheng, et al., (2017)	Daily data from 1993-2013	Japan, China, South Korea, Hong Kong, Taiwan, Singapore, Indonesia, Malaysia, and Thailand	Examines industry herding for nine Asian markets.	CSAD	Herding exists in the Chinese market but is more prevalent at the industry level. All industries herd except the Utility industry. The reported industry herding is more pronounced in down markets and low trading volume markets. China herds with the US market.
Li, et al., (2017)	Daily returns from 2006-2015	CSI 300 index stock	Investigates herding in the Chinese market using several time-varying coefficients	Time-varying CSAD	Weak evidence of herding using CSAD. More evidence of herding behaviour during turbulent than in tranquil periods. Using the time-varying fixed-coefficient regression model. US return dispersion had a strong influence on Chinese stock markets before 2015 but not in 2015.

2.5. Conclusion

The extensive review of relevant behavioural finance literature that has been carried out in this chapter has demonstrated that as a field, it challenges traditional finance assumptions. Specifically, it mainly challenges the rationality assumption by revealing that investors are influenced by non-rational factors such as biases and they use heuristics to simplify investment decision making when faced with complexities. Consequently, these biases and heuristics are evident in their individual trading strategies as well as collectively. Subsequent empirical chapters provide novel insights on herding, a persistent behavioural pattern motivated by various factors as earlier discussed.

The first empirical chapter investigates the determinants of industry herding in the US stock market. The reviewed empirical evidence yields interesting findings on herding in the US as summarised in Table 2.1 below. At the market level, the mixed evidence has been largely due to the methodology employed in the study. On one hand, studies that used the CSSD and CSAD models obtain results inconsistent with herding, on the other hand, results consistent with herding were obtained using Hwang and Salmon's (2004) state space model. When the effect of crisis on herd behaviour was examined, the results were also mixed, with some studies finding no herding during crisis (for example Christie and Huang, 1995), with evidence of herding only recorded during the GFC crisis mainly because the crisis originated from there (for example BenSaida, 2017). Furthermore, evidence on industry herding asymmetry is limited. The few studies which have focussed on industry herding only find herd behaviour mainly in nonfinancial industries such as the Healthcare and Public utilities sectors.

Overall, the evidence reveals the empirical issues relating to herding at the market and sector level. Following from these evidences, we would expect to find herding at the industry level and during crises but not at the market level. In addition, we expect to find herding asymmetry at both the market and industry levels. Indeed, the anticipated lack of herding the market is consistent with the reviewed evidence that herding is not significant in developed markets (Chiang and Zheng, 2010). Despite the numerous studies that investigate herding in the US, there is sparse in-depth research herding conditioned upon rising and declining market returns, high and low trading volume and volatility as well as crisis.

The final empirical chapter investigates the determinants of herding in the Chinese market. The papers examined in this section highlight the inconclusive evidence of herding in the Chinese market and its determinants (see Table 2.2). The differences in the results may be due to the methodology employed, the data frequency or the sample period. The determinants of herding have also produced mixed findings especially with regards to market return and trading volume. Studies like Demirer and Kutan (2006), Fu and Lin (2010), Lao and Singh (2011) find that the market herds when market returns are declining. In contrast, Tan, et al (2008), Chiang and Zheng (2010) and Lee, et al. (2013) document herding when the market is rising. On the one hand, Chiang and Zheng (2010) point out that they do not find evidence that trading volume foments herding, and on the other, Tan, et al., (2008) report that both Shanghai and Shenzhen A and B-share markets herd in high trading volume. Studies also find evidence that other factors that influence herding in the Chinese market such as US returns (Chiang and Zheng, 2010; Luo and Schinckus, 2015; Li, et al., 2017), release of new information (Chiang, et al., 2013), regulatory reforms (Li, et al., 2017), GFC (Lao and Singh, 2011 and Yao, et al., 2014) and returns of the information technology sector (Lee, et al., 2013). In addition, studies report that herding is more significant at the industry level (Lee, et al., 2013, Yao, et al., 2014 and Zheng, et al., 2017). Based on the empirical evidences examined which documents that herding is more significant in emerging markets, we expect to find herd behaviour during crises and asymmetric market conditions at the market and industry levels.

We believe that these chapters will contribute to behavioural finance as it fills research gaps in the industry herding literature. In addition, it provides important implications for investors because when herding is present, they experience reduced benefits of diversification. Furthermore, our results are of interest to policy makers and stock market regulatory authorities because of the potential destabilising impact of herding in the market. Therefore, an examination of industry herding provides beneficial insights on its determinants in a developed and an emerging market. Lastly, in view of the recent US-China trade war, the examination of the impact of US returns on herding in the Chinese market bears important implications on the effect of their trading relationship on investor behavioural patterns.

Overall, the literature in the chapter has provided a basis for this thesis and identified the gaps in literature. The next chapter discusses the philosophical underpinnings of this thesis.

Chapter 3 Research Philosophy

3.1. Introduction

Research is usually conducted based on relevant research philosophy, research methodology and research design with the central aim of answering the research question and consequently the research objective. In the previous chapter, we reviewed relevant literature and stated the research questions. This chapter has been set out to discuss the research philosophy and research methodology employed in this thesis.

Section 3.2 discusses relevant research philosophies and philosophical paradigm employed in this thesis. Section 3.3 highlights and justifies the research approach.

3.2. Research Philosophy

According to Blaxter, Hughes and Tight (2006) research philosophy relates to a belief regarding how data is gathered, analysed and used. TerreBlanche, Durreheim and Painter (2006) suggest that research philosophy can be examined in three major ways: epistemology, ontology and methodology. Epistemology pertains to the relevant theory of knowledge that establishes the relationship between the knower and what could be known (Guba and Lincoln, 1994). Ontology focuses on reality and how it is interpreted (Blaxter, et al., 2006). Methodology refers to how research is conducted (Blaxter, et al., 2006).

Different philosophical scholars have developed theoretical classifications of research philosophies. For example, Ritchie and Lewis (2003) classify ontology into realism, critical realism, relativism, idealism and materialism. In contrast, Guba and Lincoln (1994) adopt a perspective of positivism, interpretivism realism and pragmatism. Although these philosophies are based on different perspectives and assumptions, they are mainly based on similar broader philosophies.

The two major theoretical perspectives of research philosophy in social sciences are positivism and interpretivism. Other perspectives include postmodernism, feminism and critical enquiry. Positivism, the theoretical perspective applied in this thesis is discussed in the section below.

3.2.1. Positivism

A French philosopher August Comte originated the positivist perspective. He argued that all human behaviour could be understood through observation of objective reality. Thus it consists of what is measurable by the senses which can be obtained through observation and experiments. The central theme of positivism is that knowledge exists independent of the researcher. Therefore, observations should be measurable and repeatable (Levin, 1988). To achieve this, scientific enquiry is used to gather data (Blaxter, et al., 2006). This scientific enquiry is conducted through various methodologies including deduction, quantitative analysis, laboratory experiments, nomothetic experiments and confirmatory analysis (Kothari, 2004). Positivists believe that human behaviour is passive and dependent on the external environment.

The dominant methodological approach in modern finance is inspired by the positivist philosophy (Frankfurter and McGoun, 1999). This school of thought includes the EMH and the capital asset pricing model (CAPM). Ardalan (2008) argues that research in finance takes a functionalist paradigm, which is also inspired by positivism and suggests that social issues have rational explanations. It assumes that the scientist is objective and analyses phenomenon through scientific methods, thus individuals play a passive role, and the external environment determines their behaviour.

Kolb (2010) criticised the dominance of positivism in finance research. The author argued that the positivist view is not appropriate for a field like behavioural finance, which challenges the rationality assumption. Consequently, research in finance is confined to a perspective that is based on unrealistic assumptions about human nature. Lucey (2000), advocates for an approach in finance research that includes aspects of human behaviour to facilitate the study of interactions between theoretical development, empirical evidence and research methods. However, there is no contention that advocates for the use of positivism as the mainstream philosophy in finance, the choice of methodology is solely based on judgment and the context of enquiry (Fidlay and Williams, 1981).

Another problematic area in the positivist paradigm employed in finance is the dichotomy between facts and values. Lagoarde-Segot (2015) states: "facts' are tangible, measurable and verifiable, whereas 'values' belong to the metaphysical realm, and, as such, cannot be the object of rational inquiry" (p.4). Putnam (2002) responds to the critique of the fact/value dichotomy by asserting that facts stem from initial beliefs and knowledge on how the world is perceived and is summed up in values. Lagoarde-Segot (2015) argues that research questions in finance have facts embedded with decisions based on values. This thesis can be used as an example to demonstrate the interrelationship between facts and values. On the one hand, the thesis aims to investigate the determinants of industry herding in the US and Chinese markets. Herding is investigated using empirical data analysis, whereby the data can be regarded as 'fact', which is tangible and verifiable. On the other hand, an important aspect of this thesis examines the practical implications of herding for investors and policy makers. Therefore, the research seeks to demonstrate how the herding phenomenon can inform investors' decision making and market regulation. The implication of the herding phenomenon can be interpreted as the value of the thesis.

In line with previous research in finance, the underpinning philosophy for this thesis is positivism. We acknowledge the arguments against this philosophy, but we believe that all philosophies are valuable depending on the focus of the study. Our focus is that the philosophy should be relevant to our research questions set out in chapter two. The characteristics of positivism applied in this study are displayed in Table 3.1.

Table 3.1 Characteristics of positivism

Feature	Description
Purpose of research	Understand the factors that could impact industry herding
Ontology	❖ Only scientific knowledge can reveal the reality ❖ Reality can be explored through observation and experiments ❖ The evidence is described based on scientific methods ❖ The behaviour of the individuals observed in the research is controlled by the external environment
Epistemology	❖ Knowledge is obtained through a process of quantification ❖ Supportive empirical evidence of theory or hypotheses is obtained from statistical methods ❖ A deductive approach which involves the use of a testable hypothesis is followed ❖ There is no interaction between the inquirer and the inquired ❖ Aims to establish a causal relationship between variables
Methodology	❖ Quantitative method ❖ Data is collected from the stock market database, DataStream ❖ The values of the researcher are not reflected in the research

The emphases in the methodology are the relationship between variables, analysis of empirical evidence, independence (Gray, 2014).

3.3. Research Approach

There are two major research approaches: quantitative research and qualitative research. Quantitative research focuses on studying natural phenomena while qualitative research focuses on social and cultural phenomena. Both quantitative and the qualitative methods are used in finance research. However, the quantitative research is more dominant (Ryan and Julia, 2007). Neither of these methods is superior to the other, the choice of method is determined by the context, focus and nature of research questions. The quantitative research is based on the empiricist paradigm and therefore focuses on investigating the cause and effect of social occurrences and employs empirical data, rejection/confirmation of hypotheses and logical interpretation. Hence, the quantitative method implies that the emphasis is on testing theories or hypotheses with the aim of improving them as opposed to proving them. The research process involves the collection of data based on the theory or hypotheses to be tested to which statistical methods are applied, and the results are typically displayed in graphs or tables. The thesis is about the determinants of industry herding, to gain insights into the factors that drive herding in industries. Herding is determined by investigating the relationship between market returns and the cross-sectional absolute deviation of stock returns. Thus, the research process involves formulating hypotheses and collecting data from on stocks followed by data analysis and interpretation. Then results obtained are displayed in tables and graphs. We have found that the quantitative description of the relationship in question and a deductive analysis of data as the most suitable for this research because it enhances objectivity.

Chapter 4 Herding and its determinant in the US stock market: A sectoral analysis

4.1 Introduction

This chapter presents the empirical results for the impact of market conditions on industry herd behaviour by testing for its presence in the US stock market. There is considerable amount of research on herding towards the market consensus in various stock markets at the market and industry levels (Chiang and Zheng, 2010; Gebka and Wohar 2013; Mobarek, et al., 2014; Andrikopoulos, et al., 2017; Zheng, et al., 2017). Notwithstanding, few have focused on industry herding in the U.S. While investors in the U.S. market tend to herd more at the industry level, the empirical evidence on industry herding is still sparse (Litimi, et al., 2016). In fact, Litimi, et al., (2016) and BenSaida (2017) fail to find evidence of herding in the U.S. stock market but find significant herding at the industry level during periods of market turmoil. Although these studies provide significant results of industry herding, they lack an in-depth analysis of the determinants of industry herding. Consequently, there are some unanswered questions. Specifically, in investigating industry herding we question whether it is conditional upon market returns, trading volume and volatility.

Using the CSAD model developed by Chang. et al., (2000), we conduct our research on the sample of all firms listed on the S&P 500 index from January 1990 to October 2016. We investigate herding at the market and sector level. At the sector level, we use a classification of all the firms into 19 industries. To facilitate our study on industry herding, we examine the effect of rising (declining) market return, high (low) market volatility and trading volume. To further examine the effect of crises on market and sector herding, we select two crises which originated from the US: the Dot com bubble and the Global Financial crises.

Our findings reveal the following. We find that there was no herding at the market level. However, there is evidence for herding at the sector level, particularly in the Healthcare, Industrials and Oil and Gas sectors. This evidence of herding reveals the tendency of U.S. investors to herd in and out of the same sectors. The findings are discussed in details in section 3.4.

The chapter is organized as follows. The next section sets out the hypotheses for each research objective. Thereafter, the herding measure is discussed. Next, the empirical results are presented and discussed. Lastly, the implications of the study are provided.

4.2. Hypotheses development

4.2.1. Industry Herding

Majority of the studies on herd behaviour based on the US market have found that herding is absent in the market (Christie and Huang, 1995; Chiang and Zheng, 2010). But do groups of US investors buy and sell stocks of the same industry over a period? If the answer to this question is affirmative, then we would expect that the otherwise absence of herding in the market would be found around specific industries.

There are a few theoretical explanations why investors choose to engage in herd behaviour. These explanations are based on the investors' motive which can be intentional or unintentional, purposefully following the crowd's decision is termed as intentional herding while unintentional herding is accidental (Bikhchandani and Sharma,2001). Some investors could be driven to herd intentionally because of the expectation of a career/reputational payoff (Trueman, 1994), where low-ability managers try to protect their reputation by mimicking the investment decision of better managers because they are evaluated relative to the performance of their peers. As a result, their low- ability is not incorporated in the individual assessment process and thus difficult to detect whether the manager picked a successful investment or mimicked their peers (Scharfstein and Stein ,1990). An expectation of informational payoff is another motive for intentional herding and it occurs when an investor imitates other investors because he perceives that they possess superior information (Devenow and Welch, 1996). When it gets to a point where these investors completely ignore their own private information, in favour of those of their predecessors an informational cascade is formed (Banerjee, 1992). This may eventually lead to informational inefficiency because the available aggregate information which is incorporated into security prices does not accurately reflect the sequence of decisions. Investors, particularly fund managers may also be driven to herd because their compensation is often measured relative to a market benchmark (Maug and Naik, 1996).

Unintentional herding occurs when investors independently take similar investment decisions because of the information signals they receive (Froot, et al., 1992). Characteristic trading is another example of unintentional herding, whereby, investors such as funds select stocks based on investment style (for example industry) and stock characteristics (for example past performance) (Economou, et al., 2015). In fact, industry herding can be linked to characteristic trading where investors select stocks based on industry membership. A major implication of this kind of trading is a correlation in prices of assets without a corresponding change in fundamental value (Barberis, and Shleifer 2003). Relative homogeneity also promotes spurious herding because it can result in similar investment decisions due to congruities such as educational background and regulatory framework (Holmes, et al., 2013). Consquently, these congruities generate collerated trades without the intent to copy others.

Investors are motivated to herd due to several reasons. From a behavioural perspective, they may be motivated to herd in the prescence of overconfidence bias (propounded by Daniel, et al., (1998)). For example, investors may keep investing in an industry where they have obtained a positive return because they believe they possess superior stock picking skills, which leads them to take more risks. Industry herding can also be driven by the representative heuristic and conversavatism bias (presented by Kahneman & Tversky (1972)). In the former case, an investor may prefer to invest in an industry that had abnormally high prior returns (that they extrapolate the retuns for the whole industry), which destabilses stock prices. In the later case, investors may favour prior positive (negative) information about a particular industry over new information.

Andrikopoulos, et al., (2017) suggest that industry herding can also be motivated by other reasons including benchmarking, sector dominance, style investing and fads. Several funds such as exhange traded funds strictly follow the sectors in their benchmark-indexes, thus this can increase the investment in these sectors and consequently herding (Gleason, et al., 2004). There is evidence that investors exhibit a familarity bias, they prefer sectors that dominate their country's economy because they are more familiar with these sectors (Gavriilidis, et al., 2013). Barberis and Shleifer (2003) suggest that investors group stocks into 'styles' based on their similarities. Style investing can foment herding when institutional investors reallocate styles based on current positive performance (Choi and Sias, 2009). Bikhchandani, et al., (1998) suggests that investors are driven by fads. Fads can create herding whereby investors invest in specific sectors because their populatity, for example, the populaity of technology stock during the Dotcome bubble period.

Following from these motivations to herd, it is therefore important to investigate the presence of herding in the US market (sector). This can be stated in the following hypothesis:

H1. There is no herding effect in the US market/ industry.

If industry herding is present in market/sector returns then we would expect a nonlinear relationship between the cross-sectional dispersion and the market return, that is, a disaproportionate increase (decrease) in the dispersion with the market return.

4.2.2. Determinants of Industry Herding

The approach suggested by Tan, et al., (2008) will be applied to investigate the asymmetric patterns that can be observed in the presence of herding at different levels of market return, volatility and trading volume. The rationale behind measuring this asymmetric pattern is that the changes these factors are pronounced during periods of market stress. Thus, the response to these changes can potentially explain the level of herd behaviour under different market conditions.

Market/sector return**:**

Research provides evidence that herding varies depending on whether the market is rising or declining (Demirer, et al., 2010; Economou, et al., 2011; Gavriilidis, et al., 2013; Economou, et al., 2015a; Zheng, et al., 2017). However, it has been observed that investors have a propensity to herd when market returns are declining than in rising conditions (Gavriilidis, et al., 2013; Ecomonou, et al., 2011). A possible explanation for this behavior is that loss aversion is more pronounced when market returns are declining, thus investors are driven by the psychology that potential losses when the market is declining looms larger than potential gains when the market is rising (Kahneman and Tversky, 1979). Consequently, they are driven to herd more during periods of declining market returns. Fund managers also herd more when market returns are declining (Gavriilidis, et al., 2013). More specifically, low-ability fund managers who are evaluated relative to their peers may prefer to mimic the investment decisions of their better peers (Gavriilidis, et al., 2013). Scharfstein and Stein (1990) termed this behaviour as the “sharing the blame” effect in which low-ability managers mimic the behaviour of better managers to be perceived as smart even when they are observing the same market signals. Such behaviour makes it difficult to assess the performance of managers. In contrast, periods of rising market return can also prompt optimistic investors to herd, because they believe that prices will continue to rise and thus decide to ride the presumed upward trend in the market (De Long et al., 1990). From an institutional investor perspective, low-ability managers might prefer to copy the trades of their better peers when returns are rising, since a poor performance during such periods can potentially reveal their low ability (Economou, et al., 2015b). Therefore to investigate whether herding is impacted by market/sector returns, we specify the following hypothesis.

H2a: Industry herding is contingent upon market/sector returns

If industry herding is contingent upon market/sector returns, then we would a expect relationship between herding and market returns with differences in periods rising and declining returns. The empirical evidence on the relationship between herding and market returns have been mixed. On the one hand, Demirer, et al., (2010), Economou, et al., (2011), Gavriilidis, et al., (2013), Mobarek et al. (2014); Yao, et al., (2014), Economou, et al., (2015a) find that herding is more prevalent during declining markets. On the other hand, Economou, et al., (2015a) and Economou, et al., (2015b) report herding when market returns are rising. Other studies like those of Chiang, et al., (2010) and Zheng, et al., (2017), find evidence of herding in both rising and declining markets.

Market/sector volatility:

Periods of high volatility and information flow may increase the propensity to herd (Gleason, Mathur and Peterson, 2004). Investors make investment decisions based on the information generated in stock markets which stock prices have already responded to, in periods of high levels of information flow these prices can become more volatile (Gavriilidis, et al., 2013). During such periods, some investors may have difficulty in obtaining reliable information and prefer to follow the herd. In addition, the rise of information flow during highly volatile markets may also make information processing more difficult, thus making herding tempting for less skilled investors. Herding can also take place during periods of low volatility as the tranquility in the market makes the trade of others more visible (Gavriilidis, et al., 2013).

Moreover, research provides evidence that herding is prevalent when market volatility is high (see Economou, et al., 2015b) and when it is low (see Economou, et al., 2015b). Given the relationship between herding and market volatility, the mixed evidence leads to the following hypothesis.

H2b: Industry herding is contingent upon market /sector volatility

If industry herding is contingent upon market/sector volatility, then we would expect a relationship between herding and volatility with differences in periods of high and low volatility.

Market/sector volume:

Research has shown that herding is significant when trading volume is high (for example, Tan, et al., 2008), therefore we focus on determining if changes in volume affects industry herd behaviour. High trading volume can contribute to herding when investors trade vastly on a stock. For example, if an investor perceives that a stock is highly profitable, they would increase their investment in the stock, hence increasing its liquidity. Other investors who are uncertain about the future profitability, invest in the stock based on its liquidity neglecting their private information, leading to a herd formation. Low trading volume can also boost herding because during such periods, investors tend to solely focus on stocks with sufficient trading volume and as a result trading becomes clustered (Economou, et al., 2015a).

It is important to point out that although many studies report significant herding during periods of high volume, some studies like those of Tan, et al. (2008) and (Economou, et al., (2011) provide evidence of herding during periods of low trading volume. This mixed evidence leads to the following hypothesis.

H2c: Industry herding is contingent upon market/sector volume.

If industry herding is contingent upon market/sector volume, then we would expect a relationship herding and volume with differences in behaviour in periods high and low volume.

4.2.3. Herd behaviour in periods of crisis

Research by Christie and Huang (1995) suggests that herding is more prevalent during periods of market stress marked by extreme stock price movement. However, the empirical evidence of herding during crisis is mixed with authors such as Chiang and Zheng (2010) and Mobarek et al., (2014) finding that herding is more prevalent following a crisis while other authors like Choe et al., (1999) and Hwang and Salmon (2004) demonstrate that herding decreases following crises.

It is reasonable to suggest that investors may be driven to herd during a crisis due to increased uncertainty regarding the future value of assets during such periods. In contrast, herding may decrease following a crisis due to increased liquidity in the stock market (Economou, et al., 2015). Crises have been associated with bubbles. Indeed, Ball (2009) argues that crises occur when asset bubbles are not detected. Shiller (2003) points out that bubbles can be examined from two perspectives: Rational and irrational. Santos and Woodford (1997) explain that rational (or asset pricing) bubbles occur when the price of an asset exceeds its fundamental value, that is, it also has a bubble component. Irrational bubbles occur when prices rise above a level than can be rationally explained due to exaggerated beliefs about the future stock earnings or capabilities of new technologies. According to the finance literature, investor irrationality is a major cause of bubble bursts. Bubble bursts occur as means by which the market corrects prices to their fundamental values (Abreu & Brunnermeier, 2003). During the bubble building phase, uncertainty drives investors to make investment decisions based on herd instincts and psychological biases rather than the fundamental value of the asset.

Behavioural finance literature has offered some explanations on bubble formation. These theories have been classified into investor beliefs and preferences. From the beliefs perspective, there are three major theories. The first theory is based on the argument that bubbles are formed in the presence of short selling constraint and when investors have diverging views regarding the prospective value of assets (Scheinkman and Xiong, 2003). According to Scheinkman and Xiong (2003) if there are short selling restrictions and some investors are optimistic while the others are pessimistic about the prospective value of the asset. Then asset price will only reflect the price expectation of the optimistic investors, the pessimistic investors will refuse to invest. As a result, the asset will be overvalued because these optimistic investors believe that they can sell at higher prices to other optimistic investors. The second belief based-theory of bubble formation proposes that investors who exhibit the extrapolation bias can create bubbles by overvaluing assets. Extrapolation bias has the tendency to overweigh past returns or growth rates when making investment decisions (Barberis and Thaler, 2003). The third theory argues that investors' overconfidence particularly on the accuracy of their investment predictions (Daniel, et al., 1998) can result in overvaluation of assets. As earlier stated, overconfidence can make investors think that their valuation of the fundamentals of an asset is reliable.

From the preference perspective, there are two major theories. The first theory is based on the house money effect first proposed by Thaler and Johnson (1990). It refers to when investors become less risk-averse after a profitable investment. This motivates them to invest more, thus pushing asset prices further away from its fundamental value. The second theory is based on Barberis and Huang's (2008) proposition that bubbles tend to occur in assets associated with new technology. They explain that because investors regard investments as lotteries, therefore they will receive lottery-like gains if the new technology is successful. Kahneman and Tversky (1972) argue that this preference occurs when people overweigh low probabilities which makes investments attractive and may result in the overvaluation of assets. The Dot com bubble can be interpreted using this argument, investors may have caused overvaluation of Internet Technology stocks because they expected to obtain lottery-like gains if the technology was successful.

In relation to herding in industries, Gebka and Wohar (2013) argue that during periods of uncertainty a ‘flight to quality’ might occur where investors may rebalance their portfolios in which they shift from investing in more risky industries to less risky ones.

As a result, of the differences in herd behaviour following crises periods, our final hypotheses examine the effects of the Dotcom bubble and the GFC crises on herd behaviour in the US market (sector). The hypothesis is as follows:

H3: herd behaviour is stronger during the Dot com bubble period

The Dot com started by the advent of the internet led to a large investment in a new company called Netscape communications. The evolution of the internet gave rise to other fast growing ‘Dot com companies’ which saw increased investments from investors and made the value of these stocks rise quickly. As the number of companies continued to grow, investors ignored the fundamental value of the stocks and followed the crowd, including sophisticated investors (for example fund managers) who planned to ride to bubble and exit the market promptly before it crashed. Indeed, Cooper, Dimitrov and Rau (2001) provide evidence that changes to internet-related names, dubbed the dotcom effect produced 74 per cent abnormal returns ten days subsequent to the announcement.

In 1996, the then Federal Reserve Chairman, Alan Greenspan in a speech described the soaring stock prices of ‘Dot com’ companies as ‘irrational exuberance’. These companies grew fast too quickly without sustained profitability resulting in losses. In March 2000, Internet Technology stocks crashed after investors suddenly realised that these stocks were overvalued and frantically sold their stocks leading to a collapse in the sector which saw approximately 800 companies vanish (Goodnight and Green, 2010). The market did not fully recover from the crash until October 2002.

The Dot com provides evidence of how investors' irrationality driven by herd instinct and psychological biases led to the deviation of Technology stocks from its fundamental value. Indeed, studies that examine herding during the Dot com bubble provide evidence of its existence (Galariotis, et al., 2015; Litimi, et al., 2016; BenSaida, 2017). Bubbles are typically divided into three phases: the pre-bubble, the bubble (when the bubble occurs) and the bubble burst (stock market downturn). If herding is stronger following these periods, we expect to find differences in herd behaviour pre, during and post bubble.

H4: herd behaviour is stronger during the GFC crisis period.

Almost 8 years after the Dot com bubble another bubble burst occurred in the US Real Estate sector which triggered the 2008-2009 Global Financial Crisis. Some authors suggest that the Dot com bubble helped to create the housing bubble because after the crash investors turned to the Real Estate stocks as a secure investment alternative (Wheale and Amin, 2003; DeLong and Magin, 2006 and Goodnight and Green, 2010). Between October 2002 and October 2006, house prices rose by 31.6 percent. According to the Financial Crisis Inquiry (2011), prices rose in the housing market because of the increased demand for mortgages. Also, homeownership gradually increased until it reached its peak at of 69.2 per cent in 2004 (Financial Crisis Inquiry, 2011). However, the bubble began to burst in 2007 when interest rates began to rise accompanied by an increase in risk premium which discouraged investors from investing. Housing prices plummeted followed by a massive sale of mortgaged assets. The collapse of the investment bank, Lehman Brothers in September 2008 also contributed to a wave of global panic selling.

Although, herding is supposed to be more significant during crises, the empirical evidence of herding during the GFC demonstrates that this may not always be the case. Yao, et al., (2014) and Vo and Phan (2017) find that herding is absent during the crisis, while Chiang and Zheng (2010), Lao and Singh (2011), and Zheng, et al., (2017) find evidence of herding during the crisis. However, other studies (Economou, et al., 2011; Gebka and Wohar, 2013; Philippas, et al., 2013; Kabir, 2018) document that herding is not stronger during the GFC, while Andrikopoulos, et al., (2017) find that it is less significant during the crisis. In contrast, Galariotis, et al., (2015), Litimi, et al., (2016) and BenSaida (2017) report that the GFC triggered herding. In relation to the US market, Chiang and Zheng (2010) and Galariotis, et al., (2015) find that investors in the US markets examined herd during the GFC. It can be therefore hypothesised that investors in the US markets have a tendency to herd towards the market consensus during the GFC. Like the, Dot com bubble, we examine herding pre, during and post GFC. If herding is stronger following these periods we expect to find differences in herd behaviour pre, during and post crisis.

4.3. Data

For the empirical analysis, we use daily prices for all S&P500[43] constituents stock between January 1990 and October 2016, to incorporate periods of significant volatility in the US market: the 1997 Dot Com boom and the 2008 credit market crisis. This is in line with previous studies which provide evidence that herding behaviour is more plausible during periods of extreme market movement. The S&P500 index, popularly known as the gauge of the US market is based on the market capitalization of 500 leading US stocks listed on the NYSE or NASDAQ. The index has a total market capitalization of approximately $ 23.87 trillion[44] (as of July 2018) and it covers approximately 80 % of the available US total equity

[43] S&P500 is used as a proxy for the US market
[44] Source: S&P500 factsheet

market capitalisation. The local currency daily closing prices and trading volume data for both market and sector levels are obtained from Thomson- Reuters DataStream database.

Due to limited availability of data, the 19 major sectors examined based on the DataStream sector classification are Automobile, Banks, Basic Resources, Chemicals, Construction, Consumer Services, Financials, Healthcare, Industrials, Insurance, Media, Personal & Household, Real Estate, Retail, Travel and Leisure, Oil and Gas, Utilities, Telecommunications, and Technology which amount to 6,991 daily observations of 505 individual firm stock prices.

We select two crises which originated from the US: the Dot com bubble and the Global Financial crises. We split the whole sample into pre, during and post herding. For the Dot com bubble period, our sub samples are: Pre-Dot com bubble phase (01/01/1990 - 31/12/1994), Dot com bubble (01/01/1995 - 10/03/2000), Dot com bubble crash (13/03/2000 - 9/10/2002). For the Global Financial Crisis, we have: Pre-crisis (01/05/2002- 31/07/2007), Crisis (01/08/2007 - 30/03/2009) and Post crisis: (01/04/2009 - 11/10/2016). Various researchers have studied dating of the crisis. We date the pre-crisis phase from 01/05/2002 to 31/07/2007. This based on Philip and Yu’s (2011) and Caballero, Farhi and Gourinchas’s (2008a) assertion that the bubble in the real estate market emerged in May 2002, when the interest rate on 10-year US government bonds fell below 2%. Our crisis phase commences from 01/08/2007 to 30/03/2009. We choose this phase in line with Beltrattia and Stulz (2012) and Philip and Yu (2011) who suggest that the onset of the crisis was the beginning of August 2007 after Bear Stearns liquidated two of its hedge funds. The endpoint of the crisis was chosen based on the Bank of International Settlements (BIS, 2009) timeline. The post-crisis phase refers to the period between 01/04/2009 and 11/10/2016.

STATA software package was used for regression tests to determine the relationship between industry herding and the market return, volatility and trade volume.

4.4. Research Methodology

4.4.1. Model specification

Christie and Huang (1995) conducted a seminal study to test for herding towards the market consensus. They developed a methodology, the CSSD which is based on the intuition that when the dispersion of returns is low in relation to their cross-sectional average, it implies that investors ignore their information and herd with the market consensus. It is defined using the following equation:

$$CSSD_t = \beta_0 + \beta_1 \mathrm{D}_t^{\mathrm{UP}} + \beta_2 D_t^{DOWN} + \varepsilon_t \tag{1}$$

Where β_0 is the average dispersion of the sample excluding the regions covered by the dummy variables. The dummy variable $\mathrm{D}_t^{\mathrm{UP}}$ takes the value of one if the market return on day *t* lies in the extreme upper tail of the distribution and zero otherwise. D_t^{DOWN} takes the value of one if the market return on day *t* lies in the extreme lower tail of the distribution and zero otherwise. Negative and significant β_1 and β_2 coefficients implies herd behaviour. CSSD is calculated as follows

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{n} (r_{i,t} - r_{m,t})^2}{n-1}} \tag{2}$$

Where $r_{i,t}$ is the return[45] on firm *i* on day *t* and $r_{m,t}$ is the cross-sectional average of the *n* returns in the market portfolio on day *t*. While, this methodology is intuitive, it suffers from some drawbacks. First, it appears to only capture herding during extreme price movement conditions and thus ignores the possibility that herding might also occur during periods of market stability (Hwang and Salmon, 2004). Second, the model is based on the linear

[45] The return is calculated by taking logarithmic difference of the closing stock prices

relationship between CSSD and market returns; but, when herding is present this relationship no longer holds and becomes nonlinear (Chang, et al., 2000). Chang, et al., (2000) argue that investors tend to follow the market trend uniformly during periods of significant price movements, increasing the correlation among stock returns. Therefore, this would result in a less than proportional increase (decrease) in the corresponding dispersion of asset returns. Under these conditions, the relationship between the CSAD and the market return is expected to become nonlinear. Consequently, the authors develop an alternative non-linear approach, CSAD.

To detect herding, the CSAD measures its presence by assessing the observed return of all stocks and the cross-sectional average return; a statistically significant negative (positive) coefficient indicates the presence (absence) of herd behaviour. Gebka and Wohar (2013), argue that positive γ_2 coefficients, also suggests the presence of 'negative herding' whereby during periods of extreme price movements, the dispersion of returns is lower rather than higher than the predictions of rational asset pricing models, signifying that investors largely do not ignore their private information in favour of the market consensus.
To overcome the drawbacks of the CSSD model, we use the CSAD model to test for herding as stated in H1.

It is specified 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 log differenced return on stock i at time t, N is the number of stocks the market and $R_{m,t}$ is the cross-sectional average of market returns at time t.

The base model to test for herding is estimated by the following regression:

$$CSAD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 \ R_{m,t}^2 + \varepsilon_t \tag{4}$$

where$\left|R_{m,t}\right|$is the market (sector) return used to capture the nonlinearity in the relationship, $R_{m,t}^2$ is the squared market return, α is the constant, γ_1, and γ_2 are coefficients and ε_t is the error term at time t. Therefore, if herding is absent, then we expect $\gamma_1 > 0$ and $\gamma_2 > 0$ in equation (2). It is important to point out that, this model allows us to capture the linear and non-linear relationship between the cross-sectional dispersion of returns and the absolute market returns.

Following Gebka and Wohar (2013) the level of dispersion for the model is estimated for each industry sector and the aggregate market. It is reasonable to expect that industry herding may be affected by market conditions characterised by market returns, volatility and trading volume. This further prompts us to test whether herding is contingent upon high and low market return, market volatility and volume.

To test hypothesis H2a, the specification of the Tan, et al., (2008) by Chiang and Zheng (2010) which is regarded as more robust is implemented. To achieve this, we estimate the following model:

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{m,t}\right| + \gamma_2\ (1 - D^{up})\left|R_{m,t}\right| + \gamma_3\ D^{up}(R_{m.t})^2 + \gamma_4\ (1 - D^{up})(R_{m.t})^2 + \varepsilon_t \qquad (5)$$

D^{up} is a dummy variable with a value of 1 for days with positive market returns and a value of 0 for days with negative market returns, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients. The coefficients of interest are γ_3 and γ_4. Therefore, in the absence of herding effects, we expect $\gamma_3 > 0$ and $\gamma_4 > 0$ in equation (3) and statistically insignificant. If herding effects are prevailing, we expect $\gamma_3 < 0$ and $\gamma_4 < 0$ and statistically significant, with $\gamma_3 < \gamma_4$ if these effects are more significant on days with positive market return. Specifically, to confirm the presence (absence) of herding, the coefficients of interest must be negative (positive) and statistically significant.

To test for the second hypothesis, H2b, the following model is estimated:

$$CSAD_t = \alpha + \gamma_1 D^{\sigma^2-High} \left|R_{m,t}\right| + \gamma_2 \left(1 - D^{\sigma^2-High}\right)\left|R_{m,t}\right| + \gamma_3 \ D^{\sigma^2-High}(R_{m.t})^2 + \gamma_4 \left(1 - D^{\sigma^2-High}\right)(R_{m.t})^2 + \varepsilon_t \quad (6)$$

WhereD^{σ^2-High} is 1 for days with high market volatility and 0 otherwise. Volatility is defined as high (low) if it is greater (lower) than the previous 30 day moving average.

In line with Tan, et al., (2008) volatility is calculated as the square of the market return [reflected through $(R_{m.t})^2$ in Eq (6)]. If herding is absent, then we expect $\gamma_1 > 0$ and $\gamma_2 > 0$ in equation (4). If herding is present, then we expect $\gamma_3 < 0$ and $\gamma_4 < 0$ and statistically significant, with $\gamma_3 < \gamma_4$ if these effects are more evident during days with high market volatility.

To test for the third hypothesis, H2c, the following model is estimated:

$$CSAD_t = \alpha + \gamma_1 D^{vol-High} \left|R_{m,t}\right| + \gamma_2 \left(1 - D^{vol-High}\right)\left|R_{m,t}\right| + \gamma_3 \ D^{vol-High}(R_{m.t})^2 + \gamma_4 \left(1 - D^{vol-High}\right)(R_{m.t})^2 + \varepsilon_t \quad (7)$$

$D^{vol-High}$ is 1 for days with a high trading volume and 0 otherwise. Trading volume is defined as high (low) if it is greater (lower) than the previous 30 day moving average.

A cross-sectional dummy variable regression proposed by Chiang and Zheng (2010), a modification of the Chang, et al., (2000) measure, will be used to measure if herding is more apparent in periods of financial crisis. To measure this, we estimate equation (3) with for each of the sub-sample periods. Therefore, if the effect of herding is more prevalent during the crisis periods then we expect $\gamma_2 < 0$ in equation (3) and statistically significant.

4.5 Empirical Results

4.5.1. Summary Statistics

Table 4.1 Summary statistics: average daily market return and cross-sectional standard deviations, US

Industry	No of Firms	Mean	Maximum	Minimum	Std.Dev	Skewness	Kurtosis
Panel A: daily market return							
Market (All industries)	505	0.039%	10.670%	-10.719%	1.130%	-0.4062	10.707
Automobile	8	0.031	11.707	-11.248	1.555	-0.1884	5.913
Banks	17	0.023	11.435	0.000	0.719	4.4800	38.353
Basic Resources	5	0.009	16.421	-16.678	1.770	-0.2093	8.119
Chemicals	14	0.030	12.133	-12.359	1.353	-0.3996	9.180
Construction	9	0.040	11.423	-15.666	1.510	-0.2961	7.174
Financials	28	0.050	15.067	-16.392	1.681	-0.2204	11.063
Food & Beverage	22	0.039	8.235	-6.911	0.920	-0.0235	5.614
Healthcare	51	0.051	11.771	-8.046	1.148	-0.4011	5.802
Industrial Goods	72	0.043	9.731	-9.951	1.155	-0.2752	7.136
Insurance	22	0.028	14.453	-17.777	1.477	-0.3598	19.835
Media	18	0.038	12.898	-10.648	1.457	-0.1031	7.010
Oil & Gas	36	0.031	19.472	-18.708	1.713	-0.4616	11.197
Personal & Household	33	0.043	8.324	-8.664	1.174	-0.2441	6.000
Real Estate	28	0.033	20.532	-19.293	1.492	-0.1090	28.618
Retail	40	0.051	11.115	-9.010	1.281	-0.0285	5.395
Technology	50	0.057	15.206	0.000	1.860	0.0341	1.510
Telecommunication	5	1.336	10.754	-9.755	1.432	-0.0827	5.403
Travel & Leisure	18	0.046	15.865	-24.452	1.594	-0.6020	12.636
Utilities	29	0.017	12.670	-10.046	1.039	-0.1428	12.349
Panel B: cross-sectional standard deviation							
Market (All industries)		1.310%	5.503%	0.000%	0.572%	1.090	4.111
Automobile		0.0109	0.0883	0.0000	0.0001	2.2124	9.7230
Banks		0.901	19.852	-22.887	1.889	-0.128	25.032
Chemicals		0.936	12.604	0.000	0.496	3.031	47.295
Basic Resources		1.202	8.385	0.000	0.817	2.009	7.429
Construction		1.095	24.610	0.000	0.762	5.845	135.594
Financials		1.170	7.800	0.000	0.685	1.924	8.137
Food & Beverage		1.036	6.867	0.000	0.537	1.474	6.960
Healthcare		1.397	4.938	0.000	0.679	0.751	1.452
Industrial Goods		1.101	5.660	0.000	0.521	1.012	3.585
Insurance		0.928	12.710	0.000	0.723	4.845	42.395

Media	1.100	8.005	0.000	0.680	1.908	7.280
Oil & Gas	1.194	6.235	0.000	0.540	1.065	4.215
Personal & Household	1.241	5.270	0.000	0.588	1.030	3.187
Real Estate	0.988	9.029	0.000	0.628	2.918	17.355
Retail	1.395	12.156	0.000	0.690	1.348	10.390
Technology	1.643	6.378	-11.461	0.863	0.918	4.051
Telecommunication	0.005	18.237	0.000	1.092	3.554	27.178
Travel & Leisure	1.359	10.997	0.000	0.832	2.659	21.186
Utilities	1.114	9.652	0.000	0.628	3.209	23.911

Note:
This table presents the average daily market return $R_{m,t}$ (Panel A) and cross-sectional absolute standard deviation (CSAD) (panel B) for the market (all industries) and the nineteen individual industries for the sample period (Janaury1990- October 2016). $R_{m,t}$ is defined as the cross-sectional average of daily returns. CSAD is defined by the measure

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

Where $R_{i,t}$ is the logged differenced return on stock i at time t and $R_{m,t}$is the cross-sectional average of market returns at time t.

Table 4.1 reports the summary statistics for average daily log market returns, the daily CSAD for the market (all industries), the nineteen individual industries as well as the number of firms in each industry. Examining Panel A, we observe that the average market daily returns for all industries are 0.039% with values ranging from -10.719% to 10.670% and a high standard deviation (and therefore high volatility) of 1.130%. The high standard deviation may imply that the market has an unusual cross-sectional variation resulting from unusual news or shocks in the market. The number of firms in each sector range from 5 to 72. The daily mean returns for the industry range from 0.009% (Basic resources) to 1.336% (Telecommunications) with their standard deviations ranging from 0.719% (Banks) to 1.860% (Technology). The low standard deviation for the Banking sector may be due to its characteristic highly regulated nature. The high standard deviation for the Technology sector indicates the riskiness and volatility of the sector. In addition, it may also reflect the popularity of the Internet stocks during the 1990s. The Banking sector has the highest kurtosis value, which implies that its returns have large frequencies around the centre and tail of the distribution. The high kurtosis may be due to the extremely high profitability in the Banking sector before the financial crisis (Tregenna, 2009).

The minimum and maximum industry daily returns values range from to -24.452 (Travel and Leisure) to 20.532 % (Real Estate). The skewness is negative for the market and most sectors. The distribution for the daily market return and sectors is leptokurtic.

The CSAD is a measure of dispersion, therefore it tends to increase as the returns deviate from the market return. Panel B shows that the market CSAD has a mean value of 1.310% showing that the returns do not move in unison with the market. The minimum and maximum values range from between 0% to 5.503%, the standard deviation is a high value of 0.572%. The descriptive statistics are similar to those reported by Chiang and Zheng (2010) who report a mean of 0.8486%, the minimum value of 0.2891% maximum value of 4.754 % and a standard deviation of 0.4185%. Noticeably, the kurtosis for the Construction sector is high, this indicates large shocks are likely to be present in the sectors' returns. The high kurtosis value may also be associated with the boom in the US economy especially in the pre-crisis period.

Across industries, the mean value range between 0.011% (Automobile) to 1.643% (Technology). The low mean for the Automobile sector may indicate a co-movement among its stocks, while the high mean value for the Technology sector implies a high variation of industrial returns compared to other sectors.

The minimum and maximum range between 0% (for most industries) and 24.61% (construction), the standard deviation have values between 0.496% (Chemicals) and 1.889% (Banks). Most of the CSADs are positive and therefore highly skewed. The distribution for the CSAD and sectors is leptokurtic.

4.5.2. Industry herding and its determinants

4.5.2.1. Empirical results for market herding

Equation (4) was estimated using ordinary least squares (OLS) regression to examine whether investors in the US stock market exhibit herd behaviour for the period 1990 through to 2016. As previously stated, a negative (positive) statistically significant value of the regression coefficient for $R_{m,t}^2$ that is γ_2 indicates the presence (absence) of herd behaviour. Table 4.2 presents the results from the estimation of equation (3).

The results of the analysis show that the value of γ_2 is positive and statistically insignificant. This suggests that there is no nonlinear relationship between market returns and CSAD. Specifically, consistent with H1, there is no herding effect in the US market. The absence of herding in the US market may be due to the sophisticated investors', high degree of regulation in the financial market and transparency in financial reporting. In general, our results are consistent with those obtained by other authors using the CSAD model. Our results are consistent with those reported by Chang, et al., (2000), who test for herd behaviour using the daily stock data of all firms listed on NYSE and AMEX for the period 1963 to 1997. They explain that their results may be due to the high government involvement and efficient information disclosure at the firm level. In addition, our results support those of Chiang and Zheng (2010), who report no evidence of herding in the US market. They suggest that the lack of herding may originate from the different views of financial companies or the media, which reduces investor homogeneity and consequently, the tendency to herd. Our results are also in line with recent evidence by Galariotis, et al., (2015), Lee (2017), Bohl, et al., (2017) and BenMabrouk and Litimi (2018) that use the CSAD model and find no evidence of herding in the US market.

Notably, our results contrast with the evidence provided by BenSaida, et al., (2015) and Litimi, et al., (2016) who find inconclusive evidence of herding when they employ daily data from firms in the US stock market. The difference in the results obtained from the study of BenSaida, et al., (2015) may be due to their use of a shorter sample of 4 years.

Our results are also different from those obtained by Hwang and Salmon (2004) who use an alternative methodology for detecting herding that measures the cross-sectional dispersion of the factor sensitivity of assets within a market. They find evidence of herding in the S&P 500 index dependent on the return volatility and the level mean return.

Table 4.2 Estimates of herding for the overall US market

Estimated parameters	α	γ_1	γ_2	Adj. R^2
	0.0107	0.3254	0.2216	25.08%
	(115.9)***	(25.68) ***	(0.93)	

Note: Table 4.2 reports the estimates from the following equation:

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

where $R_{m,t}$is the cross-sectional average of market returns in at time t, the squared market return $R_{m,t}^2$ is used to capture the nonlinearity in the relationship, $CSAD_t$ is the cross-sectional absolute deviation of returns for the market, α is the constant, γ_1, and γ_2 are coefficients, and ε_t is the error term at time t. The equation is estimated for the 01/01/1990 to 16/10/2016. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

4.5.2.2. Empirical results for industry herding

On analysis of sector level data, some evidence of herding becomes visible. Equation (4) is used to examine whether US investors herd in and out of industries. An analysis of the regression results presented in Table 4.3 shows mixed results for the presence of herding at the sector level. Negatively significant γ_2 coefficients are reported in Healthcare, Industrial Goods, Oil and Gas, Retail and Technology sectors indicating that the CSAD decreases with the size of the market return. Among these industry sectors, we observe that Healthcare and

Oil and Gas have the strongest degree of herding. This herding may be because of information based herding observed in these industries possibly driven by industrial characteristics such as firms' market capitalisation (Hoitash and Krishnan, 2008).

Moreover, it is interesting that the Healthcare sector has the highest degree of herding, given that it is the fourth largest sector in the US economy[46]. This could be perhaps due to quick reaction to the announcement of good and bad news regarding the pharmaceutical industry for example, which could increase herding. Given that the US Healthcare has experienced reforms with each administration, its investors may face increased investment risk. Consequently, from an investors' perspective, this implies that investors who focus on the Healthcare sector can achieve the same sector performance by investing fewer stocks (Demirer, et al., 2010). Herding observed in the Oil and Gas sector is interesting, given that the US is the third largest oil producing country in the world[47].

Overall, there is limited evidence of herding across the sectors. Our evidence supports those of Gebka and Wohar (2013) who do not find evidence of herding in the worldwide equity markets examined but detect herding specifically in the Basic Materials, Consumer Services and Oil and Gas industries. In contrast, our results are inconsistent with those obtained by Christie and Huang (1995), who find no evidence of herding across all US sectors examined. However, when they compare the magnitude of coefficients obtained across industries, they find that the Utility industry which is highly regulated reported the lowest level of dispersion. Our results are also different from Choi and Sias (2009) who examined US institutional industry herding and find evidence that they herd in and out of industries. They suggest that this herding may be driven by stock herding. On the contrary, the results we obtain show the reverse may be the case, as herding is only observed at the sector level and not the market

[46] Source: Bureau of Economic Analysis, 2016
[47] Source: US Energy Information Administration,2016

level. Furthermore, our evidence differs from the results obtained by Litimi, et al., (2016), who tested a modified version of the CSAD model and report negatively significant γ_2 coefficients for only two sectors: Public Utilities and Transportation. They argue that US investors herd based on information on the market condition rather than the sector return. Further, our results are in contrast with the recent evidence provided by BenMabrouk and Litimi (2018), who find no herding in US sectors. Interestingly, they find that the sectors all exhibit 'negative herding' which implies that investors massively ignore the industry consensus as a group. Owing to the uniqueness of this study, the inconsistent results compared to other US based studies may be due to differences in methodology, sample size and research focus.

From the context of other developed markets, our results are also from different Henker, et al., (2006) who find no evidence of industry sector herding in all but the Property Trusts sector of the Australian market using intraday data. They argue that their results imply that investors in the Australian market have sufficient flow of firm-specific information. International evidence reported by Gebka and Wohar (2013) finds herding in sectors such as Oil and Gas, Basic Materials and Consumer Services.

Table 4.3 Estimates of herding in US sectors

Industry	α	γ_1	γ_2	Adj. R^2
Automobile	0.0077	0.2759	0.9365	25.76%
	(62.10)***	(20.84)***	(4.27)***	
Banks	0.0062	0.2323	0.6457	41.40%
	(65.99)***	(29.52)***	(9.89)***	
Basic Resources	0.0085	0.2966	-0.1643	20.25%
	(59.79)***	(24.18)***	(-1.04)	
Chemicals	0.0075	0.1936	0.7699	22.40%
	(90.51)***	(20.68)***	(5.01)***	
Construction	0.0085	0.1702	3.2400	26.65%
	(67.33)***	(13.11)***	(15.63)***	
Financials	0.0084	0.3047	-0.0385	31.75%
	(80.25)***	(31.39)***	(-0.32)	
Food & Beverage	0.0081	0.3528	-0.0945	17.60%
	(82.00)***	(21.42)***	(-0.21)	

Healthcare	0.0111	0.3922	-2.0876	14.32%
	(88.12) ***	(23.18) ***	(-5.58) ***	
Industrial Goods	0.0090	0.2782	-0.9514	15.48%
	(97.16) ***	(21.55) ***	(-3.48) ***	
Insurance	0.0062	0.2979	1.8752	52.64%
	(71.40) ***	(31.76) ***	(17.19) ***	
Media	0.0078	0.3324	-0.2048	25.68%
	(68.48) ***	(26.53) ***	(-0.97)	
Oil & Gas	0.0096	0.2129	-0.3827	19.27%
	(106.04) ***	(27.87) ***	(-4.23) ***	
Personal & Household	0.0097	0.3395	-0.2157	22.87%
	(94.06) ***	(23.51) ***	(-0.68)	
Real Estate	0.0074	0.2910	0.1113	34.66%
	(86.56) ***	(32.32) ***	(1.24)	
Retail	0.0108	0.3735	-1.0577	19.20%
	(87.15) ***	(23.98) ***	(-3.31) ***	
Technology	0.0117	0.3872	-0.7800	28.05%
	(78.96) ***	(28.35) ***	(-3.66) ***	
Telecommunication	0.0069	0.6121	2.1903	46.29%
	(42.94) ***	(32.72) ***	(6.30) ***	
Travel & Leisure	0.0098	0.3227	0.9566	28.91%
	(76.21) ***	(29.43) ***	(7.30) ***	
Utilities	0.0085	0.3555	1.6473	27.84%
	(85.80) ***	(25.46) ***	(6.23) ***	

Note:
Table 4.3 reports the estimates from the following equation
$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 \ R^2_{m,t} + \varepsilon_t$
where $R_{m,t}$ is the average value of sector return in each sector, the squared market return $R^2_{m,t}$ is used to capture the nonlinearity in the relationship, α is the constant, γ_1, and γ_2 are coefficients, and εt is the error term at time t, $CSAD_t$ is the cross-sectional absolute deviation of returns for the market, the equation is estimated over the whole sample period for each sector. We utilize the DataStream industry classification. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. *****, **** and ***** represent statistical significance at the 1%, 5%, and 10% level, respectively.

In comparison to evidence obtained for developing markets our results are similar to the findings of Gavriilidis, et al., (2013) for Spanish mutual funds, who only document significant herding in Consumer services, Industrials and Technology sectors (a sector where we also find herding) out of the 9 sectors examined. However, our results are different from those reported for the Chinese sectors by Demirer and Kutan (2006) and find no evidence in support of herd formation.

The above results demonstrate that US investors do not herd at market level. Evidence from the sector level indicates limited evidence of herding. Next, we investigate herd behaviour based on market return, volatility and trading volume for the overall market and individual sectors.

4.5.3. Determinants of industry herding

Previous studies have examined return asymmetries (Tan, et al., 2008; Gleason, et al., 2004). Christie and Huang (1995) argue that herd behaviour is more prevalent during periods of extreme price movements. Moreover, in a seminal study, Tan, et al., (2008) suggested that asymmetry in herd behaviour is possible, contingent on whether the market return is rising or declining, high (low) volatility and trading volume. Therefore, we examine the determinants of industry herding by estimating possible asymmetric effects of herd behaviour based on the direction of the market and levels of volatility and trading volume at both the market and sector levels. The empirical results are discussed in the sections below.

4.5.3.1. The effect of market returns on herding

To examine whether herding is contingent upon rising or declining market returns, a dummy variable as specified in Equation (5) is used to capture the differences in the CSADs. γ_3 and γ_4 represent the coefficients for rising and declining market conditions respectively.

Table 4.4 presents the market-wide results of herding conditioned upon market returns. The evidence suggests that in rising market conditions, the coefficient γ_3 is positive and not statistically significant, indicating that there is no evidence of herding. The results show that there is no difference in the CSAD in rising or declining markets. This finding is in line with the predictions of rational asset pricing models that asset dispersion increases during periods of significant price movement (Demirer and Kutan, 2006).

Table 4.4 Estimates of herding in rising and declining markets, US

Estimated Parameters	α	γ_1	γ_2	γ_3	γ_4	Adj. R^2
	0.0107	0.3394	0.3093	0.3699	0.2024	25.18%
	(115.81) ***	(22.04) ***	(20.45) ***	(1.12)	(0.67)	

Note: Table 4.4 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{m,t}\right| + \gamma_2\ (1 - D^{up})\left|R_{m,t}\right| + \gamma_3\ D^{up}(R_{m.t})^2 + \gamma_4\ (1 - D^{up})(R_{m.t})^2 + \varepsilon_t$$

D^{up} is a dummy variable with a value of 1 for days with positive sector returns and a value of 0 otherwise, $R_{m,t}$ is the sector's average return, $CSAD_{i,t}$ is the cross-sectional absolute deviation of returns for the market, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients and $\varepsilon_t$is the error term at time t. The equation is estimated over the whole sample period. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Likewise, during declining market conditions, the coefficient γ_4 is positive and not statistically significant. The results also indicate that there is no evidence of herding. From these results, it appears that there is no asymmetric relationship between herding and market condition. Hence, there is no difference between herd behaviour in rising or declining market returns. Contrary to H2a, there is no evidence that herding is contingent upon market returns. It is interesting to note that when the coefficients of γ_3 and γ_4 are compared, the γ_4 coefficient is smaller suggesting that the increase in dispersion is greater in rising than in declining market conditions. Thus, this gives an indication that during periods of extreme price movements, the equity returns dispersion increases. These results also show that US investors do not exhibit herd behaviour in response to rising or declining market returns.

Our findings are in line with those of Chang, et al., (2000) who report that the US has the highest rate of increase in dispersion in up markets than down markets. They explain that it may be due to directional asymmetry (proposed by McQueen, Pinegar and Thorley,1996), whereby large and small US stocks react quickly to negative macroeconomic news, however, some small stocks adjust slowly to positive macroeconomic news. In the same light, our results are similar those obtained by Demirer and Kutan (2006), who investigate herding using the Chinese stocks listed on the Shanghai and Shenzhen Stock Exchanges and find that return dispersions are much lower during declining market condition than rising conditions, indicating that investors tend to follow the market consensus known as ‘flight to safety'.

However, our findings challenge the evidence obtained by Henker, et al., (2006) who document a greater increase in dispersion for declining market conditions for the Australian market.

These results are different from the predictions of herding which suggests that the level of equity returns dispersion decreases during periods of market stress. Also, our results do not support the prediction that the tendency to herd is higher during rising market conditions due to overconfidence (Daniel, et al., 1998; Staman, et al., 2006). Similar results were also obtained by Chang, et al., (2000) and Chiang and Zheng (2010) for the US market for rising or declining market returns.

Our result is at odds with those from studies on developing markets that mainly report herding asymmetry. Goodfellow, et al., (2009) investigate the trading behaviour of investors in the Polish stock market during rising and declining market conditions. They find that investors herd mostly during declining market conditions. Similarly, Zhou and Lai (2009) find that herding in the Hong Kong Composite market is more prevalent during declining market conditions. Demirer, et al., (2010) examine herding in the Taiwanese stock market, according to their results, herding is more prevalent in periods of declining market conditions. The authors explain that this may be due to loss aversion during periods of market decline which causes investors to have a greater propensity to avoid losses than make gains. Economou, et al., (2011) report that with exception of the Greek market, all other markets (Spanish, Italian, Portuguese) examined herd in declining market conditions. Similar results were obtained for Spanish funds by Gavriilidis, et al., (2013), who report significant herding during periods of negative market returns. For Portuguese funds, Homles, et al., (2013) report that herding is more dominant during periods of market decline.

In contrast to these findings, Tan, et al., (2008) provide empirical evidence that for dual-listed Chinese A-share and B-share stocks, herding occurs in both rising and declining market conditions. Likewise, Guney, Kallinterakis and Komba (2017) examine herd behaviour in 8 African frontier markets and report that herding occurs in both up and down-market conditions.

Overall, our results provide consistent evidence that the highest level of return dispersion occurs during rising market conditions. For other developed markets, the dispersion increases during declining market conditions. The results we obtain may be different from those obtained in other developed market due to unique market structures of each market. (For example, stock market regulations).

Table 4.5 Estimates of herding for sectors in rising and declining markets, US

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Automobile	0.0077	0.3173	0.2355	0.1168	1.7042	25.99%
	(62.08)***	(20.21)***	(15.04)***	(0.40)***	(6.13)***	
Banks	0.0062	0.2341	0.2301	0.6551	0.6411	41.38%
	(65.76)***	(23.15)***	(24.73)***	(6.99)***	(8.03)***	
Basic Resources	0.0085	0.3013	0.2919	0.0955	-0.3720	20.37%
	(59.79)***	(20.83)***	(19.81)***	(0.46)***	(-1.80)*	
Chemicals	0.0074	0.2420	0.1643	-0.5535	1.5230	23.03%
	(89.94)***	(20.72)***	(15.06)***	(-2.38)**	(8.36)***	
Construction	0.0083	0.2695	0.1208	0.7188	4.4901	27.70%
	(66.21)***	(16.31)***	(8.10)***	(2.22)**	(18.73)***	
Financials	0.0084	0.3251	0.2799	-0.0121	0.0111	32.02%
	(80.24)***	(27.09)***	(24.40)***	(-0.07)	(0.07)	
Food & Beverage	0.0080	0.3613	0.3550	0.5837	-1.2067	17.78%
	(81.72)***	(19.35)***	(17.23)***	(1.06)	(-1.83)*	
Healthcare	0.0110	0.4053	0.3778	-1.7840	-2.2119	14.41%
	(87.95)***	(21.05)***	(17.93)***	(-3.70)***	(-4.37)***	

Industrial Goods	0.0090	0.2826	0.2715	-0.6996	-1.0974	15.53%
	(97.10) ***	(18.24) ***	(17.64) ***	(-1.88) *	(-3.17) ***	
Insurance	0.0062	0.2883	0.3064	1.9698	1.7993	52.64%
	(71.26) ***	(4.35) ***	(27.48) ***	(12.51) ***	(13.56) ***	
Media	0.0078	0.3647	0.2957	-0.3730	0.0586	26.00%
	(68.56) ***	(25.27) ***	(19.04) ***	(-1.42)	(0.20)	
Oil & Gas	0.0096	0.2240	0.2022	-0.5264	-0.2623	19.30%
	(105.98) ***	(24.23) ***	(22.09) ***	(-3.99) ***	(-2.34) *	
Personal& Household	0.0097	0.3471	0.3227	0.2440	-0.3733	23.04%
	(94.14) ***	(20.03) ***	(18.97) ***	(0.56)	(-0.96)	
Real Estate	0.0074	0.2821	0.3039	0.2576	-0.0896	34.69%
	(86.37) ***	(25.92) ***	(26.59) ***	(2.31) **	(-0.70)	
Retail	0.0108	0.3857	0.3644	-0.6531	-1.5834	19.43%
	(87.14) ***	(21.34) ***	(19.25***)	(-1.63)	(-3.63) ***	
Technology	0.0116	0.4130	0.3579	-1.0309	-0.4329	28.16%
	(78.63) ***	(26.61) ***	(20.44) ***	(-4.16) ***	(-1.34)	
Telecom	0.0069	0.6612	0.5629	1.3267	3.0614	46.41%
	(42.95) ***	(29.83) ***	(25.38) ***	(2.93) ***	(6.83) ***	
Travel & Leisure	0.0097	0.3858	0.3064	-0.2837	1.1686	29.13%
	(72.38) ***	(22.52) ***	(24.10) ***	(-0.87)	(8.47) ***	
Utilities	0.0086	0.3570	0.3084	0.5596	3.8208	28.48%
	(86.52) ***	(21.89) ***	(17.37) ***	(1.80)	(9.43) ***	

Note:

Table 4.5 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{m,t}\right| + \gamma_2\ (1 - D^{up})\left|R_{m,t}\right| + \gamma_3\ D^{up}(R_{m.t})^2 + \gamma_4\ (1 - D^{up})(R_{m.t})^2 + \varepsilon_t$$

D^{up} is a dummy variable with a value of 1 for days with positive sector returns and a value of 0 otherwise, $R_{m,t}$ is the average value of sector return in each sector, $CSAD_{i,t}$ is the cross-sectional absolute deviation of returns for the sectors, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients and ε_t is the error term at time t. The equation is estimated over the whole sample period. T-test statistics based on Newey-West. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4.5 presents results for the industry sector CSADs in rising and declining price movements. Again, the results are similar to those obtained for herding in industry sectors. During upmarket conditions, negative statistically significant γ_3 coefficients of interest are reported in the Chemicals, Healthcare, Industrial Goods, Oil and Gas and Technology sectors. Evidence of herding is strongest in the Technology and Oil and Gas sectors.

Interestingly, the highest level of herding is observed in the Technology industry rather than the Healthcare sector reported in previous results.

In declining markets, negative statistically significant γ_4 coefficients of interest are reported in the Basic Resources, Food and Beverage, Healthcare, Industrial Goods, Oil and Gas and Retail. Basic Resources and Food and Beverage industries show the highest level of herding. In contrast to H2a, there is limited evidence that herding is contingent upon sector returns. It is interesting to note that herding occurs in the Healthcare and Industrial Goods sectors in both up and down-market states. This gives an indication that investors in these sectors herd irrespective of the market condition. Due to lack of empirical evidence on herding (to the best of our knowledge) conditioned upon the market return for the US, our results are compared to the findings of non-US based research.

Again, our results are significantly different from those obtained from developing markets. Gavriilidis, et al., (2013) provide evidence of significant herding in the Spanish Consumer Services, Financials and Industrial sectors during quarters of low market /sector returns. In contrast, Demirer and Kutan (2006), find lower return dispersion during declining market conditions in most sectors with some sectors having a dispersion that is 50 percent smaller in down markets than in up markets. Demirer, et al., (2010), document herding mainly during down markets for the sectors examined. Gebka and Wohar (2013) find a significant difference in the level of herding for up and down markets. In up markets, they report herding in Financials and Industrials, while no evidence of herding is reported in down markets.

4.5.3.2. The effect of volatility on herding

Gavriilidis, et al., (2013) state that periods of increasing volatility may lead to an environment with a excessive information whereby less skilled managers prefer to mimic their more skilled counterparts. The high flow of information may make information processing difficult. Conversely, in periods of decreasing volatility, these less skilled managers may be prompted to herd due to the ease with which the trades of more skilled managers can be observed. This can be explained by the increased visibility that such periods entail.

Finding a relationship between herding and volatility will provide evidence on whether volatility has an asymmetric effect on herding. To examine this relationship, we use a dummy variable as shown in equation (6) to capture a possible asymmetric relationship between CSAD and return volatility. The findings for the overall market are presented in Table 4.6.

Table 4.6 Estimates of herding during periods of high and low volatility for the overall US market

Estimated Parameters	α	γ_1	γ_2	γ_3	γ_4	Adj. R^2
	0.0099	0.3054	0.6365	0.6574	-4.4121	27.95%
	(92.54) ***	(23.84) ***	(21.84) ***	(2.78) ***	(-4.04) ***	

Note: Table 4.6 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 D^{\sigma^2-High}\left|R_{m,t}\right| + \gamma_2\left(1 - D^{\sigma^2-High}\right)\left|R_{m,t}\right| + \gamma_3\, D^{\sigma^2-High}(R_{m.t})^2 + \gamma_4\left(1 - D^{\sigma^2-High}\right)(R_{m.t})^2 + \varepsilon_t$$

Where $D^{\sigma2\text{-}High}$ is 1 for days with high market volatility and 0 otherwise, based on the previous 30-day moving average. $R_{m,t}$ is the market's average return, $CSAD_{i,t}$ is the cross-sectional absolute deviation of returns for the market, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients and εt is the error term at time t. The equation is estimated over the whole sample period. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. *******, ****** and ***** represent statistical significance at the 1%, 5%, and 10% level, respectively.

An analysis of the results reveals that herd behaviour is only present in low volatility periods, the coefficient for γ_4 is negative and statistically significant. This implies that herding is more likely on days with low volatility, which supports the argument of Holmes, et al., (2013) that investors tend to herd more during periods of low volatility. Holmes, et al., (2103) explain that investors tend to herd during this period because the direction of the market is clearer direction, so they can easily follow the market consensus. Moreover, this result contrasts with the H2b hypothesis which predicts that herding is contingent upon market volatility for the US market. Our results support the findings of Economou, et al., (2011) who document herding in low volatility periods for the Italian and Portuguese markets. Our results are also in line with those obtained by Holmes, et al., (2013) for the Portuguese stock market using mutual fund data, where herding is more prevalent during periods of declining market volatility.

Our results are in contrast with evidence from developing markets. Tan, et al., (2008) provide evidence for the Chinese stock market where herding is only documented in periods of high volatility. Similarly, Blasco, et al., (2012) find that investors in the Spanish stock market herd more during periods of high volatility. Guney, et al., (2017), report that most markets in their sample display herd behaviour during periods of both high and low volatility, with herding more pronounced during periods of low volatility. We now examine the effect of high (low) volatility on herding at the sector level.

Table 4.7 Estimates of herding for US sectors in periods of high and low volatility

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj. R^2
Automobile	0.0073	0.2479	0.3747	1.3626	3.4226	27.35%
	(48.63) ***	(18.24) ***	(11.91) ***	(6.18) ***	(2.99) ***	
Banks	0.0058	0.1840	0.3778	0.9406	1.1222	45.07%
	(53.88) ***	(22.65) ***	(19.61) ***	(14.47) ***	(2.76) ***	
Basic Resources	0.0077	0.2932	0.5014	-0.0063	-3.0514	21.35%
	(45.26) ***	(23.51) ***	(17.76) ***	(-0.04)	(-3.93) ***	
Chemicals	0.0069	0.1893	0.3785	0.9499	-2.5247	23.89%
	(70.61) ***	(19.85) ***	(17.11) ***	(6.19) ***	(-3.24) ***	
Construction	0.0078	0.1579	0.3508	3.5176	1.5373	27.70%
	(51.64) ***	(11.88) ***	(11.00) ***	(16.90) ***	(1.32)	
Financials	0.0074	0.2888	0.5831	0.2313	-3.6816	34.78%
	(60.62) ***	(29.31) ***	(24.50) ***	(1.92) *	(-5.24) ***	
Food & Beverage	0.0074	0.3462	0.6618	0.5326	-7.1843	19.41%
	(60.80) ***	(0.54)	(15.97) ***	(1.17)	(-2.65) ***	

Healthcare	0.0097	0.4023	0.8912	-1.6165	-16.9343	17.27%
	(63.37) ***	(23.39) ***	(21.02) ***	(-4.35) ***	(-7.79) ***	
Industrial Goods	0.0083	0.2701	0.5480	-0.5496	-7.1753	17.38%
	(75.63) ***	(20.52) ***	(17.96) ***	(-2.01) ***	(-5.22) ***	
Insurance	0.0057	0.2450	0.4817	2.3238	3.4356	56.33%
	(57.83) ***	(25.98) ***	(21.86) ***	(21.78) **	(5.77) ***	
Media	0.0070	0.3209	0.5792	0.1535	-4.7197	27.33%
	(51.88) ***	(25.09) ***	(19.98) ***	(0.73)	(-4.49) ***	
Oil & Gas	0.0090	0.2114	0.3561	-0.3051	-2.2187	20.54%
	(85.32) ***	(27.35) ***	(20.37) ***	(-3.38) ***	(-5.32) ***	
Personal & Household	0.0091	0.3206	0.5657	0.3238	-2.7346	24.61%
	(73.95) ***	(21.80) ***	(17.20) ***	(1.03)	(-1.87) *	
Real Estate	0.0072	0.2530	0.3760	0.3417	1.4465	36.77%
	(74.28) ***	(27.32) ***	(17.98) ***	(3.80) ***	(3.29) ***	
Retail	0.0096	0.3620	0.7875	-0.3917	-9.5840	22.55%
	(64.61) ***	(22.97) ***	(21.33) ***	(-1.24)	(-5.82) ***	
Technology	0.0098	0.3634	0.8472	-0.0369	-8.0505	33.32%
	(54.99) ***	(26.29) ***	(24.20) ***	(-0.18)	(-6.56) ***	
Telecommunication	0.0057	0.6124	0.9963	2.6203	-8.6854	47.27%
	(29.76) ***	(31.85) ***	(22.42) ***	(7.47) ***	(-4.70) ***	
Travel & Leisure	0.0087	0.3154	0.6111	1.1241	-1.7207	31.46%
	(53.34) ***	(27.69) ***	(17.21) ***	(8.63) ***	(-1.27)	
Utilities	0.0076	0.3210	0.7081	2.2690	1.5347	32.46%
	(64.88) ***	(22.87) ***	(20.03) ***	(8.78) ***	(0.91)	

Note: Table 4.7 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 D^{\sigma^2-High}\left|R_{m,t}\right| + \gamma_2\left(1 - D^{\sigma^2-High}\right)\left|R_{m,t}\right| + \gamma_3\, D^{\sigma^2-High}(R_{m.t})^2 + \gamma_4\left(1 - D^{\sigma^2-High}\right)(R_{m.t})^2 + \varepsilon_t$$

Where $D^{\sigma2\text{-}High}$ is 1 for days with high sector volatility and 0 otherwise, based on the previous 30-day moving average. $R_{m,t}$ is the average value of sector return in each sector, $CSAD_{i,t}$ is the cross-sectional absolute deviation of returns for the sectors, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients and εt is the error term at time t. The equation is estimated over the whole sample period. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. *******, ** and ***** represent statistical significance at the 1%, 5%, and 10% level, respectively.

The evidence for the industry sectors is presented in Table 4.7. Notably, there is no evidence of herd formation during periods of high volatility in most sectors except for Healthcare, Industrial Goods and Oil and Gas during periods of high volatility. These investors may have been driven to herd due to high flow of information caused by uncertainty making it difficult to interpret information.

Most regression estimates are positive and statistically significant indicating an increasing relationship between equity return dispersion and high market volatility. This implies that investors mostly ignored market wide information in favour of information from superior investors. A possible explanation for this result is an excessive ‘flight to quality’ where the US investors may have rebalanced their portfolios whereby they shifted their investment from more risky assets (uncertain markets) to safer ones (Gebka and Wohar, 2013).

This presents strong evidence that most of the investors in the US market do not herd during periods of high market volatility. Moreover, this evidence is contrary to the herding literature which argues that during periods of high volatility, investors have the tendency to herd due to increased risk and uncertainty about future market conditions (Holmes, et al., 2013). A closer analysis of the negative coefficients shows that herding is strongest in the Healthcare and Industrial Goods sectors. This gives an indication that during periods of high return volatility, investors in these sectors appear to suppress their own belief in favour of the market consensus resulting in a low dispersion of market returns.

It is interesting to note that the results for low volatility are a significant contrast from those obtained for high return volatility. Indeed, we find evidence of herd formation in most sectors except for Automobile, Bank, Construction, Insurance, Real Estate, Travel and Leisure and Utility. Our results are consistent with the predictions of H2b, there is strong evidence that herd behavior is contingent upon volatility. This supports the herding literature which argues that intentional herding occurs during stable periods, where motivated by reputational concerns, poor performing managers herd behind high performing managers (Holmes, et al., 2013). Remarkably, as illustrated in Table 4.7 herding occurs in the Healthcare, Industrial Goods and Oil and Gas sectors irrespective of whether the sector volatility is high or low, which suggests that the level of investment in these sectors is driven by demand rather than market volatility. Our results are consistent with those obtained by Gavriilidis, et al., (2013) who report that institutional industry herding is more prevalent when sector volatility is low. Specifically, they find herding at both high and low volatility for the Technology sector, only in low volatility periods for the Industrials sector and high volatility for Industrial and Oil and Gas sectors.

4.5.3.3. The effect of volume on herding

Tan, et al., (2008) argue that the extent of herding may be affected by trading volume. Therefore, to further investigate herd behaviour in periods of high and low trading volume, we utilise a dummy variable as in equation (7) to capture a possible asymmetric relationship between CSAD and trading volume.

Table 4.8 Estimates of herding during periods of high and low volume for the overall US market

Estimated Parameters	α	γ_1	γ_2	γ_3	γ_4	Adj. R^2
0.0108		0.2682	0.3542	1.3925	-0.2175	25.32%
	(110.94) ***	(13.19) ***	(24.98) ***	(2.06) **	(-0.85)	

Note: Table 4.8 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 D^{vol-High} \left|R_{m,t}\right| + \gamma_2 \left(1 - D^{vol-High}\right)\left|R_{m,t}\right| + \gamma_3 D^{vol-High}(R_{m.t})^2 + \gamma_4 \left(1 - D^{vol-High}\right)(R_{m.t})^2 + \varepsilon_t$$

Where $D^{vol-High}$ is 1 for days with high market volume and 0 otherwise, based on a 30-day moving average $R_{m,t}$ is the the average value of market return, $CSAD_{i,t}$ is the cross-sectional absolute deviation of returns for the market, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients and εt is the error term at time t. The equation is estimated over the whole sample period. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

The results for the overall market are reported in Table 4.8. These results are similar to those obtained for return volatility, this similarity is not surprising as previous studies have demonstrated that there is a positive relationship between volume and volatility (Jones, Kaul and Lipson, 1994). A closer analysis of the results reveals the absence of herding in high and low trading volume, respectively. In periods of high trading volume, the γ_3 coefficient is positive and statistically significant, indicating that the cross-sectional dispersion is higher compared to levels suggested by rational asset pricing models. Hence, there is no asymmetric effect of herding during periods of high trading volume. The evidence for low trading volume yields a negative γ_4 coefficient that is not significantly different from zero. Specifically, in contrast to H2c, herding is not contingent upon high (low) trading volume. However, comparing the coefficients, the γ_3 coefficient is greater than the γ_4 coefficient, this implies that equity return dispersion is greater when trading volume is high, thus, investors tend to follow the market consensus when the level of trading activity is high. The evidence shows that using market level data, investors do not herd regardless of the trading volume hence herding is not related to trading volume.

Our results are inconsistent with the evidence provided by Economou, et al., (2011) who find evidence of herding in low volume periods for the both Greek and Italian stock markets. Evidence from the Chinese stock market reported by Tan, et al., (2008) is mixed, in high volume periods, herding is present in the Shanghai and Shenzhen A and B- share market, while for low volume periods herding is only observed in the B share market. To gain additional insight on whether herd behaviour exhibits an asymmetry associated with the trading volume, we examine evidence using the sector level data.

Table 4.9 Regression estimates for herd behaviour during high and low trading volume, US

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj. R^2
Automobile	0.0078	0.2617	0.2821	1.3623	0.7614	25.81%
	(61.53)***	(14.97)***	(19.18)***	(3.78)***	(3.06)***	
Banks	0.0062	0.2457	0.2243	0.6009	0.6809	41.52%
	(64.80)***	(24.03)***	(24.37)***	(6.48)***	(8.41)***	
Basic Resources	0.0085	0.2906	0.3096	-0.3333	-0.2351	20.30%
	(58.05)***	(16.14)***	(22.35)***	(-0.93)	(-1.38)	
Chemicals	0.0075	0.1768	0.2180	0.5627	0.5230	22.68%
	(84.84)***	(10.49)***	(20.45)***	(1.06)	(3.21)***	
Construction	0.0082	0.2638	0.1583	0.1552	3.9137	27.48%
	(64.08)***	(14.43)***	(10.99)***	(0.39)	(17.30)***	
Financials	0.0084	0.3080	0.3077	-0.2048	-0.0424	31.79%
	(77.25)***	(21.41)***	(28.10)***	(-0.74)	(-0.32)	
Food & Beverage	0.0081	0.2944	0.3524	3.7521	-0.6331	17.83%
	(80.68)***	(12.74)***	(18.78)***	(3.90)***	(-1.27)	
Healthcare	0.0111	0.3575	0.4020	-0.6322	-2.3927	14.41%
	(85.31)***	(14.42)***	(21.12)***	(-0.75)	(-5.90)***	
Industrial Goods	0.0090	0.2401	0.3037	-0.3470	-1.3788	15.67%
	(95.29)***	(13.47)***	(21.13)***	(-0.66)	(-4.54)***	
Insurance	0.0062	0.3050	0.3052	1.2692	1.9507	52.83%
	(69.75)***	(23.73)***	(28.66)***	(6.34)***	(15.93)***	
Media	0.0078	0.3306	0.3322	-0.0858	-0.2173	25.72%
	(66.01)***	(17.56)***	(23.72)***	(-0.18)	(-0.96)	
Oil & Gas	0.0090	0.2114	0.3561	-0.3051	-2.2187	20.54%
	(85.32)***	(27.35)***	(20.37)***	(-3.38)***	(-5.32)***	
Personal & Household	0.0097	0.3257	0.3643	-0.4633	-0.5018	22.92%
	(92.12)***	(16.95)***	(21.74)***	(-0.79)	(-1.41)	
Real Estate	0.0075	0.2548	0.3117	0.5062	-0.0533	34.90%
	(84.42)***	(19.49)***	(29.79)***	(2.64)***	(-0.54)	
Retail	0.0108	0.3386	0.3807	0.9175	-1.6773	19.55%
	(86.27)***	(16.70)***	(21.61)***	(1.71)*	(-4.59)***	
Technology	0.0117	0.3716	0.3967	-0.4730	-0.9105	28.14%
	(75.99)***	(18.17)***	(25.95)***	(-1.03)	(-3.94)***	

Telecommunication	0.0069	0.5826	0.6165	3.9659	1.5254	46.57%
	(42.91)***	(24.71)***	(28.73)***	(7.38)***	(3.76)***	
Travel & Leisure	0.0099	0.2918	0.3245	1.7653	0.8918	29.03%
	(71.69)***	(15.13)***	(26.07)***	(4.11)***	(6.54)***	
Utilities	0.0086	0.2858	0.4247	2.0291	0.8026	28.62%
	(82.03)***	(11.92)***	(26.35)***	(2.16)***	(2.85)***	

Note:

Table 4.9 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 D^{vol-High} \left|R_{m,t}\right| + \gamma_2 \left(1 - D^{vol-High}\right)\left|R_{m,t}\right| + \gamma_3 \, D^{vol-High}(R_{m.t})^2 + \gamma_4 \left(1 - D^{vol-High}\right)(R_{m.t})^2 + \varepsilon_t$$

Where $D^{vol-High}$ is 1 for days with high sector volume and 0 otherwise, based on the previous 30-day moving average $R_{m,t}$ is the average value of sector return in each sector, $CSAD_{i,t}$ is the cross-sectional absolute deviation of returns for the sector, α is the constant, γ_1 , γ_2 , γ_3 , γ_4 are coefficients and ε_t is the error term at time t. The equation is estimated over the whole sample period. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. The t-test statistic tests for the difference in level of significance between the γ_3 and , γ_4 coefficients. *******, ****** and ***** represent statistical significance at the 1%, 5%, and 10% level, respectively.

The results presented in Table 4.9 shows that during high trading volume periods, the γ_3 coefficients are negative and statistically significant in only the Oil and Gas sector. An explanation for herding in this sector could be due to the increased participation of sophisticated traders' because of the high level of trading activity within the sector, making it easier for less informed traders to mimic their trades (Economou, Gavriilidis and Yordanov, 2015).

This gives an indication that high trading volume does not affect the dispersion of returns in the US sectors examined. Specifically, this is inconsistent with H2c, herding is not contingent upon trading volume. However, our results are in contrast with those obtained by Gavriilidis, et al., (2013), who find that Spanish fund managers' herd more in periods with high volume specifically in the Technology, Utilities and Consumer Service sectors.

An analysis of herding during low volume periods shows negative and statistically significant γ_4 coefficients in the Healthcare, Industrial Goods, Oil and Gas, Retail and

Technology sectors. Herding is strongest in Healthcare and Oil and Gas. The evidence of herding in these sectors during periods of low trading volume may be due to the difficulty fund managers investing in these sectors might face in selling their portfolios during low volume periods which may drive them to herd (Economou, et al., 2015).

Remarkably, herding is present in the Oil and Gas sector at both periods of low and high trading volume, indicating that the investors in this sector herd regardless of the level of trading activity. This herding may have resulted from the unprecedented surge in oil prices recorded in 2003-2008. Indeed, Boyd, Buyuksahin, Haigh and Harris (2015) find supportive evidence of herding in oil futures market which may be due to the disagreement among money managers who follow dispersed information flows. Gavriilidis, et al., (2013) also report significant herding of Spanish funds in the Oil and Gas sector during quarters of declining sector volume.

Overall, the results for herding conditioned on trading volume at both the market and sector level, provide limited evidence in support of the presence of stronger levels of herding during high (low) volume periods. This contrasts with herding literature which suggests that herd behaviour may be more significant when trading volume is high. However, there is strong supportive evidence that US investors exhibit ‘negative herding’ as most of the coefficients during the high and low volume periods are positive and statistically significant.

4.5.4. Herding and market stress

4.5.4.1. Dot Com Bubble

The Dot com bubble which occurred in the late 1990s was triggered by the significant investment in the Technology sector. However, due to the sector’s lack of sustained growth without profitability, investors panicked and sold these internet stocks which lead to a 39% decline in the NASDAQ-100 Index, on the 9th of October 2002. This, in turn, resulted in a collapse of stock prices between the spring of 2000 to October 2002 (Wheale and Amin, 2003).

Previous literature suggests that investors have a greater tendency to herd during periods of extreme price movement (Christie and Huang, 1995). Consequently, we examine the Dot com bubble period to determine whether it influenced US investors' herd behaviour. To achieve this as stated earlier, we divide the daily data into sub-samples as follows: Pre-Dot com bubble phase (01/01/1990- 31/12/1994), Dot com bubble (01/01/1995 - 10/03/2000), Dot com bubble crash (13/03/2000- 9/10/2002). The results for the overall market and sectors are discussed in the sections below.

4.5.4.1.1. Results for the overall market

Regressions are estimated for the three sub-samples using Equation (4). Table 4.10 presents the results of the regression for the overall market. It is important to note that the coefficient for γ_2 is negative and significant during the pre-bubble and bubble phases which implies that investors ignore their assessment of the stocks and follow the market consensus. This is consistent with the prediction of H3 that herding is stronger during the Dot Com bubble. Therefore, these returns display greater correlation in trades during such periods. As a result, investors will require more stocks in their portfolios to achieve the benefits of diversification.

Remarkably, there is no evidence of herding during the bubble crash period which is inconsistent with the literature that argues that herding occurs during periods of high price movement and volatility. The results for the bubble crash are consistent with those obtained by Galariotis, et al., (2016) who report that there is no evidence of herding during the Dot-com bubble burst. It is important to point out that these results are similar even though they use a shorter sample period (1989-2011), S&P 100 index and a bubble burst period that is slightly shorter (January 2000 - June 2000).

The test of herding effect in the pre, bubble and bubble crash phases of the Dot Com crisis shows that herding occurs in the pre-bubble and bubble phases and not during the bubble crash suggesting that investors only herd in the bubble forming period. During the pre-bubble and bubble periods investors may have decided to herd with other investors who embraced the Dot Com mania, because they preferred to fail with the crowd than to be wrong alone. A possible explanation for the absence of herding recorded during the bubble crash is that stock prices had returned to their pre-bubble levels maybe probably due to the government's intervention. The absence of herding could also be due to investors having a pessimistic view of the future development in the market. In addition, herding during a crisis could dissipate because the pre-crisis fundamentals that supported that herding may no longer be valid. (Economou, et al., 2015b). A closer examination of herd behaviour results at the sector level will give more insight on whether herd behaviour is widespread.

Overall, a clear pattern established in finance literature can be gleaned from our results, where a possible rise in prices during the bubble building phase (marked by herding) is followed by a sharp fall(s) in stock prices at the bubble burst phase, accompanied by high return volatility. Our results lend support to the theoretical argument earlier discussed that irrational investors make their decisions based on herd instincts and psychological biases cause bubbles.

Table 4.10 Regression estimates for market herd behaviour for the Dot Com bubble, US

Period	α	γ_1	γ_2	Adj. R^2
Pre-bubble	0.0117	0.4342	-5.7797	23.47%
	(81.26) ***	(11.76) ***	(-3.51) ***	
Bubble	0.0126	0.4651	-2.4761	24.06%
	(66.27) ***	(13.33) ***	(-2.40) ***	
Bubble crash	0.0158	0.3820	-0.7625	22.31%
	(38.87) ***	(6.54) ***	(-0.50)	

Note: Table 4.10 reports the estimates from the following equation:

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

where $R_{m,t}$is the cross-sectional average of the market returns in at time t, the squared market return $R_{m,t}^2$ is used to capture the nonlinearity in the relationship, $CSAD_t$ is the cross-sectional absolute deviation of returns for the market, α is the constant, γ_1 and γ_2 are coefficients, and ε_t is the error term at time t. The model is run for the separately for the pre-crisis, crisis and post-crisis periods. Pre-bubble refers to the period between 1/01/1990 and 31/12/1994. Bubble refers to the period between 01/01/1995 and 10/03/2000. Bubble crash refers to the period between 13/03/2000 and 09/10/2002. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4.11 Regression estimates for industry herd behaviour for the Dot Com bubble

	Pre-bubble				Bubble				Bubble			
Industry	**α**	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj. R^2
Automobile	0.0094	0.0605	8.8787	19.71%	0.0076	0.3286	0.6149	20.35%	0.0090	0.3002	-1.1871	17.77%
	(30.34) ***	(1.31)	(7.09) ***		(29.17) ***	(8.15) ***	(0.55)		(20.67) ***	(7.27) ***	(-1.62) *	
Banks	0.0090	0.4266	-1.2691	25.94%	0.0072	0.2741	-0.7373	28.40%	0.0063	0.2603	-1.1976	30.82%
	(44.48) ***	(10.24) ***	(-0.85)		(43.08) ***	(11.25) ***	(-1.22)		(24.73) ***	(9.89) ***	(-2.43) **	
Basic Resources	0.0083	0.1348	5.7468	10.05%	0.0101	0.3395	0.3271	18.47%	0.0124	0.2215	0.7170	10.80%
	(27.26) ***	(2.35) **	(2.73) ***		(28.82) ***	(8.79) ***	(0.43)		(18.88) ***	(3.14) ***	(0.50)	
Chemicals	0.0080	0.3332	-2.8771	15.15%	0.0083	0.3447	-2.3232	18.77%	0.0081	0.2701	-1.7833	19.96%
	(41.99) ***	(7.90) ***	(-1.69) *		(42.62) ***	(10.20) ***	(-2.28) ***		(26.86) ***	(8.70) ***	(-3.05) ***	
Construction	0.0076	0.3701	1.0505	19.18%	0.0077	0.4642	-2.2443	18.14%	0.0132	0.0019	8.5748	55.08%
	(25.95) ***	(6.44) ***	(0.51)		(27.12) ***	(9.67) ***	(-1.61)		(24.10) ***	(0.05)	(17.33) ***	
Financials	0.0093	0.3712	-0.9918	24.14%	0.0108	0.3812	-1.1373	25.54%	0.0117	0.2174	1.5007	31.18%
	(43.44) ***	(9.72) ***	(-0.84)		(38.31) ***	(12.46) ***	(-2.01) **		(26.17) ***	(5.28) ***	(2.15) **	
Food & Beverage	0.0100	0.2771	8.0382	22.34%	0.0111	0.3625	-0.2830	15.78%	0.0100	0.3511	0.5803	23.71%
	(39.79) ***	(5.29) ***	(4.03) ***		(46.11) ***	(7.89) ***	(-0.17)		(31.61) ***	(6.99) ***	(0.41)	
Healthcare	0.0145	0.3740	-3.0707	14.53%	0.0147	0.4541	-3.0237	18.29%	0.0160	0.5154	-4.5396	18.90%
	(57.86) ***	(9.31) ***	(-2.64) ***		(57.09) ***	(11.96) ***	(-3.23) ***		(30.05) ***	(7.80) ***	(-2.97) ***	
Industrial Goods	0.0101	0.3942	-4.4054	21.03%	0.0108	0.4533	-1.4784	26.62%	0.0142	0.2832	-0.8263	14.26%
	(67.67) ***	(10.07) ***	(-2.42) **		(53.58) ***	(12.45) ***	(-1.34)		(32.60) ***	(4.69) ***	(-0.54)	
Insurance	0.0076	0.2850	1.5384	21.50%	0.0076	0.3494	0.5060	30.72%	0.0081	0.3639	-1.7283	33.32%
	(49.06) ***	(7.59) ***	(0.99)		(39.17) ***	(10.37) ***	(0.51)		(26.71) ***	(11.99) ***	(-3.32) ***	
Media	0.0094	0.3164	3.0494	25.66%	0.0099	0.4346	-2.1762	21.49%	0.0111	0.2399	1.2173	26.27%
	(33.43) ***	(7.38) ***	(2.62) ***		(33.43) ***	(12.30) ***	(-2.94) ***		(22.82) ***	(5.38) ***	(1.65) *	
Oil & Gas	0.0108	0.3927	-4.7139	14.24%	0.0106	0.3896	-1.4228	30.28%	0.0114	0.1344	2.5852	31.11%
	(50.51) ***	(8.72) ***	(-2.77) ***		(45.72) ***	(12.39) ***	(-1.85) *		(30.24) ***	(3.81) ***	(4.02) ***	
Personal &	0.0115	0.3451	-1.4001	17.49%	0.0117	0.4488	-1.9016	21.75%	0.0133	0.3622	-1.4673	16.73%
	(55.38) ***	(8.76) ***	(-1.08)		(51.47) ***	(12.05) ***	(-1.87) *		(30.86) ***	(6.51) ***	(-1.14)	
Real Estate	0.0090	0.3872	8.2659	29.08%	0.0077	0.4755	-0.6184	29.24%	0.0096	0.3665	8.0689	36.27%
	(40.58) ***	(7.03) ***	(3.37) ***		(50.22) ***	(12.87) ***	(-0.47)		(25.68) ***	(4.89) ***	(3.08) ***	

Retail	0.0146	0.1820	5.7788	21.47%	0.0145	0.4616	-3.0106	22.36%	0.0149	0.3989	-1.1247	23.80%
	(50.93) ***	(4.18) ***	(4.77) ***		(57.56) ***	(13.49) ***	(-3.86) ***		(30.50) ***	(8.06) ***	(-1.28)	
Technology	0.0154	0.3319	-1.8471	17.48%	0.0177	0.2816	-0.1385	19.07%	0.0205	0.3136	-0.7049	28.20%
	(52.54) ***	(8.18) ***	(-1.74) *		(48.18) ***	(8.39) ***	(-0.23)		(30.49) ***	(8.27) ***	(-1.65) ***	
Telecom	0.0069	0.5244	1.4885	32.14%	0.0094	0.2801	11.7829	43.47%	0.0151	0.2929	8.3063	46.69%
	(24.94) ***	(9.83) ***	(0.79)		(26.41) ***	(5.90) ***	(10.59) ***		(16.60) ***	(3.56) ***	(5.91) ***	
Travel & Leisure	0.0095	0.2768	-0.4105	13.29%	0.0114	0.4043	-0.0024	19.39%	0.0138	0.4023	0.7879	38.67%
	(32.17) ***	(7.31) ***	(-0.47)		(31.84) ***	(8.64) ***	(0.00)		(23.78) ***	(10.71) ***	(3.33) ***	
Utilities	0.0090	0.3960	-3.3160	14.87%	0.0103	0.1530	7.9190	18.57%	0.0128	0.4264	3.2452	41.89%
	(53.74) ***	(8.55) ***	(-1.50)		(56.17) ***	(3.57) ***	(4.47) ***		(23.92) ***	(7.63) ***	(3.53) ***	

Note: Table 4.11 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 \; R_{m,t}^2 + \varepsilon_t$$

where $R_{m,t}$is the cross-sectional average of sector returns in at time t, the squared sector return $R_{m,t}^2$ is used to capture the nonlinearity in the relationship, $CSAD_t$ is the cross-sectional absolute deviation of returns for the sector, α is the constant, γ_1 and γ_2 are coefficients, and ε_t is the error term at time t. The model is run for the separately for the pre-crisis, crisis and post-crisis periods. Bubble refers to the period between 01/01/1995 and 10/03/2000. Bubble crash refers to the period between 13/03/2000 and 09/10/2002. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

4.5.4.1.2. Results for industry sectors

Having found some evidence of herd behaviour during the pre-bubble and bubble phases for the overall market, we next focus on sector-based results to investigate probable herd behaviour among US investors in specific sectors. To achieve this, we run similar tests on the companies classified into sectors.

Table 4.11 presents the regression results for equation (4). At a first glance, herding is present in some sectors across different periods. A closer examination reveals that, in the pre-bubble phase, negative and significant γ_2 coefficients of interest are reported in the Healthcare, Industrial Goods, Oil and Gas, Technology, and Chemicals sectors. This suggests that these five industries display greater correlation in returns during stable periods, due to herd behaviour. Specifically, herding observed in the Technology sector supports the theory of bubble formation proposed by Barberis and Huang (2008) which argue that investors may have caused Internet Technology stocks to be overvalued because they expected to obtain lottery-like gains if the new technology was successful.

During, the bubble phase, the negative significant γ_2 coefficients of interest are reported in the Chemicals, Healthcare, Financials, Media, Oil and Gas, Personal and Household and Retail. It is interesting to note that herding occurred in the Oil and Gas sector during the pre-bubble and bubble phases. This gives an indication that these stocks were overvalued when compared to their intrinsic values and were possibly popular stocks maybe more popular than technology stocks, thus creating a herd behaviour. This herd behavior may have resulted in an increased demand for Oil and Gas stocks. Sornette, Woodard and Zhou (2008), explain that before 2005, the supply for US Oil and Gas exceeded its demand, however, since 2006, the sector experienced increased uncertainty and speculation. Furthermore, Johansen and Sornette (1999) contend that herding is not only prevalent during bubbles but herd behaviour also leads to ‘anti-bubbles’, whereby market evaluation of stocks decelerates following all-time highs.

Herding that was hitherto absent during the bubble burst phase at the market level, surfaces in 6 sectors. Statistically significant negative γ_2 coefficients are recorded in the Automobile, Banks, Chemicals, Healthcare, Insurance and Technology sectors. Noticeably, herding occurred in the Technology sector during the crash phase, which suggests that the dramatic fall in Internet stocks during this phase, led investors to follow the market consensus. It is also noteworthy that herding occurs in the Healthcare sector during all three phases of the Dot com bubble. This finding suggests that during these phases, investors in these sectors display herd behaviour regardless of the prevailing market condition. Our results contrast with that of BenSaida (2017), who employed a modified version of the CSAD on all stocks in the US market and do not find herding during the Dot com bubble. The contrast in results may be due to the different herding measures employed and the sample size.

Overall, the results for herding at different phases of the Dot com bubble reveals that US sectors most likely herd before and during the bubble, but not during the bubble crash, inconsistent with H3, there is limited evidence that herding in the US sectors is stronger during the Dot Com crisis.

4.5.4.2. Global Financial Crisis

The Global Financial Crisis (GFC) has been described as the worst financial crisis in the US since the Great Depression. The crisis was brought about by the real-estate bubble and led to serious damage in the financial market. House prices increased in the US and were accompanied by a fast increase in credit. However, this led to a decline in lending standards which resulted in intensified loan defaults and an eventual crisis in the financial market (Claessens, Kunt, and Moshirian, 2009).

Indeed, the events surrounding the crisis gave rise to an increased level of research on investor herding during financial crisis amongst behavioural finance academics. In the same light, we investigate the GFC related herding behaviour by dividing the daily data into sub-samples as follows: Pre-crisis (01/05/2002- 31/07/2007), Crisis (01/08/2007 - 30/03/2009) and Post crisis (01/04/2009 - 11/10/2016). The results for the overall market and sectors are discussed in the sections below.

4.5.4.2.1. Results for the overall market

Table 4.12 contains the regression estimates for the overall market. Regressions are estimated for the three sub-samples using Equation (4). Noticeably, herding is only observed in the pre-crisis phase, the γ_3 coefficient is negative and significant. Investors may have herded during this period due to the uncertainty regarding the fundamental value of the assets.

The evidence gives an indication that herding vanished from the US market following the commencement of the GFC. In all, there is no supportive evidence for H4 that herding effect is stronger during the GFC. The result supports the Hwang and Salmon's (2004) argument that herding is more prevalent during tranquil market conditions. The intuition behind this argument is that high volatility during extreme market conditions makes it difficult to observe the direction of the market and thus, makes it difficult to herd towards the market. In contrast, during tranquil conditions, investors have a better view of the direction of the market and can thus herd towards it more easily. It is interesting to note that the γ_3 coefficient is positive and significant during the post-crisis period. A possible explanation is that after the crisis, US investors exhibited localised herding, where they may have moved as a group into (out) of assets/markets resulting in price increase (decrease) as well as an increased dispersion across assets (Gebka and Wohar, 2013). Another explanation is the overconfidence of investors probably due to positive returns after the crisis resulting in focusing on their own information and ignoring the market wide consensus (Goodfellow, et al., 2009). If this occurs at a large scale then it could lead to greater dispersion in views and return, which in turn increases the CSAD. Hence, our results do not support the argument that herding is more prevalent in extreme market conditions, therefore herding may not have contributed to the effects of the crisis.

It is worth noting that our results are inconsistent with those obtained by Chiang and Zheng (2010) and Galariotis, et al., (2015) who find that herding occurs in the US market during the crisis. The contrasting results obtained may be due to the difference in sample sizes and time horizons. From the developing market's perspective, our results are similar to those obtained by Economou, et al., (2011) for the Spanish and Italian stock markets. They find that these markets did not herd during the GFC and further explain that these returns anti-herd, that is, diverge from market returns. Furthermore, our results are inconsistent with those obtained by Mobarek, et al., (2015), who report evidence of herd behaviour in France, Italy, Spain and the Nordic market during the GFC period. In addition, our results are different from the evidence provided by Guney, et al., (2017), who find herding occurred in most of the markets examined, during and after the crisis.

Table 4.12 Regression estimates for market herd behaviour for the Global Financial Crisis, US

Period	α	γ_1	γ_2	Adj. R^2
Pre- crisis	0.0086	0.3036	-3.5040	19.52%
	(61.27) ***	(8.99) ***	(-2.27) **	
Crisis	0.0125	0.3888	-0.7204	50.49%
	(22.23) ***	(8.86) ***	(-1.32)	
Post-crisis	0.0078	0.2299	1.4306	35.77%
	(64.79) ***	(13.20) ***	(3.53) ***	

Note: Table 4.12 reports the estimates from the following equation:

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

where $R_{m,t}$is the cross-sectional average of sector returns in at time t, the squared sector returns $R_{m,t}^2$ is used to capture the nonlinearity in the relationship, $CSAD_t$ is the cross-sectional absolute deviation of returns for the sector, α is the constant, γ_1, and γ_2 are coefficients, and ε_t is the error term at time t. The model is run for the separately for the pre-crisis, crisis and post-crisis periods. Pre-crisis refers to the period between 01/05/2002 and 31/07/2007. Crisis refers to the period between 01/08/2007 and 30/03/2009. Post crisis refers to the period between 01/04/2009 and 11/10/2016. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. *******, ****** and ***** represent statistical significance at the 1%, 5%, and 10% level, respectively.

4.5.4.2.2. Results for sectors

The results presented in Table 4.13 corresponds to the base model in Equation (4). The results are estimated for each sector for the three sub-sample periods. The results from the pre-crisis phase show significantly negative γ_3 coefficients for the Financials, Food and Beverage, Healthcare, Industrial Goods, Oil and Gas, Personal and Holding, Retail, Technology sectors. The presence of herding in these sectors may be due to optimistic investors investing in these sectors in a herd-like manner. This optimism may have been in response to the prevailing low interest rates following the Dot com bubble. Optimism may have also made investors exhibit overconfidence bias regarding the expected value of stocks in these sectors. With the US having the largest and most liquid financial market in the world, we note that herding took place in the high-growth Financials sector. This herding may have been attributed to the increased lending by banks, thus increasing the attractiveness of the sector resulting in investors herding towards the Financials sector.

During the crisis phase, the coefficients are negative and significant for the following sectors: Healthcare, Industrial Goods, Oil and Gas, Technology and Utilities. This suggests that the outbreak of the crisis promoted herding towards these sectors. A possible explanation for herding during this period is that investors may have reacted emotionally amidst the uncertainty such that their investment decision making was affected by the availability heuristics and thus used immediate examples when evaluating investment decisions. Our results are different from that of BenSaida (2017), who finds activities herding in 10 out of 12 sectors of all domestic US firms during the GFC. The difference in results may be due to difference in sample size and specification of crisis period.

For post crisis results we report negative significant coefficients in the following sectors: Healthcare, Oil and Gas. From these results, we find that herd behaviour manifested pre, during and post the crisis in Healthcare, Technology and Oil and Gas. This implies that there is a decrease of the returns in these sectors relative to the market return with or without crisis conditions. Furthermore, there is limited evidence for H4 that herding effect is stronger across sectors during the GFC. Consistent with the results for the overall market, the results for the sectors indicates that there is limited evidence of herding activities during the GFC.

Table 4.13 Regression estimates for industry herd behaviour for the Global Financial Crisis, US

	Pre-crisis				Crisis				Post-crisis			
Industry	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj. R^2
Automobile	0.0081	0.2253	3.0540	17.18%	0.0116	0.3196	0.2781	33.76%	0.0063	0.2255	0.7910	27.64%
	(25.31) ***	(4.62) ***	(2.19) **		(11.32) ***	(4.84) ***	(0.38)		(32.52) ***	(10.74) ***	(2.09) ***	
Banks	0.0038	0.1604	-0.5860	17.67%	0.0099	0.2522	0.4850	48.42%	0.0043	0.2308	0.4625	44.07%
	(39.40) ***	(8.91) ***	(-1.00)		(8.28) ***	(5.50) ***	(1.75) *		(25.34) ***	(18.01) ***	(4.05) ***	
Basic Resources	0.0074	0.2373	-0.7551	13.47%	0.0119	0.2510	-0.2182	23.98%	0.0076	0.1998	2.1298	25.95%
	(25.44) ***	(6.07) ***	(-0.74)		(11.33) ***	(4.59) ***	(-0.49)		(27.98) ***	(7.17) ***	(4.20) ***	
Chemicals	0.0062	0.1750	0.2500	11.47%	0.0100	0.1818	0.9508	35.21%	0.0059	0.2104	-0.3651	23.05%
	(33.47) ***	(4.89) ***	(0.19)		(14.11) ***	(3.89) ***	(1.95) *		(43.16) ***	(12.00) ***	(-0.93)	
Construction	0.0072	0.2090	1.7690	14.01%	0.0125	0.1685	1.0679	33.01%	0.0065	0.2156	0.4286	21.80%
	(24.86) ***	(4.50) ***	(1.23)		(15.91) ***	(3.34) ***	(1.87) *		(33.96) ***	(9.88) ***	(0.96)	
Financials	0.0072	0.2564	-1.6799	20.19%	0.0136	0.2089	0.4096	38.00%	0.0058	0.2208	0.5727	37.61%
	(43.81) ***	(8.87) ***	(-1.80) **		(16.45) ***	(4.98) ***	(1.17)		(42.62) ***	(16.00) ***	(2.79) ***	
Food & Beverage	0.0064	0.4251	-7.5557	16.08%	0.0095	0.3242	-0.5159	33.05%	0.0057	0.1896	1.6922	17.41%
	(36.84) ***	(8.60) ***	(-2.77) ***		(19.49) ***	(6.40) ***	(-0.60)		(48.06) ***	(7.79) ***	(1.86) *	
Healthcare	0.0086	0.3874	-4.2881	18.45%	0.0106	0.3156	-1.0218	32.52%	0.0071	0.2544	-2.2000	17.33%
	(43.58) ***	(8.85) ***	(-2.24) **		(23.48) ***	(7.67) ***	(-1.82) *		(58.85) ***	(12.65) ***	(-3.65) ***	
Industrial Goods	0.0072	0.2639	-2.9762	17.55%	0.0096	0.2727	-0.9262	35.53%	0.0058	0.1863	0.2745	29.36%
	(51.16) ***	(8.73) ***	(-2.37) **		(21.65) ***	(7.46) ***	(-1.84) *		(57.82) ***	(12.80) ***	(0.79)	
Insurance	0.0055	0.1338	6.2956	37.34%	0.0076	0.4968	0.2674	65.87%	0.0047	0.2014	2.8159	52.77%
	(40.92) ***	(5.14) ***	(7.86) ***		(8.02) ***	(9.41) ***	(0.61)		(30.73) ***	(12.36) ***	(12.40) ***	
Media	0.0060	0.2158	0.7510	20.25%	0.0091	0.2394	0.5164	37.99%	0.0063	0.1770	1.7969	29.41%
	(37.56) ***	(7.16) ***	(0.77)		(13.94) ***	(5.23) ***	(1.03)		(42.36) ***	(9.05) ***	(4.28) ***	

Oil & Gas	0.0070	0.1812	-1.9791	14.38%	0.0105	0.1973	-0.3707	42.88%	0.0077	0.2238	-0.5963	25.84%
	(44.76) ***	(8.08) ***	(-3.08) ***		(23.30) ***	(9.05) ***	(-2.36) **		(47.79) ***	(12.77) ***	(-1.77) *	
Personal & Household	0.0075	0.3388	-3.3771	19.37%	0.0112	0.4026	-1.3450	40.57%	0.0070	0.2762	1.0105	35.65%
	(43.28) ***	(8.54) ***	(-1.95) *		(18.03) ***	(7.67) ***	(-1.69) *		(50.81) ***	(14.23) ***	(2.23) **	
Real Estate	0.0061	0.2185	-0.8125	15.36%	0.0082	0.3504	-0.2508	56.07%	0.0048	0.2516	0.2680	47.47%
	(35.39) ***	(6.49***)	(-0.65)		(10.57) ***	(9.99) ***	(-0.98)		(38.11) ***	(20.33) ***	(1.82) *	
Retail	0.0083	0.2815	-3.1914	15.12%	0.0111	0.2973	-0.7919	34.76%	0.0074	0.2478	-0.2187	22.61%
	(49.40) ***	(8.77) ***	(-2.70) **		(20.70) ***	(7.30) ***	(-1.40)		(56.53) ***	(11.86) ***	(-0.38)	
Technology	0.0098	0.3317	-2.7780	23.05%	0.0122	0.2577	-1.0071	26.60%	0.0079	0.2135	-0.9884	19.21%
	(43.92) ***	(9.90) ***	(-2.98) ***		(23.04) ***	(6.54) ***	(-1.94) *		(58.75) ***	(11.25) ***	(-2.09) **	
Telecom	0.0063	0.5534	4.2335	42.02%	0.0084	0.6220	-0.3325	44.57%	0.0058	0.4764	5.4390	43.15%
	(19.69) ***	(10.93) ***	(2.82) ***		(6.61) ***	(6.85) ***	(-0.30)		(23.54) ***	(13.01) ***	(5.54) ***	
Travel & Leisure	0.0088	0.2401	1.8279	16.60%	0.0143	0.3311	-0.0057	34.34%	0.0081	0.2816	0.0204	28.26%
	(34.05) ***	(5.73) ***	(1.42)		(13.99) ***	(5.14) ***	(-0.01)		(43.41) ***	(13.15) ***	(0.05)	
Utilities	0.0081	0.2666	1.4262	17.45%	0.0092	0.4786	-1.3438	48.75%	0.0068	0.2230	-0.7262	11.99%
	(39.62) ***	(6.20) ***	(0.88)		(17.63) ***	(10.56) ***	(-2.43) **		(47.22) ***	(8.41) ***	(-0.80)	

Notes: Table 4.13 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 \, R^2_{m,t} + \varepsilon_t$$

where $R_{m,t}$ is the cross-sectional average of sector returns in at time t for each sector, the squared sector return $R^2_{m,t}$ is used to capture the nonlinearity in the relationship, $CSAD_t$ is the cross-sectional absolute deviation of returns for the sectors, α is the constant, γ_1, and γ_2 are coefficients, and ε_t is the error term at time t. The model is run for the separately for the pre-crisis, crisis and post-crisis periods. Pre-crisis refers to the period between 01/01/2003 and 09/10/2007. Crisis refers to the period between 10/10/2007 and 06/03/2009. Post crisis refers to the period between 09/03/2009 and 11/10/2016. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. The t-test statistic tests for the difference in level of significance between the γ_1 and γ_2 coefficient. *******, ****** and ***** represent statistical significance at the 1%, 5%, and 10% level, respectively.

4.6. Conclusions

This chapter investigates the impact of market conditions on industry herd behaviour by testing for its presence in the US stock market from January 1990 to October 2016. We use firm level data from the S&P 500 classified into 19 different sectors. We examine whether or not herd behaviour is contingent upon high (low) market return, days with high (low) volatility and trading volume. We also investigate the impact of two crises which originated from the US, the Dot Com bubble and the GFC on herding.

We test for herding using the widely used CSAD measure which is based on the intuition that in the presence of herding there is a decrease in the CSAD during periods of extreme market movements. As illustrated in Table 4.14 results show that market wide herding is absent in the US market. However, limited evidence of herding becomes visible at the sector level, especially in the Healthcare, Industrial Goods and Oil and Gas sectors. When we closely investigate this evidence, we find weak evidence of herding asymmetry with respect to up and down-market conditions. Further, we find evidence that herding is more significant on days with low trading and low volatility. We also report weak evidence that herding is prevalent during days with low trading volume.

When we examine the effect of the Dot com bubble on herding and we find that the US herds during the pre-bubble and bubble periods, however herding is manifested in various sectors during and after the bubble. During the GFC crisis we find that the US market only herds during the pre-crisis period, although herding is present across sectors during and after the GFC.

Our findings have important implications for US financial market investors and stock market regulatory authorities. From the investors' perspective, it is important to know the impact of industry herding as it could potentially affect their investment strategies, especially those interested in investing in specific sectors. For the regulatory authorities, our evidence suggests that it would be useful to encourage investors to diversify their sector investments. Regulatory authorities can achieve this by providing information on the correlations of different markets and sectors to the public. As this information can potentially inform the investors' investment decisions.

We suggest some issues that future studies can examine. First, we employ the CSAD model to measure herding. It would be interesting to see whether other models like CAMP-based models produce similar results especially at the sector level. Second, we find that herding is prevalent in the Healthcare and Oil and Gas sectors respectively. Future studies can conduct an in-depth investigation on these sectors to provide empirical evidence on the sub-sectors that herd in these sectors. Third, we use the S&P 500 index as a proxy for the US market, future studies can provide recent evidence using all data from all the listed firms in the US market. Finally, it would be interesting to examine cross-sector herding interactions.

Table 4.14 Summary of US Results

Test	Market findings	Industry findings
Herding	No	Yes (Healthcare, Industrial Goods, Oil & Gas, Retail and Technology)
Market Returns	No	Up days(Chemicals, Healthcare, Industrial Goods, Oil & Gas and Technology) Down days (Basic Resources, Food & Beverage, Healthcare, Industrial Goods and Retail)
Trading Volume	No	High (Oil & Gas) Low (Healthcare, Industrial Goods, Oil & Gas, Retail and Technology)
Volatility	Only in low volatility	High(Healthcare, Industrial goods and Oil and Gas) Low(all except: Automobile, Bank, Construction, Insurance, Real Estate, Travel and Leisure and Utility)
Crisis: Dot com bubble	Pre-bubble and post-bubble	Pre-bubble (Healthcare, Industrial Goods, Oil and Gas, Technology, and Chemicals) Bubble (Chemicals, Healthcare, Financials, Media, Oil and Gas, Personal and Household and Retail) Post-bubble (Automobile, Banks, Chemicals, Healthcare, Insurance and Technology)
GFC	Only pre-crisis	Pre-crisis (Financials, Food and Beverage, Healthcare, Industrial Goods, Oil and Gas, Personal and Holding, Retail, Technology) Crisis (Healthcare, Industrial Goods, Oil and Gas, Technology and Utilities) Post-crisis (Healthcare, Oil and Gas)

Chapter 5 Herding and its determinant in the Chinese stock markets: A sectoral analysis

5.1 Introduction

Chinese markets provide an interesting setting for investigating herding due to its unique segmented structure, where two different classes of shares are traded simultaneously. Given that the Chinese market has also been associated with a lack of transparency and frequent government intervention, it is important to understand the behaviour of investors.

Consequently, various studies have investigated the existence of herd behaviour in the Chinese market (Tan, et al., 2008; Lao and Singh, 2011; Yao, et al., 2014; and Luo and Schinckus, 2015), with few studies at the sector level (Demirer and Kutan, 2006; Lee, et al., 2013; and Zheng, et al., 2017). In general, these studies provide evidence of herding towards the market consensus. The research by Tan, et al., (2008) is closely related to ours, however, they only focused on the market, not sectors. Therefore, this study aims to bridge this gap in the literature by investigating herding asymmetry at both market and sector levels.

Using the Cross-Sectional Absolute Deviation model developed by Chang, et al., (2000), we conduct our research on the sample of all firms listed on the Shenzhen and Shanghai exchanges from January 1990 to October 2016, classified into 19 sectors. We investigate the presence of herding when market returns are rising (declining), market volatility and trading volume are high (low). The rationale behind this investigation is that the conditions in the market may not be like sector conditions, which has been confirmed by the evidence provided by Yao, et al., (2014) that herding is more prevalent at the industry level in the Chinese market. To further test the strength of our results, we examine the effect of crises on market (sector) herding. We select two recent major crises: the Asian crisis and the Global Financial Crisis. Also, we investigate the impact of the US market (sector) returns on herding in Chinese markets (sectors). The rationale for this is due to the strong trade relationship between the US and China as well as the empirical evidence by Chiang and Zheng (2010) that the US returns plays a role in herding in China.

Overall, our results indicate that investors in Chinese markets significantly herd at the market level and sector level, with herding more prevalent in the Shenzhen stock exchange. The other findings are discussed in section 4.5. The remainder of this chapter is organised as follows. The next section reviews literature and empirical evidence of herding. Section 3 describes the research methodology and design. Section 4 reports and discusses the results, and section 5 concludes.

5.2 Contextual Framework – Chinese Stock Market

5.2.1 The Chinese stock market: structure and characteristics

5.2.1.1 Stock market structure

Stock trading in China dates to the 18th century, however, the two official stock exchanges: Shenzhen Stock Exchange (SZSE) and Shanghai Stock Exchange (SHSE), were only established in 1990. Based on market capitalisation, the SZSE and the SHSE rank 8th and 4th in the world, respectively[48]. Figure 1 illustrates the exponential growth in the market between 1991 and 2016. Combined, both markets have grown to become the second largest stock markets in the world by market capitalisation, with over 3,400 listed firms and $8.5 trillion market capitalisation as at 2017 (Carpenter and Whitelaw, 2017). According to the World Federation Exchanges statistics for 2017, the Chinese market has the highest trading volume, globally. The SZSE and SHSE combined have a trading volume of approximately $5.4 trillion compared to the approximately $2.9 trillion for the NYSE and NASDAQ.

[48] Rankings as of April 2018, obtained from The World Federation of Exchanges

Industries in China have also experienced rapid expansion, which has been supported by its high savings, investment and export-oriented culture (Lee and McKibbin, 2018). As at 2013, the industrial sector, which consists of manufacturing, construction, public utilities and mining accounts for about 27% of China's Gross Domestic Product (GDP) (World Bank National Accounts Data, 2017). In fact, by 2010 China became the largest manufacturing country in the world (Nagaraj, 2017). As illustrated in Figures 2 and 3, the manufacturing industry is the major industry in both exchanges.

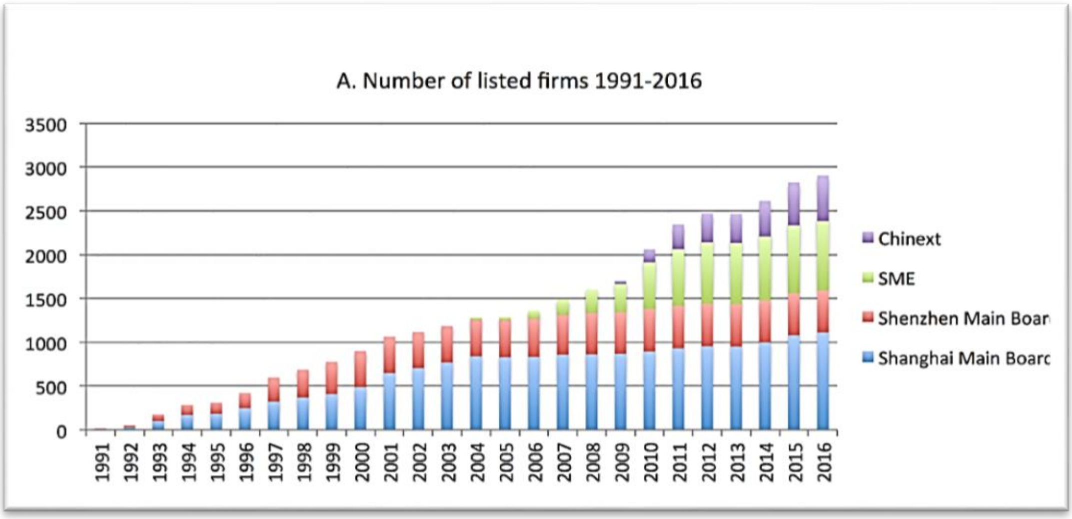

Figure 5.1 Number of Listed Firms on the Chinese Stock Exchanges (Carpenter & Whitelaw, 2017)

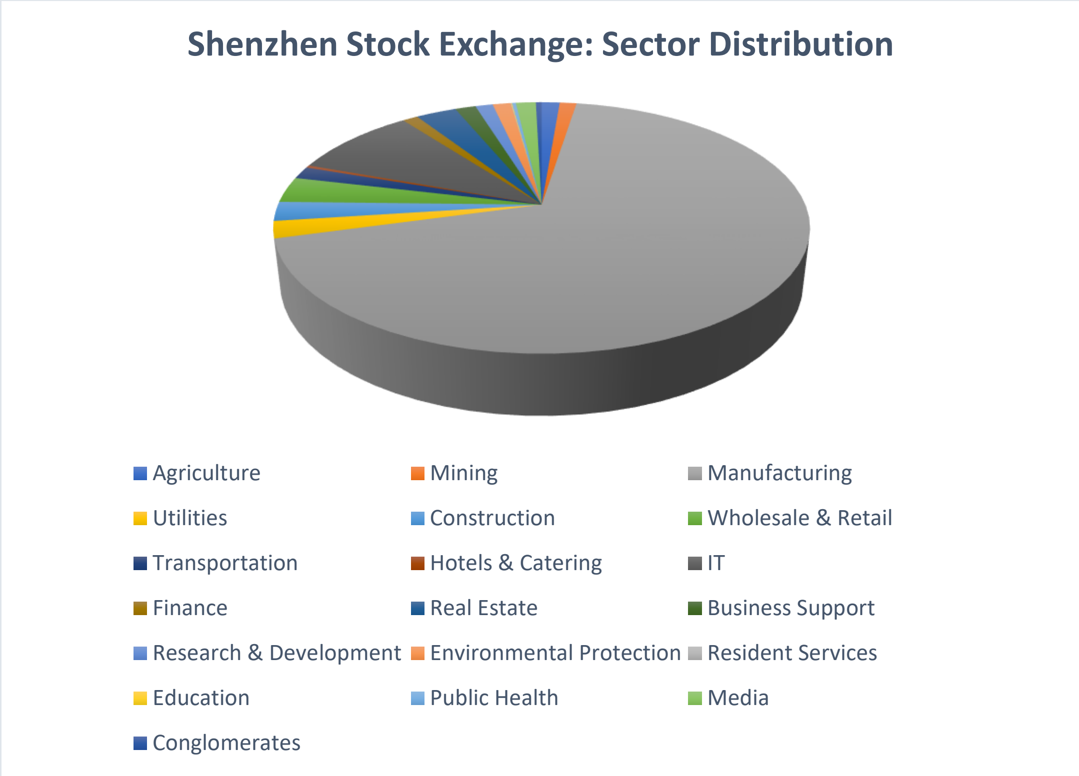

Figure 5.2 Shenzhen Stock Exchange: Sector Distribution (2017) [49]

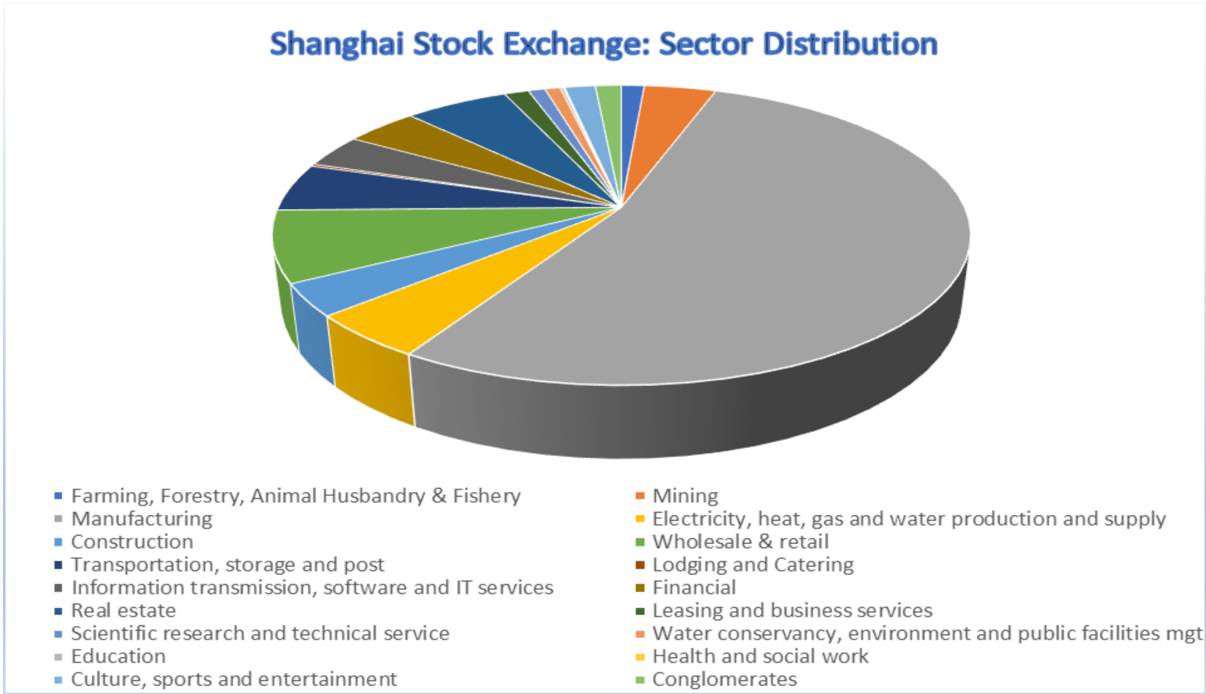

Figure 5.3 Shanghai Stock Exchange: Sector Distribution (2017) *50*

[49] Source: 2017 Shenzhen Stock Exchange Factbook
[50] Source: 2017 Shanghai Stock Exchange Factbook

There are two different classes of shares traded on either the Shenzhen or Shanghai exchanges. A-shares which are dominated by domestic investors and denominated in the local currency, Renminbi (RMB). The B-share market which was only open to foreign investors until 2001 is now dominated by foreign and domestic investors; denominated in US dollars (Shanghai) and Hong Kong dollars (Shenzhen).

5.2.1.2 Market Characteristics

Shenzhen and Shanghai exchanges have different characteristics. Regarding market size, Shenzhen is smaller than the Shanghai (in 2016 the market capitalisation for the Shenzhen and Shanghai market was $3.2 trillion and $4.1 trillion, respectively[51]). Regarding trading volume, as at 2018, the trading volume for Shenzhen stock exchange was reported at approximately 15 trillion Renminbi, while the trading volume for Shanghai stock exchange was reported at approximately 40 trillion Renminbi.

The size of firms in both exchanges is also different. The Shenzhen market consists of small to medium-sized firms, in contrast, the Shanghai market consists of large, state-owned firms. Consequently, the Shenzhen market is dominated by less educated investors and is less influenced by the government, as opposed to the Shanghai market which is deemed to have more sophisticated investors and receives more investment from the government (Demirer and Kutan, 2006). Researchers have also documented differences between both markets (see for example Sjoo and Zhang, 2000 and Wang, Kutan and Yang, 2005). One of such differences is the information asymmetry between both exchanges. Sjoo and Zhang (2000) provide evidence that for the Shenzhen market, information flows from domestic to foreign investors. Furthermore, Wang et al., (2005) find both the Shenzhen and Shanghai exchanges exhibit significant sector information flows which extend to the market level.

[51] 2016 Shenzhen and Shanghai Stock Exchange Factbooks

In general, developing markets including China have strengths and weaknesses that are significantly different from those of advanced markets. Some of the strengths possessed by these markets that contribute to economic growth include a large labour force, a good saving culture, the growth in middle-class citizens and government support (Lao and Singh, 2011).

Despite these strengths, developing markets have been plagued by inefficiencies and anomalies (Li, 2008). These inefficiencies may be due to the dominance of less educated retail investors, government dominance, lack of transparency and poor quality of financial reporting (Demirer and Kutan, 2006). Demirer and Kutan (2006) argue that the financial reporting requirements for listed companies in China are not as comprehensive and stringent as that for advanced countries. Moreover, the appointment of some managing directors of state-owned firms by the Chinese government has also been widely criticised (Liu and Lu, 2007). The government appoints these managing directors because they are the controlling shareholders. However, this control increases the likelihood of channelling resources from the firms for their benefit (Liu and Lu, 2007).

In response to these weaknesses, the Chinese government has launched various reforms to improve the efficiency of the stock market (for example, 1997, 1998, 2001, 2004 and 2008 reforms[52]). These reforms focused on different aspects of the market ranging from increasing investor protection to strengthening corporate governance (Liu and Wang, 2017). Academic research has provided conflicting evidence of the impact of these reforms on market efficiency. While Chong, Lam and Yan (2012) examine the profitability of trading strategies and find that market efficiency has improved since the 2005 state share reform, Carpenter, Lu and Whitelaw (2014) argue that the Chinese market exhibits anomalies. Despite the

[52] These reforms are carried out by the Chinese government (Li, 2012)

conflicting evidence, the reforms are a welcome development. There are other unique characteristics of Chinese investors which are discussed in the next section.

5.2.2 Characteristics of Chinese Investors

Chinese investors are the most ambitious, optimistic and aggressive investors in the world, according to a recent Legg Mason Global Investment survey[53]. In fact, they expect to receive a 97% rate of return on their investment in 2018. Interestingly, Mei, Scheinkman and Wei (2005) argue that the overconfidence of the Chinese investors is due to the lack of trading experience.

The Chinese market consists of individual and institutional investors. Individual investors who dominate the market account for an estimated 80% of the markets' trading volume[54], they are commonly classified as being less experienced and less informed than institutional investors. Institutional investors in China consist of mutual funds, insurance companies and authorised securities firms. As of 2012, institutional investors accounted for 17.40% of Chinese investors[55], a small percentage compared to individual investors. However, between 2004 and 2011 the percentage of tradeable assets held by institutional investors has increased from 25 per cent to 44 per cent (Deng and Xu, 2011).

Academic research on the impact of these institutional investors reveal, interesting findings. Notably, in their study, Tian, Wu and Wu (2018) find that institutional investors on the SHSE buy significantly more stocks that individual investors during extreme market swings, thus may contribute to the destabilisation of the market during such periods. Institutional investors also engage in trend-chasing in rising market conditions, potentially driving prices

[53] According to the 2017 Legg Mason Global Investment Survey based on sample size 4,500 investors from Asia (Hong Kong, Singapore, Japan, Taiwan and China)
[54]According to the China Securities Regulatory Commission

[55] sse.com.cn

away from their fundamental values. Other researchers investigate the behaviour dynamics of Chinese investors and provide insights on different factors that influence this behaviour.

Using a survey of 1,547 individual investors, Wang, Shi and Fan (2006) show that Chinese investors engage in speculation, underestimate risks and exhibit poor investment skills. Also, institutional information such as market policy greatly influences investment decisions stemming from the collectivism culture in China.

Chen, Kim, Nofsinger and Rui (2007) examine decision making in the Chinese stock market using data from brokerage accounts. They find that Chinese investors exhibit three behavioural biases: (i) disposition effect whereby they sell winning stocks but not losing stocks, (ii) they may be overconfident, and consequently trade very often, (iii) representative bias, they believe that future returns are based on past returns. However, they contend that experienced investors are less likely to exhibit these biases.

Li, Rhee and Wang (2017) investigate the difference between institutional and individual investors in herding with a measure based on trading volume. They provide evidence that while institutional investors are more prudent about their investments, individual investors allocate their trade evenly. Also, they provide evidence that individual investors significantly depend on public information and are consequently affected by market sentiment. They note that regardless of their differences, both types of investors glean information from each other's trade.

The collective oriented culture in developing markets has also been highlighted as a contributing factor to market inefficiency (Chang and Lin, 2015). With the presence of this culture, it is easy for investors to engage in collective behaviour such as herding. Indeed, Chang and Lin (2015) report that the Confucian culture (a cornerstone of Chinese culture) influences herding in the Chinese market. This culture promotes behavioural norms such as collectivism, low individualism and uncertainty avoidance. Therefore, these characteristics increase investors' tendency to herd.

With the increase in internet use, more Chinese investors obtain investment information from social trading sites like imaibo.net and xueqiu.com. (Tham, 2016). The author argues that dependence on these sites aggravates herding because these sites study the actions of informed investors. Furthermore, Tham (2016) associates the swings in the Shanghai market that occurred in 2014/15 to the index sensitivity to blog sentiments.

Chong, Liu and Zhu (2017) examine the underlying motives of herd behaviour in the Chinese market, using the CSAD model. They find that the following factors motivate herding: (i) the number of analysts following: Higher levels of herding are observed when followings are above the median, (ii) speculation, (iii) the riskiness of the stock, (iv) companies with high turnover ratio.

5.3. Hypothesis Development

5.3.1. Industry Herding

Most studies on herd behaviour in the Chinese market find evidence in support of herding (Tan, et al., 2008, Lao and Singh, 2011 and Lee, et al., 2013). Indeed, Demirer and Kutan (2006) suggest that herding is more likely to occur in the non-financial sectors dominated by retail investors than in financial sectors dominated by institutional investors. Literature has shown that investors tend to herd in and out of industries (see for example Choi and Sias (2004) and Gebka and Wohar (2013)) for several reasons. One, investors may be motivated to herd due to overconfidence bias (propounded by Daniel, et al., (1998)). Two, investors may keep investing in an industry where they have obtained a positive return because they believe they possess superior stock picking skills, which leads them to take more risks.

Industry herding can also be driven by the representative heuristic and conversavatism bias (presented by Kahneman & Tversky (1972)). This is because an investor may prefer to invest in an industry that had abnormally high prior returns (that they extrapolate the retuns for the whole industry), which destabilses stock prices. Thus, investors can collectively react favourably to positive information about a particular industry. Consistent with the above expectations, we predict that there is herding in the chinese market.

H1. There is herding effect in the Chinese market and industry.

5.3.2. Determinants of Industry Herding

5.3.2.1. Market/sector return:

Investors have a propensity to herd when market returns are declining because such periods are marked by increased uncertainty relating to investment profitability. Lao and Singh (2011) find that Chinese investors herd more when the market is declining. They suggest that a possible explanation of the observed herding from a behavioural finance perspective is loss aversion; losses have greater emotional impact than gain, and thus people select options where gains are probable (Tversky and Kahneman, 1986). Because the Chinese market is dominated by individual investors who are deemed to be inexperienced and less informed than their institutional peers, they tend to herd more when the market is declining to avoid the pain of making losses.

Periods of rising market return can also prompt investors to herd. Indeed, Tan, et al., (2008), Chiang, et al., (2010) and Chiang, et al., (2013) provide evidence that herding is stronger in the Chinese when the market is rising. Chiang, et al., (2013) suggest that herding is stronger when the market is rising because investors focus more on large stocks as they herd. Large stocks are traded more frequently and receive high levels of analyst coverage. As a result, individual investors in the Chinese market who typically lack investment expertise and frequently follow analyst recommendations, tend to follow the market consensus in their trades. In addition, Tan, et al., (2008), explain that this herding might be a consequence of government intervention, where investors in stocks owned by companies financed by the government are more likely to herd in rising markets due to optimism and overconfidence. Based on these studies, we predict that there is a relationship between herding and market returns with differences in behaviour in periods rising and declining returns. This prediction is specified in the following hypothesis:

H2a: Industry herding is contingent upon market/sector returns

5.3.2.2. Market/sector volatility:

There is a probable relationship between herd behaviour and stock return volatility (Tan, et al., 2008). Tan, et al., (2008) provide evidence that herding is prevalent in the Chinese market during periods of high volatility. Similarly, Javaira and Hassan (2011) find that the Pakistani investors herd during periods of high volatility. Gavriilidis, et al., (2013) argue that herding can occur in either low or high volatility conditions. Periods of increasing volatility may create an environment with increased information flow where less skilled managers prefer to mimic their better-skilled peers. Furthermore, high information flow during high volatility periods may prompt investors to herd due to difficulties in information processing.

Conversely, during periods of decreasing volatility, these less skilled managers may be driven to herd because of the ease with which the trades of their better-skilled peers can be viewed. Holmes, et al., (2013) also suggest that investors are more likely to herd in periods of low volatility. Moreover, Economou, et al., (2011) document herding in low volatility periods for Italian and Portuguese markets. Consistent with these expectations, we predict that a relationship between herding and volatility with differences in behaviour in periods high and low volatility. This prediction is stated in the following hypothesis:

H2b: Industry herding is contingent upon market /sector volatility

5.3.2.3. Market/sector volume:

Tan, et al., (2008) argue that the extent of herding may be affected by trading volume. High trading volume can contribute to herding when investors trade vastly on a stock. For example, if an investor perceives that a stock is highly profitable, they would increase their investment into the stock, hence increasing its liquidity. Other investors who are uncertain about the future profitability, invest in the stock base on its liquidity neglecting their private information, leading to a herd formation. Low volume may also prompt or inhibit herding. During low volume periods, herding is less feasible because trades cannot be executed. Low volume may also boost herding if investors only trade stocks in which the low volume is concentrated at.

Evidence from the Chinese stock market reported by Tan, et al., (2008) is mixed, in high volume periods, herding is present in the Shanghai and Shenzhen A and B- share market, while for low volume periods herding is only observed in the B share market. In the same vein, Lao and Singh (2011), find that investors in Shanghai A-share market herd during high volume conditions. They explain that due to the collective nature of the Chinese culture, they may be lured to mimic other investors with similar investment objectives to trade more actively. They suggest that high trading volume may be indicative of the presence of herd behavior. Interestingly, Yao et al., (2014) report that the Shanghai B-market herds in both high and low volume states. Consistent with these expectations, we predict that there is a relationship between herding and volume with differences in behaviour in periods high and low volume. This prediction is stated in the following hypothesis:

H2c: Industry herding depends on market/sector volume.

5.3.3. Herd behaviour in periods of crisis

The 1997 currency crisis in East Asia has been described as one of the major currency crises of the 1990s (Goldstein, 1998). It had a devastating effect on the economies of Thailand, Korea, Indonesia, Philippines and Malaysia. Bowe and Domuta (2004) investigate herding among foreign and domestic investors in the Jakarta Stock Exchange and find evidence that both herd pre, during and post-crisis. Chiang and Zheng (2010) find evidence of herd behaviour during the crisis in the all the neighbouring markets (US, Indonesia, Korea and Singapore) examined except Malaysia. Hwang and Salmon (2004) reach an opposite conclusion, they find that herding behaviour in the Korean market during the Asian crisis helped to reduce herd behaviour. China was the only country in the region that experienced growth during the crisis (Goldstein, 1998). Fernald and Babson (1999) argue that China was immune from the crisis because it had strengthened its currency through devaluation, had faster productivity, low debt, and a strong foreign reserve. However, growth in foreign trade slowed down (Kaminsky, 1999).

In fact, Zheng, et al., (2017) find herding in 8 out of 10 industries examined during crises periods in their study which includes the Asian crisis. Therefore, the hypothesis is as follows:

H3: herd behaviour changes during the Asian crisis

A decade after the asset bubble burst during the Asian crisis another bubble burst occurred in the US Real Estate sector which triggered the 2008-2009 Global Financial Crisis. Some authors suggest that the Dotcom bubble helped to create the housing bubble because after the crash investors turned to the Real Estate stocks as a secure investment alternative (Wheale and Amin, 2003; DeLong and Magin, 2006 and Goodnight and Green, 2010). Indeed, due to contagion, the crisis spread to major global markets (Corsetti, Pericoli, and Sbracia, 2005). Even the financially resilient Chinese market was not spared from the effects of the crisis mainly because of greater international integration and financial linkages via exports (Overholt, 2010). When the crisis started China experienced a sharp decline in exports, foreign companies deserted the market, and millions of workers lost their jobs (Overholt, 2010). In fact, house prices fell for the first time since 2005 and this provides a strong case for investigating the impact of the crisis on herding in the Chinese markets. Lao and Singh (2011) state that crisis reduced confidence level of Chinese investors, its market declined by 65.14%[56]. Chiang and Zheng (2010), document evidence of herding in the Chinese market during the GFC. Consistent with these studies, we predict that herding changes during the GFC, which is specified in the following hypothesis:

H4: herd behaviour changes during the GFC period.

5.3.4. The role of the US market in herding in China

Chiang and Zheng (2010) argue that the US market plays a significant role in global markets. The US has a close relationship with global markets especially China (Wei, 1996)[57]. The US-China relationship has been described as the greatest tie between an advanced country and an emerging country (Autor, Dorn and Hanson, 2013). Trade relations between both countries have increased over the years, the total share of US spending on Chinese goods increased from 0.6 per cent in 1990 to 4.6 per cent in 2007 and has even created trade frictions between both countries (Autor, et al., 2013). According to data from the Department of Commerce on the industry sector relations between both countries, while the US exports 40 percent of its agricultural pesticides to China, it imports 75 percent of its dolls from China. Financial investment relationship between both countries has also grown with more US companies investing in China after the 2005 reforms (Carpenter and Whitelaw, 2017). As a result of this relationship, it is expected that the US market plays a role in herding in the

[56] Source: Bloomberg Financial, 2009

[57] Wei, S. J. (1996). Foreign direct investment in China: sources and consequences. In Financial Deregulation and Integration in East Asia, NBER-EASE Volume 5 (pp. 77-105). University of Chicago Press.

Chinese market. Chiang and Zheng (2010) and Luo and Schinckus (2015) and Li, et al., (2017)[58] provide evidence that herding in the Chinese market is influenced by the US. Consistent with these studies, we expect the US to influence herding in China and specify the following hypothesis:

H5: US returns impact herding in the Chinese markets (sectors)

5.4. Research Methodology

5.4.1. Data

The data which are obtained from Thomson Datastream consist of daily closing prices, the trading volumes of all firms listed on the Shenzhen and Shanghai Stock Exchanges. In line with Chiang and Zheng (2010) who suggest that US returns play a role in herding in the Chinese markets, we also collect data on the US market. As the Chinese market is young when compared to other developed markets, daily updated data are used to ensure that firms that have not been listed for the entire sample period are not excluded.

The data covers the period 01/01/1990 to 18/10/2016, from the inception of the stock exchanges and includes two periods of significant volatility in the Chinese markets: the Asian crisis and GFC. To carry out our analysis, we isolate periods before and after the Asian crisis spanning from January 1993 to September 2001. The choice of this period reflects significant dates from previous studies (For example, Bowe and Domuta, 2004). On this basis, we divide our sub-sample into three sub-periods:

a) January 01, 1993- July 01, 1997: pre-crisis period. This period coincides with the period when East Asian countries were regarded as miracle economies and saw increased investment because of investor confidence.

[58]This finding was only for data before 2015

b) July 02, 1997 – December 30, 1997: crisis period. On July 02, 1997, Thailand devalued its currency relative to the dollar due to speculative pressures and marked the beginning of the crisis. In subsequent months the currencies of Malaysia, Indonesia, Philippines, Korea and Hong Kong weakened. In December 1997, the International Monetary Fund (IMF) and World Bank approved bailouts for South Korea. The IMF started a process of strengthening financial systems of the affected economies. In this context, we chose December 30, 1997, as the end of the crisis.

c) January 01, 1998- September 10, 2001: post-crisis period: The months that followed the bailouts and reforms saw the crisis contained and subsequent recovery in the stock markets.

If herding changes following these periods, we expect to find differences in herd behaviour pre, during and post-crisis. The sample will be subdivided into pre-crisis, crisis and post-crisis periods to compare herd behaviour during the financial crisis and normal periods.

Similar to the Asian crisis, we examine herding pre, during and post GFC. Similar to the previous chapter we examine the crisis in three phases: pre-crisis phase (01/05/2002 to 31/07/2007), crisis phase (01/08/2007 to 30/03/2009, and the post-crisis phase (01/04/2009 to 18/10/2016). If herding changes following these periods, we expect to find differences in herd behaviour pre, during and post-crisis. The inclusion of these crises periods is in line with previous studies which provide evidence that herding behaviour is more plausible during periods of extreme market movement.

The final dataset includes 13,986 daily observations, for both stock exchanges. The sample contains 1,481 Shenzhen firms and 978 Shanghai firms. The daily log differenced returns $R_{i,t}$ are calculated as:

$$R_{i.t} = ln\left(\frac{P_{i,t}}{p_{i,t-1}}\right) \times 100$$

Where, $p_{i,t}$ is the stock price on firm i at time t. All prices are denominated in the Chinese local currency, Renminbi.

Within each stock exchange the firms are classified into 19 sectors based on Thomson's Datastream classification: Automobile, Banks, Basic Resources, Chemicals, Construction, Consumer Services, Financials, Healthcare, Industrial Goods, Insurance, Media, Personal & Household, Real Estate, Retail, Travel and Leisure, Oil and Gas, Utilities, Telecommunications, and Technology.

5.4.2. Model Specification

To test, the first hypothesis (H1), we employ the CSAD model of Chang, et al., (2000) which is widely used to test for herding towards market consensus.

We measure the CSAD as follows:

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

Where $R_{i,t}$ is the log differenced return on stock i at time t, N is the number of stocks the market and $R_{m,t}$ is the cross-sectional average of market returns at time t.

The model for testing herding is estimated as follows:

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

where $\left| R_{m,t} \right|$ is the market (sector) return used to capture the nonlinearity in the relationship, $R_{m,t}^2$ is the squared market return, α is the constant, γ_1, and γ_2 are coefficients and ε_t is the error term at time t. Therefore, in the absence of herding effects, we expect $\gamma_1 > 0$ and $\gamma_2 > 0$ in equation (2).

To test hypothesis H2a, the specification of the Tan, et al., (2008) by Chiang and Zheng (2010) which is regarded as more robust is implement. To achieve this, we estimate the following model:

$$CSAD_t = \alpha + \gamma_1 D^{up}|R_{m,t}| + \gamma_2\ (1 - D^{up})|R_{m,t}| + \gamma_3\ D^{up}(R_{m.t})^2 + \gamma_4\ (1 - D^{up})(R_{m.t})^2 + \varepsilon_t \tag{3}$$

D^{up} is a dummy variable with a value of 1 for days with positive market returns and a value of 0 for days with negative market returns, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients. The coefficients of interest are γ_3 and γ_4. Therefore, in the absence of herding effects, we expect $\gamma_3 > 0$ and $\gamma_4 > 0$ in equation (3) and statistically insignificant. If herding effects are prevailing, we expect $\gamma_3 < 0$ and $\gamma_4 < 0$ and statistically significant, with $\gamma_3 < \gamma_4$ if these effects are more significant during days with positive market returns.

To test for the second hypothesis, H2b, the following model is estimated:

$$CSAD_t = \alpha + \gamma_1 D^{\sigma^2-High}\,|R_{m,t}| + \gamma_2\ \left(1 - D^{\sigma^2-High}\right)|R_{m,t}| + \gamma_3\ D^{\sigma^2-High}(R_{m.t})^2 + \gamma_4\ \left(1 - D^{\sigma^2-High}\right)(R_{m.t})^2 + \varepsilon_t \tag{4}$$

WhereD^{σ^2-High} is 1 for days with high market volatility and 0 otherwise.

Volatility is defined as high (low) if it is greater (lower) than the previous 30 day moving average. In line with Tan, et al., (2008) volatility is calculated as the square of the market return. In the absence of herding effects, we expect $\gamma_1 > 0$ and $\gamma_2 > 0$ in equation (4). If herding effects are prevailing, we expect $\gamma_3 < 0$ and $\gamma_4 < 0$ and statistically significant, with $\gamma_3 < \gamma_4$ if these effects are more evident during days with high market volatility.

To test for the third hypothesis, H2c, the following model is estimated:

$$CSAD_t = \alpha + \gamma_1 D^{vol-High}\,|R_{m,t}| + \gamma_2\ \left(1 - D^{vol-High}\right)|R_{m,t}| + \gamma_3\ D^{vol-High}(R_{m.t})^2 + \gamma_4\ \left(1 - D^{vol-High}\right)(R_{m.t})^2 + \varepsilon_t \tag{5}$$

$D^{vol-High}$ is 1 for days with a high trading volume and 0 otherwise. Trading volume is defined as high (low) if it is greater (lower) than the previous 30 day moving average.

To test for hypotheses H3 and H4, we estimate equation (2) with for each of the sub-sample periods. A cross-sectional dummy variable regression proposed by Chiang and Zheng (2010), a modification of the Chang, et al., (2000) measure, will be used to measure if herding is more apparent in periods of these crises. Therefore, if the effect of herding is more prevalent during the crisis periods then we expect $\gamma_2 < 0$ in equation (2) and statistically significant.

In order to investigate the robustness of our results, the regressions in Eqn. (2), (3), (4) and (5) are estimated in two subsamples of data. We split the whole sample into a 10-year period starting from 01/01/1996 to 18/10/2016 and a 5-year starting from 01/01/2011 to 18/10/2016. In addition, these subsamples provides insights on the time-varying nature of herding.

To test hypothesis H5, we use Eqn. (2) and include the US market (sector) returns as detailed in the equation below:

$$CSAD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 \, R_{m,t}^2 + \gamma_3 \, CSAD_{US,t} + \gamma_4 \, R_{US,m,t}^2 + \varepsilon_t \qquad (6)$$

Where $CSAD_{US,t}$ and $R_{US,m,t}^2$ are US market (sector) variables.

The equation is estimated at both market and sector levels, for the whole sample and the two sub-periods.

5.5 Results

5.5.1 Descriptive Statistics

Table 5.1 reports the descriptive statistics of average daily log differenced returns and CSAD for the market (i.e., all industries) and the 19 individual industries for the SZSE and SHSE over the full sample period. Panel A shows the daily returns and the CSAD for the SZSE. The number of firms ranges from 4 (Telecommunications) to 419 (Industrial Goods). It is not surprising that Industrial Goods has the highest number of firms since it is the largest industry in China as stated earlier. The average daily return for the market is 0.004%, with values ranging from -0.2716% to 0.2722%. The standard deviation is low at 0.0215%. The daily mean return for the individual industries ranges from and 0.0001% (Food and Beverage, Industrial Goods, Media, Oil and Gas and Retail) to 0.0027% (Automobile) with a minimum value of -1.0427% (Automobile) and a maximum of 1.2790 % (Automobile). The standard deviation of returns ranges from 0.0211% (Utilities) to 0.2521% (Technology). The low standard deviation for the Utilities sector may be due to dominance by state-owned firms and industry concentration. Most of the returns are positively skewed meaning it is more likely to observe large returns than small returns. The returns for Food and Beverage, Personal and Household and Telecommunications are negatively skewed. The observed negative skewness is consistent with the finding of Chen, Hong and Stein (2001) that skewness is most pronounced in stocks that have experienced increased trading volume compared to trends in prior periods. The kurtosis has a high value across all industries, indicating extreme volatility.

The CSAD for the market is 0.0158%, suggesting that the return of the individual sectors do not move simultaneously with the market return. The minimum and maximum range from 0.000% to 0.1022%, the standard deviation is at a low value of 0.0009%. The mean value for the CSAD for the industries ranges between 0.0021% (Banks) and 0.3096% (Food and

Beverage). This implies that the Banks behave more similarly as a group compared to other industries, which may be due to the highly regulated nature of the sector. Indeed, Brunnermeier, Sockin and Xiong (2017) suggest that the Chinese government imposes strict regulation and monitoring in the Banking sector because it plays a crucial role in the provision of finance and government planning. Note worthily, the Bank of China, China Construction Bank, Industrial and Commercial Bank of China Limited and Agricultural Bank of China are on the 2017 Financial Stability Board list of global systemically important banks.

The mean for the industries ranges from a minimum of 0.000% and a maximum of 3.4258% (Food and Beverage). The standard deviation is between a low of 0.0047% (Banks) and a high of 0.3247% (Food and Beverage). All the sector returns are positively skewed. A noteworthy statistic is the high value of the kurtosis particularly for the Travel and Leisure; this indicates that for the Shenzhen market, large shocks are likely to be present and the log returns may not be normally distributed. The high values obtained for the skewness and kurtosis is due to the presence of outliers in the data.

Panel B provides the descriptive statistics for the SHSE. The number of firms ranges from 4 (Insurance) to 241 (Industrial Goods). Mean daily return for the market is 0.0005%, with values ranging from a low of -0.1628% and 0.6082%. The standard deviation is at a low value of 0.0226%. The daily mean returns for the individual sectors ranges from -0.0008% (Insurance) to 0.0009% (Construction) with a minimum of -0.3677% (Technology) and a maximum of 1.0771% (Real Estate). The standard deviation of returns ranges from 0.0188% (Banks) to 0.2938 % (Technology). The level of CSAD for the market has a mean value of 0.0156% and ranges with a low value of 0.0000% to a high value of 0.6400%. The standard deviation is low at 0.0121%. The returns for the mean daily market return and CSAD are positively skewed, and the kurtosis values are extremely high. The kurtosis may reflect the presence of large shocks in the market.

Across the sectors, the mean value for the CSAD ranges between 0.0056% (Banks and Telecommunications) and 0.1546% (Travel and Leisure). It implies that these sectors behave more similarly as a group compared to other industries, which may be due to its highly regulated nature. The minimum and maximum values range between -2.9732% (Financials) and 2.8458% (Financials). All the CSADs are positive and therefore highly skewed. The kurtosis for Basic Resources, Industrial Goods, Personal and Household and Utilities sectors are extremely high, which may reflect the presence of large shocks in these sectors.

Our findings for the SHSE are in line with that of Lao and Singh (2011) who report a low daily CSAD mean and standard deviation for the Shanghai A-share market of 0.0156 and 0.0067, respectively. Further, our sector results are consistent with the summary statistics of Demirer and Kutan (2006), who report high volatility of daily returns and a low level of dispersion for the Finance and Insurance sector. They suggest that it implies the co-movement of its stocks which may be due to its regulated nature. Overall, our results are consistent with the empirical evidence which suggests that advanced markets such as the US have larger mean values for return dispersions than emerging markets (for example, Chang, et al., 2000 and Chiang, et al., 2010). Tan, et al., (2008) suggest that this may be due to the presence of sophisticated investors in advanced markets who have access to various sources of information and analytical tools and thus results in higher means and standard deviation. All the coefficients are estimated using Newey- West standard errors to obtain heteroscedastic and autocorrelation standard errors. In the next section, we analyse the results of the herding tests.

Table 5.1 Descriptive Statistics, China

Panel A: Shenzhen Stock Exchange

Industry	#Firms	Mean	Maximum	Minimum	Std.Dev	Skewness	Kurtosis
Daily market return							
Market (All industries)	1481	0.0004%	0.2722%	-0.1716%	0.0215%	0.3559	11.7623
Automobile	57	0.0027	1.2790	-1.0427	0.0943	4.2866	36.5085
Banks	2	0.0005	0.2263	-0.2007	0.0253	0.6958	11.3475
Basic Resources	85	0.0002	0.3319	-0.2162	0.0229	0.5660	21.6643
Chemicals	148	0.0002	0.3395	-0.2016	0.0236	0.4423	18.5427
Construction	91	0.0003	0.2836	-0.1801	0.0219	0.1833	13.5727
Financials	12	0.0004	0.3505	-0.2338	0.0268	1.1196	22.8692
Food & Beverage	83	0.0001	0.0953	-0.1077	0.0259	-0.5168	5.5637
Healthcare	112	0.0006	0.2436	-0.1986	0.0225	0.4248	13.2039
Industrial Goods	419	0.0001	0.2453	-0.1555	0.2132	0.0988	11.1931
Media	18	0.0001	0.3511	-0.2151	0.0264	0.8135	17.7743
Oil & Gas	25	0.0001	0.2578	-0.1842	0.0232	0.1429	12.7223
Personal & Household	115	0.0002	0.1522	-0.1103	0.1973	-0.1287	8.2053
Real Estate	68	0.0004	0.2889	-0.1820	0.0221	0.4679	15.7882
Retail	43	0.0001	0.3006	-0.1746	0.0230	0.2447	15.1178
Technology	142	0.0003	0.3527	-0.2017	0.2521	0.7313	17.3205
Telecommunication	4	0.0003	0.9542	-0.1059	0.0288	-0.3870	4.3574
Travel & Leisure	26	0.0002	0.3157	-0.1980	0.0237	0.3638	15.2949
Utilities	31	0.0004	0.3055	-0.1630	0.0211	0.2293	16.5600
Cross-sectional absolute deviation							
Market (All industries)		0.0158%	0.1022%	0.0009%	0.0085%	1.6101	9.2250
Automobile		0.0441	0.7640	0.0000	0.0573	4.2866	32.1514
Banks		0.0021	0.0458	0.0000	0.0047	3.4459	18.6019
Basic Resources		0.0136	0.0908	0.0000	0.0081	1.1507	8.0450
Chemicals		0.0140	0.1456	0.0000	0.0085	1.9220	22.0681
Construction		0.0152	0.1223	0.0000	0.0091	1.9959	16.0056
Financials		0.0125	0.4848	0.0000	0.0138	17.5910	25.3946
Food & Beverage		0.3096	3.4258	0.0000	0.3247	2.0567	9.9111
Healthcare		0.0140	0.1268	0.0000	0.0092	1.7519	16.2933
Industrial Goods		0.0158	0.1285	0.0000	0.0095	2.6619	22.9574
Media		0.1174	0.2556	0.0000	0.0111	2.6702	41.6646
Oil & Gas		0.0132	0.2341	0.0000	0.0108	2.5392	34.4415
Personal & Household		0.0163	0.1897	0.0000	0.0106	3.5528	36.1801
Real Estate		0.0015	0.1503	0.0000	0.0091	2.3598	23.7287
Retail		0.0001	0.1571	0.0000	0.0094	2.1775	19.7970
Technology		0.0148	0.1237	0.0000	0.0090	1.2120	9.9516
Telecommunication		0.0134	0.0641	0.0000	0.0118	1.0792	4.0422
Travel & Leisure		0.0132	0.2249	0.0000	0.0094	2.8703	46.7169
Utilities		0.1344	0.0834	0.0000	0.0081	1.3250	7.9642

Panel B: Shanghai Stock Exchange

Industry	#Firms	Mean	Maximum	Minimum	Std.Dev	Skewness	Kurtosis
Daily market return							
Market (All industries)	978	0.0005%	0.6082%	-0.1628%	0.0226%	3.2539	87.7238
Automobile	42	0.0002	0.3431	-0.1456	0.0231	0.8464	27.5101
Banks	9	0.0008	0.0971	-0.1082	0.0188	0.0943	7.5033
Basic Resources	97	0.0006	0.8050	-0.1929	0.0263	5.0306	145.6433
Chemicals	74	0.0002	0.2551	-0.1985	0.0222	0.2678	15.1184
Construction	59	0.0009	0.2971	-0.1760	0.0230	0.6507	17.4813
Financials	15	0.0002	0.3363	-0.1982	0.0252	0.7744	16.4635
Food & Beverage	52	0.0002	0.2240	-0.1269	0.0208	0.1998	12.5563
Healthcare	69	0.0007	0.2539	-0.1750	0.0213	0.2913	14.0694
Industrial Goods	214	0.0005	0.5395	-0.2185	0.2260	2.0217	61.2833
Insurance	4	-0.0008	0.0954	-0.1012	0.0245	0.0366	5.5019
Media	12	0.0002	0.2749	-0.2581	0.0251	0.1489	14.1569
Oil & Gas	11	0.0005	0.1426	-0.1056	0.0223	-0.1369	7.7698
Personal & Household	70	0.0002	0.2374	-0.1683	0.0213	0.1869	13.1935
Real Estate	69	0.0004	1.0771	-0.1786	0.0278	9.5714	361.4347
Retail	53	0.0007	0.4054	-0.1836	0.0250	2.1049	34.4499
Technology	47	0.0006	0.5108	-0.3677	0.2938	1.5591	47.1606
Telecommunication	2	0.0002	0.2632	-0.1225	0.0271	0.3253	9.8872
Travel & Leisure	29	0.0003	0.2598	-0.1116	0.0216	0.3068	12.7757
Utilities	50	0.0002	0.3431	-0.2591	0.0231	0.8464	27.5101
Cross-sectional absolute deviation							
Market (All industries)		0.0156%	0.6400%	0.0000%	0.0121%	22.1994	1068.752
Automobile		0.0136	0.3379	0.0000	0.0097	10.6658	18.5447
Banks		0.0056	0.1015	0.0000	0.0056	2.6776	26.0112
Basic Resources		0.0144	0.7658	0.0000	0.0133	27.2542	1501.434
Chemicals		0.0154	0.1421	0.0000	0.0092	2.2293	19.9751
Construction		0.0148	0.1097	0.0000	0.0091	1.5515	10.9704
Financials		0.0119	2.8458	-2.9732	0.1360	0.6797	131.6574
Food & Beverage		0.0266	0.3097	0.0000	0.0223	3.9018	30.0966
Healthcare		0.0154	0.1864	0.0000	0.0106	3.2841	27.3713
Industrial Goods		0.0157	0.6928	0.0000	0.0136	23.5613	1049.273
Insurance		0.0063	0.0440	0.0000	0.0054	1.8385	8.4817
Media		0.0127	0.0746	0.0000	0.0095	1.1055	5.5204
Oil & Gas		0.0102	0.2686	0.0000	0.0102	4.0342	83.8790
Personal & Household		0.0155	0.1592	0.0000	0.0093	2.6847	28.2714
Real Estate		0.0148	0.3815	0.0000	0.0106	13.0951	392.5501
Retail		0.0131	0.1054	0.000	0.0081	1.0133	8.1278
Technology		0.0142	0.1728	0.000	0.0104	1.9675	19.3050

Telecommunication	0.0068	0.1700	0.000	0.0109	2.6593	16.2115
Travel & Leisure	0.1546	0.1636	0.000	0.0113	2.8030	22.45311
Utilities	0.0136	0.3376	0.000	0.0097	10.6658	295.6490

Notes:
This table presents the average daily market return $R_{m,t}$ and CSAD for the market (all industries) and the 19 individual industries for the full sample period (January 1990 to October 2016). Panel A presents the statistics for SZSE while panel B presents those for SHSE. $R_{m,t}$ is defined as the average of daily returns. CSAD is defined by the measure:
$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|$
Where $R_{i,t}$ is the logged differenced return on stock i at time t and $R_{m,t}$is the cross-sectional average of market returns at time t.

5.5.2 Industry herding and its determinants

In this section, we present the results for herding at the market and sector level estimated using equations (2), (3), (4) and (5). All estimations are conducted for the SZSE and SHSE, using the full sample period (1990-2016), and two sub-periods (1996-2016 and 2011-2016).

5.5.2.1 Empirical results for market herding

In general, the results support hypothesis H1 that Chinese investors herd around the market consensus. Table 5.2 reports the results of estimating the herding regression in Eqn. (2), where a significantly negative value of γ_2 indicates the presence of herding. Looking at the overall results presented in the table, it shows that the adjusted R-squared ranges from 8% to 37.96%, suggesting that the estimated equation for each market has some explanatory power. That is, the CSADs are highly interdependent on the market return and vice versa. An analysis of the results in Panel A shows that the γ_2 coefficient is negative and statistically significant across all the periods, indicating that herding behaviour exists in the SZSE.

The estimated coefficients of γ_2 reported in Panel B for the 1990 and 2011 sub-periods are significantly negative, suggesting that the SHSE herds during these periods. However, the coefficient for the 1996 sub-period is significantly positive, indicating that investors engage in ‘negative herding’, that is, ignore and do not herd towards the market consensus. The observed herd behaviour is inconsistent with the predicted increased level of dispersion as proposed by rational asset pricing models.

The finding of significant herding across both exchanges and periods is not surprising due to information asymmetry in the two markets. A possible explanation for the observed herding may be due to the dominance by individual investors. According to research the Chinese stock market is dominated by unsophisticated retail investors (they own as high as 80% of the stocks[59]), who may have limited private information on the stocks (Demirer and Kutan, 2006). The dominance of these investors increases the tendency to mimic the trade of more informed investors by following the markets' consensus. The significant herd behaviour observed in these results is consistent with prior studies on the Chinese stock market using the CSAD model (see for example, Tan, et al., 2008; Chiang, et al., 2010; Lao and Singh, 2011; Lee, et al., 2013; Yao, et al., 2014, Luo and Schinckus, 2015 and Zheng, et., 2017).

Our results are different from those obtained by Demirer and Kutan (2006) and Fu and Lin (2010) who find no evidence of herding in the Chinese stock market. The difference in the models used may account for why we obtained different results from Demirer and Kutan's (2006) study; they use the CSSD model, but, we use the CSAD model. We may have obtained different results from Fu and Lin (2010) because they use monthly data.

[59] Source: China International Capital Corporation (CICC) 2015 report

Table 5.2 Estimates of market herding in the Chinese stock markets

Panel A: Regression results for Shenzhen stock Exchange

Year	1990	1996	2011
α	0.0108	0.0104	0.0106
	(76.14) ***	(61.29) ***	(36.52) ***
γ_1	0.3599	0.5057	0.4190
	(29.19) ***	(25.97) ***	(12.50) ***
γ_2	-0.2848	-3.7792	-1.1749
	(-1.76) *	(-10.16)***	(-1.99) *
Adj. R^2	40.74%	34.27%	37.96%

Panel B: Regression results for Shanghai stock Exchange

Year	1990	1996	2011
α	0.0125	0.0106	0.0099
	(52.51) ***	(68.06) ***	(37.54) ***
γ_1	0.2377	0.4846	0.3970
	(10.02) ***	(29.71) ***	(13.45) ***
γ_2	-0.3652	0.4846	-1.3189
	(-7.11) ***	(-12.59) ***	(-2.75) ***
Adj. R^2	8.00%	28.96%	31.78%

Notes: Table 5.2 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 \; R_{m,t}^2 + \varepsilon_t$$

where $R_{m,t}$is the cross-sectional average returns of the N actively traded stocks for period t, the squared market return $R_{m,t}^2$ is used to capture the nonlinearity in the relationship, $CSAD_t$ is the cross-sectional absolute deviation of securities' returns, α is the constant, γ_1, and γ_2 are coefficients, and ε_t is the error term at time t. The 1990 sample period covers 01/01/1990 to 18/10/2016, the 1996 sample period covers 01/01/1996 to 18/10/2016 and the 2011 sample period covers 01/01/2011 to 18/10/2016.The sub-sample periods were split based on the percentage annual increase of the number of firms. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.2.2 Empirical results for industry herding

Having found that herd behaviour exists at the market level, we analyse the results obtained for both stock exchanges across all the sample periods to examine whether the results are consistent. An analysis of the results in Table 5.3 provides strong evidence of herding in both stock exchanges, which supports H1 that Chinese investors herd at the industry level. The regression for each industry is estimated using Eqn. (2), γ_2 is the coefficient of interest. Looking at the overall results presented in the table, it shows that the adjusted R-squared ranges from 11.61% to 69.11%, it suggests that the estimated equation for each market has some explanatory power. That is, the CSADs are highly interdependent on the market return and vice versa. Panel A shows the results for the sectors in the SZSE across all the sample periods. For the full sample, negative and significant γ_2 coefficients are reported in Automobile, Banks, Basic Resources, Chemicals, Food and Beverage, Media, Oil and Gas, Real Estate, Technology, Telecommunication, and Utilities. For the 1996 sub-period, all industries except Automobile and Financials report negative and significant γ_2 coefficients, which indicates that during this period investors in the SZSE tend to herd towards the industry consensus. However, for the 2011 sub-period herding appears to slightly dissipate, the γ_2 coefficient is negative and significant for Banks, Chemicals, Construction, Financials, Food and Beverage, Industrial Goods, Real Estate, Retail, Technology, Telecommunications, Travel and Leisure, and Utilities. Further analysis of the industry results demonstrates an interesting herding trend for the Financials industry, the γ_2 coefficient is positive and not significant during 1990 and 1996 but becomes negative and significant in 2011.

Given that the Chinese financial industry is highly regulated, it is surprising to find that investors in this sector ignore the industry consensus as a group in only one sub-period. The observed herding is consistent with localised herding, where the movement of a subset of investors increases the dispersion of returns when they move in (out) of industries, which is in accordance to the predictions of rational asset pricing models (Gebka and Wohar, 2013). Our evidence contrasts with those of Yao, et al., (2014) who show that herding is absent for Financials. The difference in results may be due to our use of different sub-periods, which further demonstrates the time-varying characteristics of industry herding in the Chinese market. The varying results obtained in sub-periods further provides information that herding maybe be conditioned based on certain periods. Our result is consistent with Chiang, et al., (2012), who emphasise that herding in the Chinese market is time-varying. Thus, the coefficients they estimate are sensitive to new information.

The results of the regression estimates for the SHSE are reported in Panel B. Like the SZSE, most of the regressions yield negative and significant γ_2 coefficients, indicating that herding is present in most sectors across all sub-periods. However, herding occurs in more sectors compared to the SZSE. This contrasts with the explanation by Demirer and Kutan (2006) that herding occurs more in the Shenzhen market because the firms are smaller, and the investors are less informed. The difference may be because we do not distinguish between the different share classes. However, this is not the focus of this study. A closer analysis of the coefficients for the full sample shows negative and significant γ_2 coefficients for all industries except for Basic Resources, Financials, Food and Beverage, HealthCare, Industrial Goods, Oil and Gas, Personal Holding, Real Estate and Utilities, indicating that investors in these do not industries herd. Stronger levels of herding are reported for the 1996 sub-period, the γ_2 coefficient is negative and significant for all sectors except Financials, and Food and Beverage. For the 2011 sub-period, most coefficients are negative and statistically significant except for Food and Beverage, and Oil and Gas. This suggests limited evidence of time-varying herding in the SHSE, as the herding trend only varies for the full sample. It is worth noting that none of the γ_2 coefficients for the Oil and Gas industry is negative and statistically significant across all sample periods. Thus no form of herd behaviour takes place in this sector. We anticipated this result because the prices of Oil and Gas industry is highly regulated by the Chinese government, with the market playing a limited role (Wu, 2003).

Overall, there is strong evidence of herding in Chinese sectors which shows time-varying properties. Our evidence supports the proposition by Bikhchandani and Sharma (2000) that investors intentionally mimic other investors when there is uncertainty about the quality of their private information. Moreover, we also find that investors in both markets herd in different industries, which may be due to the difference in both markets as earlier discussed.

Our results are in line with Lee, et al., (2013) who also find herding in SHSE and SZSE sectors. However, in contrast to our results, they find that SZSE herds more than SHSE. A possible reason for the difference in result may be due to the regression model they used which includes the CSAD of the IT sector. Our results are also consistent with Chiang, et al, (2012)'s finding of industry level herding for both SHSE and SZSE. Yao, et al., (2014) also provide evidence consistent with herding in majority of the industry groups they examine except Agriculture, Mining and Financials. Also, our results support those of Zheng, et al., (2017) who find evidence of herding in all industries for the Chinese market except Utilities.

Notably, our evidence differs from those of Demirer and Kutan (2006) who examine sector index returns for SHSE and SZSE and find no evidence that supports the presence of herding in Chinese markets. As previously stated, the difference in the results may be due to the methodology employed in their study which mainly examines herding only during periods of market stress. However, herding might occur at other periods over the whole return distribution. An explanation for the observed herding may be linked to turbulence in the market. Later in this chapter, we will examine the herd behaviour during crisis periods.

Table 5.3 Estimates of industry herding in Chinese stock markets

Panel A: Regression results for the Shenzhen stock exchange

	1990				1996				2011			
Industry	α	γ_1	γ_2	Adj R^2	α	γ_1	γ_2	Adj R^2	α	γ_1	γ_2	Adj. R^2
Automobile	0.0064	0.7885	-0.1924	91.51%	0.0080	0.7413	0.1588	88.02%	0.0095	0.6793	-0.3152	69.11%
	(17.67) ***	(64.98) ***	(-6.26) ***		(28.65) ***	(56.28) ***	(2.17) **		(19.64) ***	(17.30) ***	(-0.60)	
Banks	0.0012 (15.40) ***	0.0873 (12.73) ***	-0.5671 (-10.05) ***	4.04%	0.0012 (12.17) ***	0.1241 (11.34) ***	-0.9182 (-6.80) ***	5.61%	0.0020 (12.16) ***	0.2509 (11.51) ***	-1.7611 (-5.24) ***	20.31%
Basic Resources	0.0102	0.2741	-1.1427	16.50%	0.0093	0.4605	-3.4194	26.69%	0.0094	0.3939	-0.4755	43.72%
	(59.37) ***	(16.55) ***	(5.97) ***		(34.54) ***	(11.52) ***	(-4.51) ***		(35.05) ***	(13.10) ***	(-0.96)	
Chemicals	0.0107	0.2378	-0.5932	15.55%	0.0097	0.4696	-3.3893	29.83%	0.0104	0.3852	-1.1508	38.62%
	(61.78) ***	(12.98) ***	(-2.04) **		(59.60) ***	(26.13) ***	(10.65) ***		(37.07) ***	(12.74) ***	(-2.40) **	
Construction	0.0106	0.3220	-0.2962	28.89%	0.0102	0.4873	-3.9585	26.08%	0.0106	0.4119	-1.8308	35.61%
	(65.66) ***	(23.45) ***	(-1.63)		(58.37) ***	(27.75) ***	(-13.60) ***		(35.40) ***	(12.71) ***	(-3.35) ***	
Financials	0.0095	0.1245	1.3120	23.04%	0.0099	0.1069	2.2823	34.05%	0.0084	0.4772	-3.7447	25.77%
	(14.00) ***	(1.54)	(1.16)		(10.45) ***	(0.92)	(1.38)		(0.00)	(14.13) ***	(-6.87) ***	
Food & Beverage	0.1241	11.3738	-27.7877	29.55%	0.1241	11.3738	-27.7877	29.55%	0.0866	4.3900	-22.9611	11.61%
	(14.73) ***	(12.70) ***	(-2.12) **		(14.73) ***	(12.70) ***	(-2.21) **		(19.91) ***	(8.27) ***	(-2.27) **	
Healthcare	0.0105	0.2685	-0.8244	14.24%	0.0097	0.5165	-3.9702	30.63%	0.0096	0.4217	-1.4255	41.55%
	(27.76) ***	(5.41) ***	(-1.08)		(57.34) ***	(26.49) ***	(-11.38) ***		(27.76) ***	(5.41) ***	(-1.08)	

Industrial Goods	0.0106	0.3703	-0.1758	35.35%	0.0104	0.4871	-3.4776	30.94%	0.0105	0.4147	-1.2541	41.25%
	(55.75) ***	(17.43) ***	(-0.51)		(55.46) ***	(20.62) ***	(-7.23) ***		(34.84) ***	(17.43) ***	(12.21) ***	
Media	0.0089	0.3983	-2.3824	5.49%	0.0089	0.3648	-2.2040	12.98%	0.0111	0.2311	4.5484	44.50%
	(33.89) ***	(8.73) ***	(-4.18) ***		(26.65) ***	(8.41) ***	(-2.78) ***		(9.49) ***	(1.17)	(1.05)	
Oil & Gas	0.0084	0.3983	-2.3824	15.47%	0.0080	0.5651	-4.2388	23.30%	0.0110	0.2483	1.8973	28.89%
	(32.53) ***	(14.21) ***	(-5.94) ***		(24.71) ***	(11.35) ***	(-4.03) ***		(10.90) ***	(1.40)	(0.47)	
Personal & Household	0.1036	0.3683	0.9746	35.01%	0.0010	0.5083	-3.3603	30.01%	0.0100	0.4278	-0.5385	42.37%
	(30.73) ***	(6.75) ***	(0.87)		(50.06) ***	(18.54) ***	(-5.55) ***		(34.42) ***	(11.74) ***	(-0.74)	
Real Estate	0.0099	0.3795	-0.4264	39.17%	0.0096	0.5305	-3.7073	33.71%	0.0088	0.4943	-2.1956	42.36%
	(63.20) ***	(24.10) ***	(-1.76) *		(52.97) ***	(22.94) ***	(-7.42) ***		(30.67) ***	(-3.94) ***	(15.32) ***	
Retail	0.0108	0.2729	-0.5501	17.70%	0.0099	0.5037	-3.8873	25.33%	0.0090	0.5002	-2.7256	35.70%
	(47.45) ***	(10.90) ***	(-1.59)		(54.59) ***	(24.13) ***	(-10.10) ***		(28.76) ***	(11.55) ***	(-3.08) ***	
Technology	0.0109	0.2663	-0.9249	15.37%	0.0105	0.4161	-2.1134	27.68%	0.0107	0.4347	1.5771	41.15%
	(53.47) ***	(14.72) ***	(-4.45) ***		(27.66) ***	(7.45) ***	(-1.94) *		(32.00) ***	(13.86) ***	(-3.07) ***	
Telecom	0.0066	0.5334	-5.3161	13.27%	0.0066	0.5334	-5.3161	13.27%	0.0072	0.6151	-4.4800	28.25%
	(19.45) ***	(18.18) ***	(-14.03) ***		(19.45) ***	(18.18) ***	(-14.03) ***		(15.45) ***	(13.31) ***	(-5.99) ***	
Travel & Leisure	0.0103	0.2113	-.5733	9.47%	0.0097	0.4445	-3.1094	23.39%	0.0086	0.4830	-1.8152	40.00%
	(48.57) ***	(8.11) ***	(-1.26)		(43.08) ***	(14.93) ***	(-5.38) ***		(31.44) ***	(14.79) ***	(-3.35) ***	
Utilities	0.0094	0.3233	-0.9882	24.73%	0.0087	0.4879	-3.5398	29.57%	0.0082	0.4473	-2.2740	35.99%
	(56.28) ***	(17.85) ***	(-3.80) ***		(50.58) ***	(22.57) ***	(-8.61) ***		(29.54) ***	(14.59) ***	(-4.56) ***	

Panel B: Regression results for the Shanghai stock exchange

	1990				1996				2011			
Industry	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj. R^2
Automobile	0.0105	0.3203	-0.3646	28.94%	0.0099	0.4521	-3.3293	26.78%	0.0099	0.3787	-1.3354	33.75%
	(65.93)***	(22.53)***	(-1.88)*		(60.08)***	(26.39)***	(-10.85)***		(33.14)***	(11.48)***	(-2.38)***	
Banks	0.0026	0.2952	-1.9460	22.92%	0.0024	0.2895	-1.8463	22.44%	0.0031	0.3080	-2.0584	32.47%
	(22.45)***	(16.06)***	(-4.73)***		(19.46)***	(13.77)***	(-3.75)***		(19.46)***	(12.14)***	(-3.86)***	
Basic Resources	0.0115	0.1528	0.8885	54.68%	0.0097	0.5042	-3.8277	28.11%	0.0089	0.4002	-1.4306	39.68%
	(45.58)***	(7.53)***	(9.43)***		(54.67)***	(24.29)***	(-10.18)***		(34.42)***	(14.83)***	(-3.32)***	
Chemicals	0.0110	0.3109	-0.3316	29.68%	0.0101	0.4698	-3.4039	30.10%	0.0101	0.3868	-1.5469	38.17%
	(58.62)***	(15.32)***	(-0.97)		(62.34)***	(27.30)***	(-11.18)***		(37.16)***	(14.08)***	(-3.61)***	
Construct	0.0106	0.1702	-0.8171	21.89%	0.0096	0.5156	-3.8952	28.85%	0.0091	0.4272	-2.1533	35.62%
	(47.30)***	(12.47)***	(-2.39)**		(56.68)***	(29.70)***	(-14.15)***		(32.76)***	(14.73)***	(-4.78)***	
Financials	0.0201	-1.2839	19.8616	6.06%	0.0153	-0.3984	10.9166	2.92%	0.0054	0.3658	-1.1495	3.41%
	(7.34)***	(-3.64)***	(3.07)***		(4.21)***	(-0.72)	(1.10)		(1.97)**	(0.86)	(-0.15)	
Food & Beverage	0.0170	-0.7531	16.0454	35.85%	0.0170	0.4830	4.5574	36.27%	0.0152	0.4856	5.0996	39.87%
	(7.59)***	(-2.41)**	(2.71)***		(53.99)***	(11.83)***	(5.40)***		(26.04)***	(5.86)***	(2.84)***	
Healthcare	0.0097	0.4105	0.0748	40.79%	0.0095	0.4865	-3.0758	33.02%	0.0090	0.4442	-1.9757	41.54%
	(51.87)***	(17.46)***	(0.20)		(51.54)***	(19.08)***	(-6.06)***		(36.45)***	(15.29)***	(-3.99)***	
Industrial Goods	0.0114	0.2426	1.8716	63.49%	0.0102	0.4964	-3.8095	30.72%	0.0094	0.4042	-1.6744	38.02%
	(45.01)***	(12.76)***	(20.71)***		(64.65)***	(29.83)***	(-13.45)***		(35.15)***	(13.50)***	(-3.42)***	
Insurance	0.0036	0.2272	-1.8410	15.21%	0.0036	0.2272	-1.8410	15.21%	0.0034	0.2150	-1.0570	23.79%
	(24.07)***	(14.61)***	(-7.68)***		(24.07)***	(14.61)***	(-7.68)***		(19.53)***	(9.59)***	(-2.42)***	
Media	0.0097	0.1620	-1.1333	10.38%	0.0084	0.4915	-4.2805	19.90%	0.0070	0.4571	-3.7939	28.01%
	(33.96)***	(6.52)***	(-5.12)***		(43.42)***	(24.22)***	(-12.79)***		(24.84)***	(17.30)***	(-9.57)***	
Oil & Gas	0.0078	0.3122	-2.7960	6.04%	0.0078	0.3122	-2.7960	6.04%	0.0101	0.1152	5.3299	38.63%
	(10.86)***	(2.87)***	(-1.48)		(10.86)***	(2.87)***	(-1.48)		(7.90)***	(0.52)	(1.12)	

Personal & Household	0.0108	0.3458	-0.1161	34.69%	0.0099	0.5138	-3.8687	30.46%	0.0104	0.3699	-0.9479	36.34%
	(60.23)***	(16.85)***	(-0.34)		(62.05)***	(30.47)***	(-14.32)***		(36.30)***	(12.32)***	(-2.13)**	
Real Estate	0.0109	0.2475	0.0878	39.21%	0.0098	0.4862	-3.6217	32.31%	0.0091	0.4433	-1.9366	41.26%
	(28.97)***	(8.64)***	(4.38)***		(60.62)***	(27.98)***	(-11.29)***		(33.67)***	(15.15)***	(-3.97)***	
Retail	0.0096	0.2830	-0.9685	21.51%	0.0094	0.4585	-3.5931	28.38%	0.0086	0.4349	-2.1925	39.44%
	(59.60)***	(18.04)***	(-6.66)***		(63.28)***	(29.03)***	(-13.79)***		(33.68)***	(14.49)***	(-4.29)***	
Technology	0.0110	0.2339	-0.7089	12.18%	0.0100	0.5162	-3.9953	29.01%	0.0098	0.4415	-2.1157	38.90%
	(48.15)***	(12.01)***	(-5.85)***		(56.51)***	(27.93)***	(-13.04)***		(33.14)***	(15.63)***	(-5.21)***	
Telecom	0.0029	0.2789	-1.6058	9.10%	0.0026	0.3947	-2.8419	12.09%	0.0023	0.7938	-7.1026	30.68%
	(13.32)***	(11.08)***	(-4.51)***		(3.73)***	(4.25)***	(-1.95)***		(6.74)***	(19.66)***	(-15.45)***	
Travel & Leisure	0.0089	0.4961	-0.8060	40.06%	0.0083	0.6705	-6.0555	33.93%	0.0073	0.5200	-2.2322	42.41%
	(48.45)***	(24.82)***	(-2.38)**		(51.85)***	(37.83)***	(-20.07)***		(27.60)***	(14.14)***	(-3.09)***	
Utilities	0.0100	0.2600	-0.1348	21.20%	0.0088	0.4714	-3.5068	29.95%	0.0081	0.4031	-1.4422	41.39%
	(29.63)***	(5.91)***	(-0.21)		(60.31)***	(28.35)***	(-12.39)***		(35.64)***	(15.00)***	(-3.59)***	

Notes:
Tables 5.3 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 \ R_{m,t}^2 + \varepsilon_t$$

where $R_{m,t}$ is the average value of market return in each sector, the squared market return $R_{m,t}^2$is used to capture the non-linearity in the relationship, α is the constant, γ_1, and γ_2 are coefficients, and εt is the error term at time t, $CSAD_t$ is the cross-sectional absolute deviation of returns for the sector, the equation is estimated over the whole sample period for each sector. We utilised the DataStream industry classification. The equation is estimated for three sample periods for Shanghai and Shenzhen markets to test whether the results are robust regardless of the number of firms in the sample. The 1990 sample period covers 01/01/1990 to 18/10/2016, the 1996 sample period covers 01/01/1996 to 18/10/2016 and the 2011 sample period covers 01/01/2011 to 18/10/2016.The sub sample periods were split based on the percentage annual increase of the number of firms. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. The t-test statistic tests for the difference in level of significance between the γ_1, and γ_2 coefficient. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.3 Determinants of industry herding

5.5.3.1 The effect of market returns on herding

In this section, we examine whether herd behaviour is contingent upon rising and declining market conditions, a dummy variable as specified in Eqn. (3) was used to capture the differences in the CSADs, γ_3 and γ_4 represents coefficients for rising and declining market conditions respectively. Results for the markets are analysed in the first section, which is followed by an analysis of industry results.

5.5.3.1.1 Results for the aggregate market

Table 5.4 presents the regression estimates for both markets Panel A reports the results for SZSE looking at the coefficient γ_3 for rising market it can be observed that it is only negative and significant for the 1996 sub-period. This indicates that all investors during this sub-period have strong herd behaviour tendencies towards the market consensus. Furthermore, the results suggest that the level of herding in the SZSE is isolated to a specific sample period. Whereas, investors' behaviour in other sample periods are in line with the predictions of rational asset pricing models that asset dispersion increases during periods of significant price movement (Demirer and Kutan, 2006). In contrast, for declining market conditions, γ_4 coefficients are negative and significant across all sub-periods, a strong indication that SZSE herding is more likely to occur during declining market conditions. This finding supports McQueen, et al. (1996)'s proposition that investors tend to herd more in declining markets due to the decrease in small stocks beta.

When we examine the results for SHSE, we observe different results. Panel B indicates that the γ_3 coefficient for rising market conditions is negative and significant across all sub-periods, indicating that herding is more pronounced in rising markets. We observe contrasting results when we examine γ_4 coefficients for declining market conditions, it is only negative and significant during the 1996 sub-period, again herd behaviour outside this period is consistent with rational asset pricing models.

In general, we find evidence of herding asymmetry in Chinese markets; herding is different in rising and declining market conditions. More, specifically, our results are mixed for both markets. While SZSE investors tend to herd during declining market conditions, those in SHSE are more likely to herd during rising market conditions. According to Tan, et al., (2008) the difference in the results may be because of government intervention. They explain that because SZSE comprises smaller firms (not predominantly stated-owned), its investors are less likely to follow the market consensus during declining market conditions, because they have confidence that the government will intervene to prevent the market from collapsing. As a result of their confidence in the government, they trade based on their own information and are less prone to panic trades. On the other hand, investors in SHSE tend to be more optimistic and confident of government support during rising market conditions. Analysing the results in its entirety reveals that consistent with hypothesis H2A, herding is contingent upon market returns. In relation to the adjusted R squared, the explanatory power of the CSAD is stronger for SZSE than SHSE.

Our results for the herding in rising and declining market conditions are in line with findings from previous studies, including those that study the Chinese market and those that study SZSE and SHSE separately. Our results are consistent with those reported in Chiang and Zheng's (2010) investigation of herding in up and down markets which provides evidence that the Chinese market herds in both up and down markets. They also show that the observed herding is stronger in up markets. We obtain similar results as Lao and Singh (2011) who find evidence that Chinese investors herd more when the market is declining, which may be due to loss aversion of the dominant group of inexperienced individual investors.

Furthermore, our results are also similar to those of Chiang, et al., (2013), who use the CSAD model to examine herding in Pacific-Basin market including the Chinese market and find that herding is stronger during rising markets than declining markets. They suggest that herding is stronger when the market is rising because investors focus more on large firms as they herd. Chiang, et al., (2010) also find evidence that herding is more pronounced in rising market conditions.

Regarding studies that separate SZSE and SHSE our results are consistent with Tan, et al., (2008), Yao, et al., (2014) and Luo and Schinckus (2015). For the SHSE, Tan, et al., (2008) find that herding is more pronounced in SHSE in rising market conditions. Further, for the SZSE, Yao et al. (2014), show evidence that investor's herd more in the A-share markets and the Shenzhen B-market in declining market conditions. In the same light, Luo and Schinckus (2015) observe that Shanghai A-share investors herd when the market is rising, as opposed to Shenzhen B-shares investors who herd when the market is declining. However, our results are different from those reported by Fu and Lin (2010), who find that both SZSE and SHSE markets herd during declining markets.

Table 5.4 Estimates of herding during periods of rising and declining market returns in Chinese stock markets

Panel A: Shenzhen stock exchange

Year	1990	1996	2011
α	0.0106	0.0104	0.0106
	(60.50) ***	(57.90) ***	(35.59) ***
γ_1	0.3486	0.4595	0.3475
	(22.64) ***	(16.10) ***	(9.09) ***
γ_2	0.4355	0.5838	0.5552
	(13.47) ***	(25.26)***	(14.83) ***
γ_3	-0.0289	-3.9718	-1.0832
	(-0.19)	(-5.11)***	(-1.13)
γ_4	-1.5932	-4.4471	-3.0022
	(-2.48) **	(-10.40)***	(-4.87) ***
Adj. R^2	41.44 %	34.65%	45.02%

Panel B: Shanghai stock exchange

Year	1990	1996	2011
α	0.0124	0.0120	0.0117
	(43.49) ***	(73.54) ***	(41.35) ***
γ_1	0.2700	0.3715	0.1831
	(6.47)***	(16.55)***	(4.34) ***
γ_2	0.2245	0.2382	0.1674
	(8.05) ***	(11.18)***	(4.33) ***
γ_3	-0.4208	-3.5021	2.7939
	(-5.39) ***	(-6.61)***	(2.58) ***
γ_4	-0.5457	-1.0866	0.3617
	(-1.23)	(-2.67)***	(0.47)
Adj. R^2	8.18%	13.88%	21.57%

Note: Table 5.4 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{m,t}\right| + \gamma_2\ (1 - D^{up})\left|R_{m,t}\right| + \gamma_3\ D^{up}(R_{m.t})^2 + \gamma_4\ (1 - D^{up})(R_{m.t})^2 + \varepsilon_t$$

D^{up} is a dummy variable with a value of 1 for days with positive market returns and a value of 0 otherwise, $R_{m,t}$ is the market's average return, $CSAD_{i,t}$ is the cross-sectional absolute deviation of returns for the market, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients and $\varepsilon_t$is the error term at time t.The 1990 sample period covers 01/01/1990 to 18/10/2016, the 1990 sample period covers 01/01/1996 to 18/10/2016 and the 2011 sample period covers 01/01/2011 to 18/10/2016. The sub sample periods were split based on the percentage annual increase of the number of firms. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. The t-test statistic tests for the difference in level of the significance between the γ_3 and γ_4 coefficients. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.3.1.2 Results for industry sectors

Table 5.5 presents the regression results for herding in industries in rising and declining market conditions. An analysis of the overall results shows that the adjusted R-squared ranges from 4.04% to 91.54%, it suggests that the estimated equation for each market has reasonably high explanatory power, that is, the CSADs are highly interdependent on the market return and vice versa.

Panel A shows the results for the SZSE across all the periods. During rising market conditions, the γ_3 coefficient for the full sample is negative and significant for Automobile, Banks, Basic Resources, Media, Oil and Gas, Personal and Household, Real Estate, Retail, Technology, Telecommunications, and Utilities. Stronger levels of herding become evident for the 1996 sub-period, we report negative and significant γ_3 coefficients for all the sectors except for Financials, Food and Beverage, Oil and Gas, and Real Estate. There are slightly more industries with non-negative and non-significant γ_3 coefficients for the 2011 sub-period: Healthcare, Media, Oil and Gas, Personal and Household, Travel and Leisure and Utilities. Our results indicate that herding dissipates over the sub-periods with more investors aligning to the predictions of rational pricing models. Notably, these results reveal a stronger evidence in support of herding compared to the overall SZSE results reported in Table 5.4, where we only find herding in the 1996 sub-period, suggesting that investors are more likely to herd at the industry level in rising market conditions. This finding supports the predictions of Bikhchandani and Sharma (2000) that investors have a greater tendency of herding at the industry level.

When we consider the γ_4 coefficients for declining market conditions, we observe strong evidence of herding. Herding is strong in the full sample, negative and statistically significant coefficient γ_4 are reported for all industries except Personal and Household. This suggests that most investors tend to collectively invest in particular sectors. Similar results are reported for the 1996 sub-period where the γ_4 coefficients are negative and significant in all industries except Automobile and Personal Household. Herding reaches its highest level in the 2011 sub-period, the γ_4 coefficients are negative and significant in all industries. The herding over the sample periods shows an increasing trend, indicating that as the market declines the tendency to herd in the SZSE increases. Thus, more investors depart from the predictions of rational asset pricing models. These results are consistent with the previous evidence in Table 5.4 that herding is more prevalent in SZSE in declining market conditions.

Panel B reports the regression results for SHSE across the three sub-periods. Like the SZSE, the majority of the γ_3 coefficients for rising market conditions are negative and significant, indicating the presence of herd behaviour in the sectors. More specifically, for the full sample, we report negative and significant γ_3 coefficients for Banks, Construction, Insurance, Media, Oil and Gas, Retail, Technology and Telecommunications. Herding becomes more pronounced for the 1996 sub-period, γ_3 coefficients are negative and significant for the all sectors except Financials, Food and Beverage, and Personal and Household. Herd formation appears to strengthen for the 2011 sub-period, negative and significant γ_3 coefficients are reported for more industries: Automobile, Banks, Construction, Industrial Goods, Media, Insurance, Real Estate, Technology, Telecommunication and Utilities. This finding suggests that herding has an increasing trend overtime.

We also report strong evidence of herding for declining market conditions. For the full sample, we obtain negative and significant γ_4 coefficients for all industries except Banks, Food and Beverage, Industrial Goods, Real Estate, Telecommunications and Utilities. On analysis of the 1996 sub-period even more industries herd, γ_4 coefficients are negative and statistically significant for all industries except Banks, Food and Beverage, Financials and Telecommunications. Herding becomes slightly stronger in the 2011 sub-period, γ_4 coefficients are negative and statistically significant for all industries except Banks, Food and Beverage, Insurance. Interestingly, we report positive and significant coefficients for the Food and Beverage sector across all sub-periods, suggesting equity returns increase during periods of significant price changes as predicted by rational asset price models. It is worth noting that we find no evidence of herding for the Banks, none of its coefficients are negative and significant across all sub-periods, suggesting that investors in the Banking sector do not herd in declining market conditions. This may be due to the dominance of state ownership in the banking sector, thus subject to more government intervention, which in turn reduces the uncertainty during declining market conditions and hence the tendency to herd (García-Herrero, Gavilá and Santabárbara, 2009).

Overall our results provide evidence that industry herd behaviour is asymmetric and is more prevalent in rising market conditions. For the both SZSE and SHSE, we find evidence that herding occurs in both rising and declining markets but is more prevalent in latter. This result is consistent with hypothesis H2a which states that industry herding is contingent upon rising (declining) market returns. In fact, we find that industry herding is stronger in rising market conditions in the SHSE than in the SZSE, while SZSE herds more in declining market conditions.

These results support the evidence provided by Lee, et al., (2013). Our results also agree with their finding that herding is more prevalent in rising markets for sectors in the SHSE. Our findings are also consistent with Zheng, et al., (2017) who report that 7 out of the 10 industries examined for the Chinese market herded more during rising markets. They explain that restraints on short-selling minimises the effect of herding when the market is declining.

Table 5.5 Estimates of industry herding during periods of rising and declining returns in Chinese stock markets

Panel A: Shenzhen Stock Exchange

		1990				
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Auto	0.0065	0.8017	0.7725	-0.2017	-0.1787	91.54%
	(17.55) ***	(60.68) ***	(44.96) ***	(-5.19) ***	(-4.03) ***	
Banks	0.0011	0.0918	0.0805	-0.6059	-0.5013	4.04%
	(15.63) ***	(10.73) ***	(9.72) ***	(-7.99) ***	(-7.14) ***	
Basic Resources	0.0100	0.2703	0.3251	-1.0378	-1.9320	16.91%
	(56.48) ***	(16.18) ***	(11.68) ***	(-7.08) ***	(-4.23) ***	
Chemicals	0.0104	0.2251	0.3375	-0.3231	-2.1014	17.26%
	(66.24) ***	(15.30) ***	(18.50) ***	(-1.26)	(-8.34) ***	
Construct	0.0104	0.3160	0.3781	-1.2450	-1.2466	29.19%
	(55.35) ***	(20.13) ***	(11.68) ***	(-1.11)	(-1.94) *	
Financials	0.0087	0.1821	0.2624	1.3950	-1.2841	26.49%
	(17.35) ***	(2.21) **	(7.09) ***	(1.12)	(-2.71) ***	
Food & Beverage	0.1319	8.5423	12.011	39.0885	-48.520	30.42%
	(14.83) ***	(6.39) ***	(11.49) ***	(1.44)	(-3.55) ***	
Healthcare	0.0103	0.3590	0.4724	0.2080	-2.048	15.20%
	(37.82) ***	(4.76) ***	(13.33) ***	(-0.53)	(-4.39) ***	
Industrial Goods	0.0103	0.2275	0.3621	-0.4116	-2.1330	36.16%
	(47.39) ***	(17.30) ***	(11.06) ***	(0.88)	(-2.32) **	
Media	0.0086	0.2104	0.2836	-0.9894	-2.3112	6.17%
	(33.89) ***	(8.63) ***	(9.75) ***	(-4.70) ***	(-5.79) ***	
Oil & Gas	0.0081	0.3967	0.4802	-2.0899	-3.8375	16.14%
	(33.75) ***	(15.45) ***	(15.29) ***	(-7.14) ***	(-7.78) ***	
Personal& Household	0.0102	0.3146	0.4764	2.4983	-1.4487	36.23%
	(36.25) ***	(6.42) ***	(8.26) ***	(2.21) **	(-1.08)	
Real Estate	0.0097	0.3841	0.4419	-0.2523	-1.6470	39.82%
	(44.70) ***	(19.23) ***	(9.95) ***	(-0.91)	(-1.87) *	
Retail	0.0106	0.2632	0.3442	-0.3266	-1.6614	16.17%
	(51.52) ***	(14.96) ***	(12.83) ***	(-5.77) ***	(-2.44) **	
Tech	0.0106	0.2702	0.3488	-0.8268	-2.2841	28.16%

	(78.63) ***	(26.61) ***	(20.44) ***	(-4.16) ***	(-5.25) ***	
Telecom	0.0065	0.5784	0.5166	-6.2735	-4.9320	13.35%
	(18.96) ***	(15.42) ***	(14.97) ***	(-11.04) ***	(-11.08) ***	
Travel & Leisure	0.0100	0.2114	0.2751	-0.3505	-1.7209	10.26%
	(52.07) ***	(8.03) ***	(11.99) ***	(-0.66)	(-5.13) ***	
Utilities	0.0092	0.3234	0.3975	-0.8388	-2.2597	25.30%
	(54.54) ***	(21.40) ***	(13.17) ***	(-5.11) ***	(-4.12) ***	

1996						
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Auto	0.0080	0.7510	0.7335	-0.1870	0.0938	88.09%
	(28.81) ***	(60.36) ***	(37.77) ***	(2.50) **	(0.79)	
Banks	0.0012	0.1302	0.1138	-0.9815	-0.7909	5.16%
	(12.55) ***	(9.44) ***	(9.24) ***	(-5.50) ***	(-4.55) ***	
Basic Resources	0.0093	0.4171	0.5126	-2.8345	-4.1216	27.07%
	(36.20) ***	(7.20) ***	(20.50) ***	(-2.03) **	(-10.56) ***	
Chemicals	0.0097	0.4277	0.5348	-3.3802	-4.019	30.85%
	(58.94) ***	(18.96) ***	(25.30) ***	(-6.18) ***	(-11.06) ***	
Construct	0.01015	0.4798	0.5524	-5.0780	-4.3971	27.53%
	(58.18) ***	(24.94) ***	(26.93) ***	(-13.23) ***	(-13.01) ***	
Financials	0.0088	0.1788	0.3009	2.4628	-1.4212	39.13%
	(12.49) ***	(1.47)	(5.97) ***	(1.31)	(-2.15) **	
Food & Beverage	0.1319	8.5423	12.0109	39.0885	-48.5196	30.42%
	(14.83) ***	(6.39) ***	(11.49) ***	(1.44)	(-3.55) ***	
Healthcare	0.0097	0.4880	0.5784	-4.2573	-4.5344	31.46%
	(57.54) ***	(21.73) ***	(25.68) ***	(-8.00) ***	(-11.49) ***	
Industrial Goods	0.0104	0.4290	0.5670	-3.1695	-4.3713	32.18%
	(50.50) ***	(10.32) ***	(24.21) ***	(-2.70) ***	(-10.74) ***	
Media	0.0084	0.3525	0.5167	-1.7706	-24.8581	14.26%
	(39.38) ***	(13.78) ***	(21.63) ***	(-2.70) ***	(-15.04) ***	
Oil & Gas	0.0080	0.4915	0.6285	-2.6743	-5.3561	23.75%
	(23.07) ***	(5.54) ***	(20.38) ***	(-1.13)	(-12.18) ***	
Personal& Household	0.0098	0.4477	0.5718	-2.5954	-4.2034	30.56%
	(36.25) ***	(6.42) ***	(8.26) ***	(2.21) **	(-1.08)	
Real Estate	0.0097	0.4664	0.5985	-2.8520	-4.5888	34.40%

	(49.72) ***	(11.94) ***	(24.88) ***	(1.16)	(-10.47) ***	
Retail	0.0099	0.4720	0.5644	-4.0478	-4.4697	25.99%
	(54.16) ***	(17.56) ***	(23.55) ***	(-5.73) ***	(-10.48) ***	
Tech	0.0105	0.3311	0.5209	-0.4306	-3.8994	29.06%
	(78.63) ***	(26.61) ***	(20.44) ***	(-4.16) ***	(-5.25) ***	
Telecom	0.0065	0.5784	0.5166	-6.2735	-4.9320	13.35%
	(18.96) ***	(15.42) ***	(14.97) ***	(-11.04) ***	(-11.08) ***	
Travel & Leisure	0.0097	0.3890	0.5002	-2.0428	-4.0372	23.81%
	(46.48) ***	(10.34) ***	(21.63) ***	(-2.16) **	(-10.62) ***	
Utilities	0.0086	0.4618	0.5367	-3.6271	-4.0003	30.05%
	(44.14) ***	(11.29) ***	(23.30) ***	(-3.36) ***	(-10.73) ***	

2011

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Auto	0.0096	0.5543	0.7965	2.2434	-2.7013	72.34%
	(20.92) ***	(18.86) ***	(15.48) ***	(7.15) ***	(-3.78) ***	
Banks	0.0028	0.2674	0.2243	-1.7334	-1.6936	20.90%
	(12.37) ***	(9.56) ***	(9.22) ***	(-3.49) ***	(-4.79) ***	
Basic Resources	0.0093	0.3796	0.4685	-1.4639	-1.3419	44.73%
	(34.32) ***	(10.84) ***	(13.07) ***	(-1.80) *	(-2.42) ***	
Chemicals	0.0105	0.3231	0.4964	-1.1643	-2.5683	40.80%
	(36.62) ***	(9.00) ***	(14.71) ***	(-1.35)	(-5.09) ***	
Construct	0.0102	0.3667	0.5384	-2.6458	-3.3320	38.56%
	(34.28) ***	(8.98) ***	(14.54) ***	(-2.62) **	(-5.78) ***	
Financials	0.0085	0.4259	0.5023	-2.7087	-4.1651	25.88%
	(24.61) ***	(9.24) ***	(12.85) ***	(-2.77) ***	(-7.23) ***	
Food & Beverage	0.0850	4.4233	5.3642	-42.2174	-33.6695	12.21%
	(18.48) ***	(5.53) ***	(8.19) ***	(-2.09) **	(-3.17) ***	
Healthcare	0.0097	0.3385	0.52247	-0.4487	-2.7514	43.25%
	(34.60) ***	(9.68) ***	(14.59) ***	(-0.49)	(-4.77) ***	
Industrial Goods	0.0105	0.3395	0.5434	-0.9585	-2.9377	43.80%
	(50.50) ***	(10.32) ***	(24.21) ***	(-2.70) ***	(-10.74) ***	
Media	0.0103	0.1173	0.6137	9.4261	-3.9847	55.87%
	(39.38) ***	(13.78) ***	(21.63) ***	(-2.70) ***	(-15.04) ***	
Oil & Gas	0.0116	-0.1475	0.4176	14.4318	-2.3895	43.24%
	(15.37) ***	(-0.67)	(6.84) ***	(2.08) **	(-2.86) ***	

Personal& Household	0.0100	0.3568	0.5440	-0.1965	-2.2140	44.00%
	(32.95) ***	(7.04) ***	(13.05) ***	(-0.12)	(-2.98) ***	
Real Estate	0.0087	0.4859	0.5828	-3.3201	-3.1772	43.47%
	(30.03) ***	(13.48) ***	(14.67) ***	(-3.77) ***	(-5.06) ***	
Retail	0.0090	0.4482	0.6028	-3.0754	-3.9434	37.29%
	(30.05) ***	(10.88) ***	(12.11) ***	(-2.85) ***	(-4.17) ***	
Tech	0.0106	0.3388	0.5372	-1.5487	-2.8418	42.59%
	(78.63) ***	(26.61) ***	(20.44) ***	(-4.16) ***	(-5.25) ***	
Telecom	0.0072	0.6376	0.5943	-4.8357	-4.1978	28.20%
	(15.55) ***	(12.55) ***	(10.72) ***	(-5.46) ***	(-4.60) ***	
Travel &	0.0086	0.4495	0.5470	-1.9016	-2.6209	
Leisure	(30.70) ***	(10.37) ***	(13.90) ***	(-1.57) ***	(-4.41) ***	40.47%
Utilities	0.0083	0.3573	0.5341	-1.0097	-3.3795	37.26%
	(29.13) ***	(8.58) ***	(14.82) ***	(-0.92)	(-6.45) ***	

Panel B: Shanghai Stock Exchange

		1990				
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Automobile	0.0103	0.3277	0.3694	-0.1840	-1.3676	29.47%
	(54.57) ***	(17.62) ***	(12.48) ***	(-0.85)	(-2.53) **	
Banks	0.0026	0.3462	0.2514	-2.9535	-1.0829	23.57%
	(22.57) ***	(19.16) ***	(10.24) ***	(-9.14) ***	(-1.61)	
Basic Resources	0.0108	0.1561	0.3618	0.9012	-1.9076	56.46%
	(40.71) ***	(5.34) ***	(15.55) ***	(11.21) ***	(-5.45) ***	
Chemicals	0.0107	0.3137	0.4143	0.0808	-2.0042	31.21%
	(36.62) ***	(9.00) ***	(14.71) ***	(-1.35)	(-5.09) ***	
Construction	0.0104	0.3211	0.3655	-0.7558	-1.8329	22.27%
	(44.42) ***	(12.43) ***	(8.98) ***	(-2.98) ***	(-2.48) **	
Financials	0.0007	3.2795	-0.5980	12.3721	-46.7060	60.06%
	(-0.17)	(7.91) ***	(-0.80)	(2.26) **	(-3.47) ***	
Food & Beverage	0.0171	0.6123	0.5578	2.8701	3.9018	35.86%
	(47.43) ***	(13.55) ***	(13.15) ***	(4.08) ***	(5.85) ***	
HealthCare	0.0095	0.3873	0.5051	0.4554	-1.4898	41.44%
	(34.60) ***	(9.68) ***	(14.59) ***	(-0.49)	(-4.77) ***	
Industrial Goods	0.1194	0.2012	0.1302	1.8813	3.8649	64.65%

	(27.02)***	(7.91)***	(1.11)	(17.45)***	(1.83)*	
Insurance	0.0036	0.2463	0.2092	-2.0234	-1.6862	15.39%
	(24.07)***	(13.21)***	(11.26)***	(-6.60)***	(-5.35)***	
Media	0.0093	0.2867	0.2731	-1.7939	-1.8114	10.39%
	(38.51)***	(11.06)***	(8.35)***	(-5.37)***	(-3.81)***	
Oil & Gas	0.0078	0.2562	0.3735	-2.1519	-3.5097	6.44%
	(15.37)***	(-0.67)	(6.84)***	(2.08)**	(-2.86)***	
Personal& Household	0.0105	0.3349	0.4514	0.2637	-1.9965	35.70%
	(53.16)***	(15.83)***	(12.89)***	(0.81)	(-3.05)***	
Real Estate	0.0109	0.2400	0.2534	0.0950	0.0109	39.21%
	(21.12)***	(6.24)***	(2.23)**	(3.15)***	(0.05)	
Retail	0.0093	0.2779	0.3755	-0.9028	-2.2688	22.48%
	(57.73)***	(15.72)***	(15.10)***	(-6.93)***	(-5.46)***	
Technology	0.0108	0.2188	0.2816	-0.5909	-1.1559	13.03%
	(51.23)***	(9.74)***	(13.94)***	(-6.33)***	(-6.37)***	
Telecom	0.0030	0.2991	0.2299	-1.8111	-1.0047	9.30%
	(9.28)***	(10.27)***	(3.65)***	(-5.26)***	(-0.94)	
Travel & Leisure	0.0086	0.5128	0.5931	-0.5162	-2.8883	41.03%
	(44.64)***	(21.81)***	(22.39)***	(-1.39)	(-5.18)***	
Utilities	0.0104	0.2644	0.1341	-0.5625	1.9543	25.93%
	(23.19)***	(10.34)***	(1.26)	(-3.14)***	(1.11)	

		1996				
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Automobile	0.00098	0.4453	0.5020	-4.2393	-3.6018	27.82%
	(58.47)***	(19.70)***	(24.82)***	(-7.80)***	(-10.18)***	
Banks	0.0026	0.3462	0.2514	-2.9535	-1.0829	23.57%
	(22.57)***	(19.16)***	(10.24)***	(-9.14)***	(-1.61)	
Basic Resources	0.0097	0.4705	0.5462	-3.5121	-4.3204	28.36%
	(53.34)***	(15.46)***	(-4.70)***	(-4.70)***	(-12.90)***	
Chemicals	0.0100	0.4646	0.5313	-4.6456	-3.7542	31.74%
	(61.76)***	(22.37)***	(27.27)***	(-9.74)***	(-11.23)***	
Construction	0.0095	0.5194	0.5397	-4.8213	-3.8220	29.41%
	(54.27)***	(20.74)***	(27.34)***	(-8.94)***	(-12.31)***	
Financials	0.0112	1.7644	-1.6843	12.3849	-4.0565	79.73%
	(10.61)	(8.60)***	(-8.80)	(2.98)**	(-0.95)	
Food & Beverage	0.0169	0.5592	0.4380	2.5302	5.5681	36.39%
	(52.44)***	(9.41)***	(10.16)***	(1.60)	(6.34)***	
HealthCare	0.0095	0.4435	0.5489	-2.9687	-3.6929	33.81%
	(48.79)***	(10.62)***	(26.03)***	(-2.68)***	(-11.86)***	

Industrial Goods	0.0101	0.4799	0.5534	-4.6296	-4.1607	31.97%
	(63.01) ***	(7.91) ***	(1.11)	(17.45) ***	(1.83) **	
Insurance	0.0036	0.2463	0.2092	-2.0234	-1.6862	15.39%
	(24.07) ***	(21.19) ***	(29.74) ***	(-8.53) ***	(-13.90) ***	
Media	0.0083	0.5031	0.4984	-4.7866	-4.2104	19.96%
	(41.27) ***	(17.30) ***	(20.42) ***	(-7.29) ***	(-10.98) ***	
Oil & Gas	0.0078	0.2562	0.3735	-2.1519	-3.5097	6.44%
	(15.37) ***	(-0.67)	(6.84) ***	(2.08) **	(-2.86) ***	
Personal& Household	0.0098	0.5087	0.5598	-4.7750	-4.1340	31.25%
	(53.16) ***	(15.83) ***	(12.89) ***	(0.81)	(-3.05) ***	
Real Estate	0.0097	0.4813	0.5441	-4.7516	-3.9317	33.78%
	(59.30) ***	(22.07) ***	(26.58) ***	(-9.12) ***	(-10.55) ***	
Retail	0.0094	0.4429	0.5082	-4.1609	-3.9411	29.26%
	(62.29) ***	(22.69) ***	(27.66) ***	(-10.02) ***	(-12.85) ***	
Technology	0.0099	0.5096	0.5577	-4.6884	-4.2130	29.65%
	(52.52) ***	(16.28) ***	(28.36) ***	(-6.11) ***	(-15.28) ***	
Telecom	0.0024	0.5339	0.3057	-5.2981	-1.2208	13.97%
	(4.68) ***	(13.66) ***	(2.96) ***	(-13.02) ***	(-0.68)	
Travel & Leisure	0.0082	0.6777	0.6987	-7.0336	-6.0457	34.36%
	(51.74) ***	(31.95) ***	(34.40) ***	(-15.61) ***	(-18.75) ***	
Utilities	0.0087	0.4763	0.4999	-4.3583	-3.5745	30.04%
	(59.44) ***	(21.94) ***	(27.30) ***	(-8.99) ***	(-11.57) ***	

			2011			
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Automobile	0.0099	0.3291	0.4632	-1.3323	-2.3337	35.04%
	(38.06) ***	(9.39) ***	(15.40) ***	(-1.70) *	(-5.00) ***	
Banks	0.0030	0.3217	0.2800	-1.9882	-1.9133	32.86%
	(22.57) ***	(19.16) ***	(10.24) ***	(-9.14) ***	(-1.61)	
Basic Resources	0.0089	-0.3423	0.4613	-0.7396	-2.2189	40.36%
	(33.75) ***	(9.42) ***	(14.77) ***	(-0.82)	(-4.83) ***	
Chemicals	0.0101	0.3152	0.4969	-1.3958	-2.8545	40.81%
	(36.63) ***	(8.93) ***	(16.56) ***	(-1.57)	(-6.42) ***	
Construction	0.0091	0.3959	0.4898	-2.4220	-2.7996	36.48%
	(31.88) ***	(10.96) ***	(14.01) ***	(-3.23) ***	(-5.42) ***	
Financials	0.0074	0.9930	-0.7977	5.5323	-1.3246	93.90%
	(9.03) ***	(4.91) ***	(-13.52) ***	(1.38)	(-1.98) **	
Food & Beverage	0.0152	0.4995	0.4490	5.3779	5.5255	39.84%
	(27.01) ***	(4.86) ***	(5.13) ***	(1.67) *	(2.82) ***	

HealthCare	0.0090	0.3553	0.5439	-0.9208	-3.2483	43.38%
	(36.36) ***	(10.27) ***	(15.76) ***	(-1.00)	(-6.14) ***	
Industrial Goods	0.0101	0.4799	0.5534	-4.6296	-4.1607	31.97%
	(63.01) ***	(21.19) ***	(29.74) ***	(-8.53) ***	(-13.09) ***	
Insurance	0.0034	0.2252	0.2063	-1.2658	-0.8608	23.74%
	(19.49) ***	(9.26) ***	(7.07) ***	(-2.82) ***	(-1.24)	
Media	0.0070	0.4534	0.4718	-3.9146	-3.9069	27.99%
	(24.32) ***	(13.41) ***	(14.65) ***	(-5.94) ***	(-8.59) ***	
Oil & Gas	0.0093	0.0166	0.4773	10.6467	-2.7210	53.03%
	(23.50) ***	(0.21)	(9.83) ***	(4.71) ***	(-2.96) ***	
Personal& Household	0.0104	0.2825	0.4893	-0.4234	-2.4467	38.79%
	(35.96) ***	(7.75) ***	(14.44) ***	(-0.49)	(-5.25) ***	
Real Estate	0.0091	0.3946	0.5431	-2.0260	-3.1313	42.91%
	(32.99) ***	(10.55) ***	(15.58) ***	(-2.05) **	(-5.88) ***	
Retail	0.0087	0.3639	0.5113	-2.0260	-3.1313	40.57%
	(33.61) ***	(9.79) ***	(14.99) ***	(-1.53)	(-5.75) ***	
Technology	0.0097	0.4169	0.5141	-2.5087	-2.9087	39.82%
	(32.21) ***	(11.60) ***	(15.40) ***	(-3.23) ***	(-6.40) ***	
Telecom	0.0022	0.8387	0.7598	-7.8425	-6.6233	30.72%
	(6.58) ***	(16.06) ***	(15.99) ***	(-11.01) ***	(-12.40) ***	
Travel & Leisure	0.0074	0.4732	0.5639	-1.4133	-2.8631	42.57%
	(27.97) ***	(11.16) ***	(13.14) ***	(-1.30)	(-3.65) ***	
Utilities	0.0081	0.3601	0.4893	-1.7958	-32.3289	43.11%
	(35.42) ***	(11.37) ***	(14.92) ***	(-2.74) ***	(-4.97) ***	

Note: Table 5.5 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 D^{up}\left|R_{m,t}\right| + \gamma_2\ (1 - D^{up})\left|R_{m,t}\right| + \gamma_3\ D^{up}(R_{m.t})^2 + \gamma_4\ (1 - D^{up})(R_{m.t})^2 + \varepsilon_t$$

D^{up} is a dummy variable with a value of 1 for days with positive sector returns and a value of 0 otherwise, $R_{m,t}$ is the average value of sector returns for each sector, $CSAD_{i,t}$ is the cross-sectional absolute deviation of returns for the sectors, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients and $\varepsilon_t$is the error term at time t. . The 1990 sample period covers 01/01/1990 to 18/10/2016, the 1996 sample period covers 01/01/1996 to 18/10/2016 and the 2011 sample period covers 01/01/2011 to 18/10/2016.The sub sample periods were split based on the percentage annual increase of the number of firms. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.3.2 The effect of volatility on herding

In this section, we investigate the relationship between herding and volatility. Specifically, we test for possible asymmetries in herd behaviour tendencies when the market is characterised by high (low) return volatility. A dummy variable as specified in Eqn. (4) was used to capture the differences in the CSADs γ_3 and γ_4 represents coefficients for rising and declining volatility conditions respectively. Results for the markets are analysed in the first section, which is followed by an analysis of industry results.

5.5.3.2.1 Results for the aggregate market

To test whether herding varies with market volatility, we define volatility as high (low) when the observed volatility exceeds (is below) the previous 30-day average. The effect of volatility is examined using the specifications in Eqn. (4) for the SZSE and SHSE for the full sample and two sub-periods, the regression estimates are presented in Table 5.6. Panel A reports the results for the SZSE, the γ_3 coefficient for herding when market volatility is high is only negative and statistically significant in 1996 sub-period, indicating that during this period, investors have a strong tendency to mimic the trades of other investors. However, this herd behaviour diminished in the 2011 sub-period, consistent with the predictions of rational asset pricing models. The estimated γ_4 for low volatility is negative and statistically significant for the whole sample and 1996 sub-period, suggesting that investors herd during these periods. However, in the 2011 sub-period, the negative coefficient γ_4 is statistically insignificant, indicating the absence of herd behaviour. This result implies that, there is no nonlinear relationship between market returns and CSAD. In addition, the observed herding trend demonstrates the time-varying characteristic of herd behaviour.

Panel B reports the regression results for the SHSE. The result shows that estimates for the γ_3 coefficient is negative and statistically significant for the full sample and 1996 sub-period, indicating that investors herd during periods of high return volatility. However, this herding diminishes in 2011, the negative coefficient γ_3 is statistically insignificant. When we consider the results for low volatility, we find that the coefficient γ_4 is negative and statistically significant for the 1996 and 2011 sub-periods. This result shows evidence consistent with herding during these periods.

From the results for both markets, we observe that in general, herd behaviour is asymmetric with respect to market volatility and more prevalent when the return volatility is low. Therefore, our findings are consistent with H2b which predicts that herding is contingent upon volatility in Chinese markets. Regarding the adjusted R squared, the explanatory power of the CSAD is stronger for SHSE than SZSE, because on average the SZSE has higher R squared values.

Our results are inconsistent with the literature which suggests that investors are more likely to herd during periods of low volatility (market stress). Specifically, our results contradict earlier findings of Tan, et al., (2008), who provide evidence that investors in the Chinese markets only herd in periods of high return volatility. The difference may be due to the data, as they only examine herding in dual-listed Chinese stocks. Our results are also contrary to those from other Asian markets. Lam and Qiao (2015) do not find evidence of herding in the Hong Kong markets in either high or low volatility conditions. Also, results are also consistent with those of Javaira and Hassan (2011), only find herding when market volatility is high in the Pakistani market.

Table 5.6 Estimates of herding during periods of high and low volatility in Chinese stock markets

Panel A: Shenzhen Stock Exchange

Year	1990	1996	2011
α	0.0093	0.0088	0.0096
	(50.03)***	(40.97)***	(25.83)***
γ_1	0.3650	0.4840	0.3536
	(29.54)***	(20.80)***	(10.14)***
γ_2	0.7378	0.9804	0.7003
	(18.83)***	(20.34)***	(8.66)***
γ_3	-0.1868	-2.9327	0.1211
	(-1.30)	(-6.29)***	(0.18)
γ_4	-8.1337	-16.9460	-2.2914
	(-5.33)***	(-7.41)***	(-0.60)
Adj. R^2	43.62%	37.14%	47.55%

Panel B: Shanghai Stock Exchange

Year	1990	1996	2011
α	0.0118	0.0091	0.0088
	(22.50)***	(45.06)***	(26.69)***
γ_1	0.2006	0.4637	0.3534
	(11.81)***	(26.00)***	(11.93)***
γ_2	0.3400	0.9569	0.7096
	(1.66)***	(19.42)***	(10.44)**
γ_3	-0.2830	-2.8179	-0.4179
	(-8.52)***	(-8.95)***	(-0.81)
γ_4	5.7024	-17.0337	-5.7021
	(0.61)	(-7.30)***	(-1.90)*
Adj. R^2	12.31%	36.59%	45.11%

Notes: Table 5.6 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 D^{\sigma^2-High} \left|R_{m,t}\right| + \gamma_2 \left(1 - D^{\sigma^2-High}\right)\left|R_{m,t}\right| + \gamma_3\, D^{\sigma^2-High}(R_{m.t})^2 + \gamma_4 \left(1 - D^{\sigma^2-High}\right)(R_{m.t})^2 + \varepsilon_t$$

Where $D^{\sigma2\text{-High}}$ is 1 for days with high market volatility and 0 otherwise, based on the previous 30-day moving average. $R_{m,t}$ is the market's average return, $CSAD_{i,t}$ is the cross-sectional absolute deviation of returns for the market, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients and εt is the error term at time t. The 1990 sample period covers 01/01/1990 to 18/10/2016, the 1990 sample period covers 01/01/1996 to 18/10/2016 and the 2011 sample period covers 01/01/2011 to 18/10/2016.The sub sample periods was split based on the percentage annual increase of the number of firms. The equation is estimated over the whole sample period. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.3.2.2 Results for industry sectors

Table 5.7 provides the regression results for industry herd behaviour during periods of high and low return volatility obtained by estimating Eqn. (4). The results for the SZSE are presented in Panel A. When we examine the full sample, the industry results show that herding is prevalent during periods of high volatility which is contrary to the evidence of no herding observed for the aggregate market. The γ_3 coefficient is negative and statistically significant for all the sectors except Chemicals, Financials, Food and Beverage, Health Care, Industrial Goods, Personal and Household, Real Estate, and Travel and Leisure. For the 1996 sub-period, the evidence indicates that the level of herding increases, the γ_3 coefficient is negative and statistically significant in most sectors except Automobile, Financials, Food and Beverage and Technology. During this period, these investors may have been driven to herd due to the high flow of information caused by stock volatility making it difficult to obtain reliable information. We obtain interesting results for the 2011 sub-period. The γ_3 coefficient is negative and significant in all industries except Automobile, Chemicals, Construction, Healthcare, Industrial Goods, Media, Oil and Gas, and Technology, which indicates the presence of herding.

We observe much stronger levels of herd behaviour during periods of low volatility, for the full sample, all the industries yield negative and significant γ_4 coefficients. Therefore, there is strong evidence that during this period, investors have a stronger tendency to herd towards the industry consensus when volatility is low. Specifically, for the 1996 sub-sample, we find evidence of herd formation in all sectors except Automobile and Telecommunications, the regression result yields mostly negative and statistically significant γ_4 coefficients. Our findings are like those we obtained for the aggregate market (herding behaviour in both high and low volatility). However, for the 2011 sub-period in low volatility states, we only report negative and statistically significant γ_4 coefficients in the Automobile, Banks, Financials, Telecommunication and Utilities sectors. The absence of industry herding in low volatility is consistent with the results reported for low volatility for the 2011 sub-period in Table 5.6. The results across the sub-periods indicate that herding gradually decreases over time, especially during low volatility. Therefore, reducing herding when volatility is low. It is interesting to note that, herding occurs in the Banks and Utilities sectors across all sub-periods. This reduction may be due to the uncertainty created by the regular government reforms and deregulation in these sectors (Bosworth and Collins, 2008).

Focusing on the SHSE results in Panel B, we observe a herding trend like that of the SZSE. We find that for the full sample, the γ_3 coefficient is negative and significant in all sectors except Automobile, Chemicals, Healthcare, Personal and Household, Oil and Gas, and Utilities. The results suggest that industry herding is prevalent in high volatility. For the 1996 sub-period, we observe that the γ_3 coefficient is negative and significant in all industries except Financials, Insurance, Industrial Goods and Oil & Gas. The results for the 2011 sub-period show herd formation, the γ_3 coefficient is negative and significant in half of the sectors, indicating that the evidence of herding in high volatility is mixed. However, herd formation is stronger in low volatility, for the full sample, the γ_4 coefficient is negative and significant in all sector except Basic Resources and Technology. For the 1996 sub-period, we report that herding is stronger during low volatility, the γ_4 coefficient is negative and significant in all industries except Financials and Telecommunications. Similarly, for the 2011 sub-period we obtained mixed evidence of herding in low volatility states, γ_4 coefficient is negative and significant in more than half of the sectors. The overall results for the SHSE is consistent with most of the results for the aggregate market in Table 5.6, except for the 2011 sub-period where herding does not exist during high volatility at the aggregate market, which may explain the mixed evidence of industry herding.

In summary, the results for industry herding in high and low volatility states is similar for both stock exchanges. We report herding in both high and low volatility states. However, the evidence shows that herding is stronger when volatility is low. Our results are consistent with the predictions of hypothesis H2b; there is strong evidence that herding is contingent upon volatility. Also, our results are inconsistent with the predicted increased dispersion during periods of market stress of rational asset pricing models. Our findings support the theory of intentional herding, where due to uncertainty higher herding is expected in stocks during periods of high volatility. The herding we observe can be explained from an informational cascade context. Investors are likely to herd during periods of high volatility due to the uncertainty marked by less accurate public information. This uncertainty can lead to a faster cascade formation, thus increasing investors' tendency to herd when volatility is high. However, this cascade can dissolve when investors react to unexpected public information. Due to lack of empirical evidence on the industry herding (to the best of our knowledge) conditioned upon volatility, our results are compared to the results of research on industry herding in Hong Kong. Our results support those of Lam and Qiao (2015) who report similar results: industry herding exists in both high and low volatility periods in the Hong Kong market.

Table 5.7 Estimates of industry herding during periods of high and low volatility in Chinese Industries

Panel A: Shenzhen Stock Exchange

			1990			
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Auto	0.0077	0.8046	0.7072	-0.2110	-0.4244	91.89 %
	(19.81) ***	(67.69) ***	(32.03) ***	(-6.95) ***	(-2.84) ***	
Banks	0.0008	0.0931	0.1799	-0.5817	-3.7729	4.49 %
	(11.69) ***	(12.25) ***	(13.26) ***	(-9.89) ***	(-9.41) ***	
Basic Resources	0.0088	0.2896	0.6416	-1.1360	-9.6932	19.47 %
	(45.19) ***	(18.32) ***	(16.73) ***	(-6.80) ***	(-7.38) ***	
Chemicals	0.0094	0.2682	0.5978	-0.6445	-10.5693	18.68 %
	(47.30) ***	(15.19) ***	(16.27) ***	(-1.26)	(-8.34) ***	
Construct	0.0091	0.3343	0.6986	-0.2438	-9.3990	30.93 %
	(46.18) ***	(26.64) ***	(18.53) ***	(-1.67) *	(-6.51) ***	
Financials	0.0084	0.1434	0.3832	1.2731	-5.1749	23.64 %
	(14.99) ***	(1.74) *	(5.81) ***	(1.12)	(-3.29) ***	
Food & Beverage	0.0873	9.5660	18.8345	0.7149	-113.822	32.36 %
	(9.47) ***	(9.84) ***	(10.22) ***	(0.05)	(-1.72) *	
Healthcare	0.0090	0.3044	0.6875	-0.9404	-15.1337	16.54 %
	(26.22) ***	(5.92) ***	(11.88) ***	(-1.21)	(-7.60) ***	
Industrial Goods	0.0090	0.3769	0.7726	-0.0312	-9.4211	37.66 %
	(42.84) ***	(20.02) ***	(18.22) ***	(-0.11)	(-5.79) ***	
Media	0.0086	0.2462	0.3571	-1.2628	-28.8070	7.90 %
	(28.62) ***	(9.32) ***	(7.82) ***	(-4.33) ***	(-7.30) ***	
Oil & Gas	0.0073	0.4329	0.7402	-2.5046	-15.0016	16.99 %
	(27.51) ***	(14.98) ***	(18.00) ***	(-6.13) ***	(-12.10) ***	
Personal& Household	0.0089	0.3477	0.7581	21.5158	-7.8274	36.80 %
	(32.51) ***	(6.48) ***	(15.72) ***	(1.37)	(-4.44) ***	
Real Estate	0.0087	0.3832	0.6756	-0.3555	-5.9590	40.93 %
	(45.87) ***	(23.19) ***	(19.29) ***	(-1.40)	(-4.73) ***	
Retail	0.0094	0.2922	0.6581	-0.5082	-10.9616	20.05 %
	(38.43) ***	(12.83) ***	(13.16) ***	(-1.70) *	(-6.22) ***	
Tech	0.0100	0.2768	0.4752	-0.9213	-5.3670	16.33 %
	(41.92) ***	(15.66) ***	(11.58) ***	(-4.81) ***	(-4.29) ***	

Telecom	0.0056	0.6065	0.8418	-5.9983	-17.9231	14.86 %
	(13.50) ***	(19.75) ***	(11.01) ***	(-15.18) ***	(-6.79) ***	
Travel & Leisure	0.0093	0.2321	0.4616	-0.6225	-7.9631	10.46 %
	(40.03) ***	(8.85) ***	(9.75) ***	(-1.37)	(-4.89) ***	
Utilities	0.0082	0.3333	0.6460	-0.9389	-8.3897	26.93 %
	(45.68) ***	(20.96) ***	(17.35) ***	(-4.44) ***	(-6.06) ***	

		1996				
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Auto	0.0085	0.7501	0.72760	0.1139	-0.3843	87.86 %
	(26.39) ***	(56.50) ***	(23.23) ***	(1.55)	(-0.72)	
Banks	0.0009	0.1275	0.2152	-0.9036	-3.8899	5.85 %
	(9.32) ***	(11.15) ***	(11.30) ***	(-6.63) ***	(-5.78) ***	
Basic Resources	0.0080	0.4401	0.8506	-2.8346	-12.9423	30.15 %
	(31.38) ***	(11.19) ***	(15.72) ***	(-3.86) ***	(-5.78) ***	
Chemicals	0.0084	0.4413	0.8550	-2.6261	-12.3442	33.72 %
	(40.77) ***	(22.38) ***	(18.13) ***	(-7.36) ***	(-5.88) ***	
Construct	0.0087	0.4760	0.9508	-3.3461	-17.2895	29.36 %
	(39.05) ***	(24.36) ***	(19.01) ***	(-10.03) ***	(-7.62) ***	
Financials	0.0084	0.1273	0.4659	2.2513	-6.7529	34.85 %
	(10.29) ***	(1.07)	(4.67) ***	(1.35)	(-3.07) ***	
Food & Beverage	0.0863	9.3945	18.9737	20.0451	-117.1859	32.52 %
	(9.39) ***	(19.93) ***	(10.46) ***	(1.61)	(-1.80) *	
Healthcare	0.0084	0.4921	0.9051	-3.2217	-14.1381	33.35 %
	(38.46) ***	(21.56) ***	(16.62) ***	(-7.64) ***	(-5.37) ***	
Industrial Goods	0.0089	0.4704	0.9409	-2.7841	-16.0885	34.50 %
	(41.09) ***	(18.34) ***	(21.09) ***	(-5.27) ***	(-8.12) ***	
Media	0.0077	0.4098	0.7489	-2.3685	-16.8546	15.56 %
	(25.09) ***	(9.30) ***	(15.88) ***	(-2.93) ***	(-11.70) ***	
Oil & Gas	0.0070	0.5579	0.8524	-3.8856	-12.5345	23.80 %
	(23.66) ***	(10.70) ***	(14.53) ***	(-3.54) ***	(-5.27) ***	
Personal& Household	0.0086	0.4854	0.8708	-2.6571	-12.5861	32.21 %
	(40.88) ***	(16.66) ***	(21.29) ***	(-4.10) ***	(-7.16) ***	
Real Estate	0.0083	0.5116	0.9077	-3.0446	-13.2632	36.19 %
	(37.17) ***	(19.91) ***	(17.22) ***	(-5.50) ***	(-5.36) ***	

Retail	0.0084 (40.31) ***	0.4662 (20.04) ***	0.9185 (21.32) ***	-0.9578 (-6.61) ***	-13.4106 (-6.95) ***	28.74 %
Tech	0.0089 (28.14) ***	0.3955 (7.25) ***	0.8280 (14.90) ***	-1.4447 (-1.36)	-11.3371 (-5.30) ***	16.33 %
Telecom	0.0074 (10.88) ***	0.7800 (13.24) ***	0.6880 (13.18) ***	-6.2123 (-6.62) ***	-0.3622 (-0.43)	38.83 %
Travel & Leisure	0.0081 (34.08) ***	0.4399 (15.02) ***	0.9124 (18.85) ***	-2.6245 (-4.63) ***	-15.8640 (-7.75) ***	26.68 %
Utilities	0.0072 (34.57) ***	0.4795 (20.00) ***	0.9472 (17.76) ***	-3.0342 (-6.75) ***	-17.6026 (-7.32) ***	32.44 %

2011

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Auto	0.0091 (17.01) ***	0.7199 (15.85) ***	0.8308 (11.83) ***	-0.7589 (-1.24)	-5.8615 (-3.14) ***	68.33
Banks	0.0017 (9.03) ***	0.2634 (11.11) ***	0.3567 (6.73) ***	-1.8489 (-5.20) ***	-6.1903 (-2.33) **	20.57
Basic Resources	0.0087 (25.58) ***	0.3051 (10.26) ***	0.5400 (7.08) ***	1.0674 (7.08) ***	2.8676 (0.80)	48.82
Chemicals	0.0097 (27.32) ***	0.2985 (10.00) ***	0.5685 (7.87) ***	0.2835 (0.55)	0.7211 (0.23)	44.73
Construct	0.0094 (24.10) ***	0.3428 (10.13) ***	0.7031 (7.97) ***	-0.4882 (-0.79)	-3.4683 (-0.82)	41.88
Financials	0.0074 (18.69) ***	-1.1061 (-2.94) ***	-1.8538 (-4.35) ***	17.1084 (2.28) **	27.9586 (2.94) ***	6.40
Food & Beverage	0.0787 (17.40) ***	3.2749 (8.66) ***	5.5748 (6.34) ***	-12.0189 (-2.03) **	-48.8180 (-1.38)	16.04
Healthcare	0.0089 (24.84) ***	0.3639 (7.93) ***	0.6027 (7.93)***	-0.3650 (-0.60)	0.4512 (0.13)	46.18
Industrial Goods	0.095 (25.49) ***	0.3475 (9.73) ***	0.6788 (9.37) ***	0.0519 (0.07)	-2.2327 (-0.70)	46.79
Media	0.0097 (10.89) ***	0.1860 (0.98)	0.5633 (3.40) ***	5.4837 (1.33)	2.9126 (0.45)	47.87
Oil & Gas	0.0098 (13.17) ***	0.2026 (1.10)	0.5570 (4.53) ***	2.9050 (0.69)	-2.7633 (-0.64)	31.39
Personal& Household	0.0091	0.3299	0.6541	1.4102	2.5222	48.86

	(24.92) ***	(8.40) ***	(8.16) ***	(1.65) *	(0.67)	
Real Estate	0.0080	0.4323	0.6785	-1.0792	-0.0295	46.51
	(21.79) ***	(13.10) ***	(8.56) ***	(-1.77) *	(-0.01)	
Retail	0.0082	0.4519	0.7411	-1.7852	-4.2440	38.97
	(22.04) ***	(9.38) ***	(9.11) ***	(-1.76) *	(-1.15)	
Tech	0.0094	0.3808	0.7304	-0.3531	-4.3841	45.56
	(22.60) ***	(11.39) ***	(9.87) ***	(-0.60)	(-1.45)	
Telecom	0.0064	0.5751	0.7584	-3.6610	-5.5328	29.09
	(12.07) ***	(10.91) ***	(89.24) ***	(-4.14) ***	(-2.06) **	
Travel & Leisure	0.0067	0.4791	0.7282	-1.4243	-3.5840	44.55
Utilities	(20.38) ***	(11.86) ***	(8.25) ***	(-1.77) *	(-0.86)	
	0.0074	0.4291	0.7089	-1.8213	-7.3524	37.55

Panel B: Shanghai Stock Exchange

		1990				
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Automobile	0.0092	0.3260	0.6316	-0.2749	-6.4432	31.09 %
	(46.00) ***	(22.61) ***	(14.64) ***	(-1.46)	(-3.79) ***	
Banks	0.0022	0.2887	0.4225	-1.7421	-5.5991	23.38 %
	(18.01) ***	(14.36) ***	(13.51) ***	(-3.93) ***	(-3.81) ***	
Basic Resources	0.0102	0.1475	0.4570	0.9046	-2.1531	56.45 %
	(27.80) ***	(6.91) ***	(5.09) ***	(10.38) ***	(-0.75)	
Chemicals	0.0095	0.3202	0.6763	-0.1999	-6.7507	32.28 %
	(38.57) ***	(15.36) ***	(10.58) ***	(-0.60)	(-2.59) ***	
Construction	0.0094	0.3265	0.6354	-0.8231	-8.7026	23.49 %
	(37.64) ***	(13.06) ***	(12.99) ***	(-2.46) **	(-4.89) ***	
Financials	0.0181	-1.2557	-0.8420	19.8339	10.8911	6.05 %
	(5.63) ***	(-3.52) ***	(-1.18)	(3.07) **	(0.41) ***	
Food & Beverage	0.0168	0.5773	0.5904	3.2505	8.5224	36.18 %
	(38.99) ***	(12.47) ***	(6.35) ***	(4.47) ***	(2.42) **	
HealthCare	0.0084	0.3961	0.7129	0.3034	-3.7108	42.89 %
	(40.66) ***	(16.69) ***	(15.10) ***	(0.83)	(-2.02) **	
Industrial Goods	0.0097	0.2495	0.6511	1.8823	-4.9624	65.10 %
	(3.68) ***	(12.04) ***	(13.08) ***	(22.72) ***	(-2.99) ***	
Insurance	0.0031	0.2187	0.3597	-1.6051	-5.2800	15.95 %
	(17.30) ***	(12.82) ***	(9.39) ***	(-6.04) ***	(-3.44) ***	

Media	0.0084	0.3081	0.4919	-1.8486	-8.1989	12.57 %
	(35.79) ***	(13.52) ***	(14.84) ***	(-6.58) ***	(-11.53) ***	
Oil & Gas	0.0068	0.3760	0.6194	-3.2844	-16.2173	8.48 %
	(12.09) ***	(3.22) **	(8.01) ***	(-1.62)	(-8.89) ***	
Personal& Household	0.0092	0.3347	0.7293	0.1298	-6.9144	37.82 %
	(45.83) ***	(17.21) ***	(16.41) ***	(0.42)	(-3.87) ***	
Real Estate	0.0098	0.2518	0.4706	0.0856	-3.1825	40.20 %
	(22.55) ***	(8.07) ***	(7.29) ***	(3.81) ***	(-1.86) *	
Retail	0.0085	0.2893	0.5721	-0.9553	-6.7711	23.87 %
	(41.00) ***	(18.19) ***	(11.34) ***	(-6.92) ***	(-4.14) ***	
Technology	0.0106	0.2184	0.3190	-0.6609	-0.3450	13.24 %
	(30.03) ***	(11.59) ***	(3.62) ***	(3.75) ***	(-0.14)	
Telecom	0.0028	0.2901	0.3234	-1.6626	-3.8657	9.26 %
	(14.30) ***	(11.18) ***	(10.31) ***	(-4.50) ***	(-4.11) ***	
Travel & Leisure	0.0075	0.4996	0.8429	-0.6868	-8.2335	41.38 %
	(36.60) ***	(24.59) ***	(20.91) ***	(-2.07) **	(-5.77) ***	
Utilities	0.0087	0.2732	0.5981	-0.1371	-7.5757	25.84 %
	(25.04) ***	(5.99) ***	(8.45) ***	(-0.21)	(-3.20) ***	

		1996				
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Automobile	0.0082	0.4471	0.9495	-2.7861	-18.4705	30.50 %
	(38.43) ***	(23.50) ***	(16.99) ***	(-8.11) ***	(-6.80) ***	
Banks	0.0027	0.1817	0.3408	0.7137	-3.0650	22.32 %
	(17.50) ***	(14.32) ***	(9.82) ***	(2.76) ***	(-2.00) **	
Basic Resources	0.0083	0.4876	0.9172	-3.1975	-15.2593	30.91 %
	(39.89) ***	(22.61) ***	(20.38) ***	(-8.29) ***	(-8.15) ***	
Chemicals	0.0086	0.4460	0.9364	-2.6016	-16.0543	34.39 %
	(40.01) ***	(22.86) ***	(17.24) ***	(-7.44) ***	(-6.36) ***	
Construction	0.0081	0.5062	0.0968	-3.3219	-16.9756	31.58 %
	(37.16) ***	(26.82) ***	(18.66) ***	(-11.05) ***	(-7.12) ***	
Financials	0.0123	-0.4524	0.2001	11.9779	8.1574	3.49 %
	(4.21) ***	(-0.81)	(0.35)	(1.20)	(0.37)	
Food & Beverage	0.0168	0.4526	0.5171	5.0359	6.3763	36.35 %
	(46.06) ***	(10.53) ***	(6.27) ***	(5.71) ***	(1.85) *	
HealthCare	0.0080	0.4665	0.9418	-2.4184	-15.6318	36.66 %
	(47.78) ***	(32.37) ***	(25.77) ***	(-10.69) ***	(-10.26) ***	
Industrial Goods	0.0087	0.4792	0.9479	-3.1301	16.7351	34.22 %

	(39.92) ***	(25.98) ***	(16.42) ***	(-9.99) ***	(-5.98) ***	
Insurance	0.0037	0.1094	0.2756	0.3479	-3.1072	14.13 %
	(19.86) ***	(11.97) ***	(7.19) ***	(1.11)	(-2.05) **	
Media	0.0075	0.4801	0.7208	-3.8993	-9.2538	21.00 %
	(32.99) ***	(22.93) ***	(16.02) ***	(-11.09) ***	(-5.33) ***	
Oil & Gas	0.0083	0.1461	0.4339	-0.2052	-12.2678	5.53 %
	(22.71) ***	(5.35) ***	(8.13) ***	(-0.77)	(-9.51) ***	
Personal& Household	0.0084	0.4844	0.9557	-3.0399	-15.5948	34.00 %
	(42.44) ***	(26.92) ***	(20.21) ***	(-10.19) ***	(-7.09) ***	
Real Estate	0.0084	0.34667	0.8886	-2.9076	-14.4848	35.53 %
	(42.40) ***	(24.28) ***	(21.70) ***	(-7.96) ***	(-8.34) ***	
Retail	0.0082	0.4386	0.8523	-2.9615	-14.1212	31.92 %
	(43.61) ***	(25.22) ***	(19.62) ***	(-10.11) ***	(-7.28) ***	
Technology	0.0086	0.4952	0.8899	-3.3181	-13.4856	32.00 %
	(40.60) ***	(26.19) ***	(19.41) ***	(-10.61) ***	(-6.54) ***	
Telecom	0.0029	0.3917	0.3214	-2.8656	-0.5610	12.10 %
	(5.29) ***	(3.83) ***	(3.95) ***	(-1.80) *	(-0.22)	
Travel & Leisure	0.0069	0.6710	1.1263	-5.6362	21.4951	35.73 %
	(34.39) ***	(34.58) ***	(21.65) ***	(-16.79) ***	(-8.58) ***	
Utilities	0.0073	0.4573	0.9355	-2.8836	16.6684	33.50 %
	(39.04) ***	(24.84) ***	(19.07) ***	(-9.05) ***	(-7.22) ***	

		2011				
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Automobile	0.0089	0.3311	0.6568	-0.3573	-3.7280	37.75 %
	(22.52) ***	(9.42) ***	(7.06) ***	(-0.57)	(-0.80)	
Banks	0.0027	0.3196	0.3408	-2.1007	-9.7472	32.87 %
	(14.53) ***	(11.65) ***	(9.80) ***	(-3.70) ***	(-4.05) ***	
Basic Resources	0.0079	0.3658	0.6893	-0.6516	-6.7399	42.47 %
	(25.12) ***	(13.31) ***	(12.23) ***	(-1.41)	(-3.66) ***	
Chemicals	0.0091	0.3413	0.6597	-0.6695	-5.4188	41.81 %
	(26.44) ***	(12.18) ***	(9.27) ***	(-1.47)	(-1.80) *	
Construction	0.0082	0.3780	0.6695	-1.2147	-3.5330	39.29 %
	(21.84) ***	(12.40) ***	(7.48) ***	(-2.45) **	(-0.81)	
Financials	0.0059	0.3522	0.2007	-1.1743	5.6710	3.22 %
	(2.78) ***	(0.75)	(0.56)	(-0.15)	(0.45)	
Food & Beverage	0.0154	0.4754	0.4257	5.1688	8.7139	39.82 %
	(23.17) ***	(5.56) ***	(3.19) ***	(2.81) ***	(1.87) *	

HealthCare	0.0080	0.4054	0.7477	-1.1600	-5.5521	45.85 %
	(25.40) ***	(14.16) ***	(9.94) ***	(-2.18) **	(-1.53)	
Industrial Goods	0.0086	0.3574	0.6303	-0.8241	-2.6842	41.83 %
	(24.91) ***	(11.48) ***	(8.44) ***	(-1.55)	(-0.81)	
Insurance	0.0029	0.1967	0.3340	-0.6878	-2.9739	24.91 %
	(14.46) ***	(7.88) ***	(6.93) ***	(-1.41)	(-1.35)	
Media	0.0065	0.4288	0.5752	-3.3630	-4.0394	29.48 %
	(19.09) ***	(15.57) ***	(9.44) ***	(-7.89) ***	(-1.90) *	
Oil & Gas	0.0083	0.1242	0.6623	5.6254	-10.8278	40.96 %
	(8.09) ***	(0.56)	(3.87) ***	(1.19)	(-2.06) **	
Personal& Household	0.0094	0.3201	0.6518	-0.0019	-4.3501	40.10 %
	(27.37) ***	(11.06) ***	(10.83) ***	(-0.00)	(-1.98) **	
Real Estate	0.0081	0.4133	0.7309	-21.2146	-6.2015	44.34 %
	(24.25) ***	(13.90) ***	(11.83) ***	(-2.32) **	(-2.58) ***	
Retail	0.0076	0.3917	0.7181	-1.4019	-6.2661	43.07 %
	(25.02) ***	(12.72) ***	(12.53) ***	(-2.53) **	(-2.95) ***	
Technology	0.0084	0.4099	0.8226	-1.2537	-9.2660	43.25 %
	(23.30) ***	(14.41) ***	(12.84) ***	(-2.91) ***	(-3.79) ***	
Telecom	0.0024	0.7892	0.7682	-7.0846	-5.3076	30.85 %
	(6.07) ***	(18.11) ***	(8.79) ***	(-14.16) ***	(-1.69) *	
Travel & Leisure	0.0067	0.4791	0.7282	-1.4243	-3.5841	44.55 %
	(20.38) ***	(11.86) ***	(8.25) ***	(-1.77) *	(-0.86)	
Utilities	0.0072	0.3486	0.6978	-0.4341	-4.3544	46.34 %
	(24.12) ***	(13.15) ***	(9.02) ***	(-1.03)	(-1.17)	

Notes: Table 5.7 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 D^{\sigma^2-High}\left|R_{m,t}\right| + \gamma_2\left(1 - D^{\sigma^2-High}\right)\left|R_{m,t}\right| + \gamma_3\, D^{\sigma^2-High}(R_{m.t})^2 + \gamma_4\left(1 - D^{\sigma^2-High}\right)(R_{m.t})^2 + \varepsilon_t$$

Where $D^{\sigma 2}$-High is 1 for days with high sector volatility and 0 otherwise, based on the previous 30-day moving average. $R_{m,t}$ is the average value of sector return for each sector, $CSAD_{i,t}$ is the cross-sectional absolute deviation of returns for the market, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients and εt is the error term at time t. . The 1990 sample period covers 01/01/1990 to 18/10/2016, the 1996 sample period covers 01/01/1996 to 18/10/2016 and the 2011 sample period covers 01/01/2011 to 18/10/2016.The sub sample periods was split based on the percentage annual increase of the number of firms. The equation is estimated over the whole sample period. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.3.3. The effect of volume on herding

Finance literature highlights the relationship between trading volume and herding. For instance, Lan and Lai (2011) find that trading volume triggers herding. However, Chiang and Zheng (2010) do not find any evidence that excess trading volume plays a significant role in determining the movements of cross-sectional dispersions. Moreover, Boyd, Buyuksahin, Haigh and Harris (2016) suggest that greater information reduces the incentives to herd. From a theoretical perspective, the intentional herding theory infers that lower trading volume is related to higher levels of herding (Galariotis, et al., 2015). We, therefore, investigate herd behaviour in periods of high and low trading volume using a dummy variable as in equation (5) to capture a possible asymmetric relationship between trading volume and CSAD at the market and industry level. The results are discussed in the sections below.

5.5.3.3.1. Results for the aggregate market

Table 5.8 presents the results for the regression estimates for the SZSE and SHSE. Panel A reports the results for the SZSE across the three sample periods. For the full sample period, we do not find evidence of herd behaviour in high volume states, the γ_3 coefficient is negative and not statistically significant. However, when we examine the coefficients for the two sub-periods, we observe that herding is present as the coefficients are negative and significant. Focusing on the results for low volume, there is no evidence of herding in any period, none of the γ_4 coefficients are negative and significant. This is consistent with the increased dispersion predicted by rational asset pricing models and depicts a volume asymmetry.

Panel B reports the results for the SHSE for all the sub-periods. An analysis of the 1990 and 1996 sub-period, shows that the γ_3 coefficients are negative and statistically significant, which confirms the presence of herding in high volume states. The observed herding does not persist in 2011 as the coefficient turns statistically insignificant, which suggests there is no nonlinear relationship between market returns and CSAD. The same pattern of herd formation is revealed in low volume states. We obtain negative and significant γ_4 coefficients for the 1990 and 1990 sub-periods which becomes positive and significant in 2011, again indicating the observed herding is short-term and thus dissipates in later periods. Furthermore, our results suggest there is no asymmetric relationship between herding and trading volume for majority of the sub-periods.

In summary, the evidence for the effect of volume on herding in both markets is mixed. While investors in the SZSE only exhibit herd behaviour when trading volume is high, for the SHSE, investors herd in both high and low volume in identical sub-periods. An intuitive explanation for the observed herding in SZSE maybe associated with the large number of small and medium-sized companies listed on the market [60]which may result in increased volume of trade especially by retail investors[61]. Consequently, it is expected that volume would be driven by information flow. Thus, the arrival of unexpected news can lead to uncertainty and increase investors' tendency to imitate the trade of others. Indeed, Chang et al., (2000) provide evidence that herding is driven by uncertain information. Our results can also be explained from a liquidity perspective, whereby investors may herd in either low or high volume states. When trading volume is high, the market is more liquid, and there is more information, which makes trading easier. Investors are motivated to herd in such

[60] as of 30th June 2010, out of the 1,012 listed companies on the market, 437 companies were listed on the Small and Medium Enterprise Board, with a total trading volume of USD 1.1 trillion in 2011[60]
[61] It's important the increased number of participants in the market increases the level of noise in the market

conditions because they can earn returns more quickly. On the other hand, low trading volume is marked by inadequate information, under these condition investors might believe that other investors are more informed than they are and hence mimic their trades. Our results are consistent with hypothesis H2C; herding is contingent upon trading volume.

Herding volume asymmetry has been examined in China and other Asian countries. Our results for the SHSE is consistent with those of Yao et al., (2014) who report that the Shanghai B-market herds in both high and low volume states, however, they do not find herding in the Shenzhen market. Tan, et al (2008) also find herding in Shanghai and Shenzhen A and B-share market in high volume states, in low volume states herding only takes places in B-share markets. Also, Lao and Singh (2011) find that herd behaviour in the Shanghai A-share market is stronger when trading volume is high. Our results are also consistent with those obtained in other Asian markets. Lan and Lin (2011) and Lam and Qiao (2015) find herding in high volume states in the Hong Kong market. However, our results are different from those reported by Javaira and Hassan (2015) who find no herding in Pakistani markets in high and low volume states.

Table 5.8 Estimates of herding during periods of high and low volume in Chinese stock markets

Panel A: Shenzhen Stock Exchange

Year	1990	1996	2011
α	0.0108	0.0110	0.0107
	(67.36) ***	(59.14) ***	(76.04) ***
γ_1	0.3818	0.5350	0.4376
	(28.70)***	(11.61)***	(24.17) ***
γ_2	0.3333	0.3158	0.3671
	(11.99) ***	(18.60)***	(29.67) ***
γ_3	-0.3370	-6.5057	-2.9119
	(-2.21)	(-2.75)***	(-7.30) ***
γ_4	-0.4532	29.7771	0.0510
	(-0.75)	(1.09)	(0.11)
Adj. R^2	41.15%	31.69%	37.62%

Panel B: Shanghai Stock Exchange

Year	1990	1996	2011
α	0.0123	0.0121	0.0114
	(46.92) ***	(73.57) ***	(39.75) ***
γ_1	0.3241	0.3615	0.1800
	(7.85) ***	(15.34)***	(4.70) ***
γ_2	0.2114	0.2364	0.2909
	(9.94) ***	(11.39)***	(5.89) ***
γ_3	-0.5001	-2.5410	-1.1378
	(-6.89) ***	(-4.63)***	(-0.84)
γ_4	-0.8849	-1.5096	0.8200
	(-3.28) ***	(-4.02)***	(1.17)
Adj. R^2	9.46%	14.38%	20.21%

Notes: Table 5.8 reports the estimates from the following equation:
$CSAD_t = \alpha + \gamma_1 D^{vol-High} \left|R_{m,t}\right| + \gamma_2 \left(1 - D^{vol-High}\right)\left|R_{m,t}\right| + \gamma_3 \ D^{vol-High}(R_{m.t})^2 + \gamma_4 \left(1 - D^{vol-High}\right)(R_{m.t})^2 + \varepsilon_t$
Where $D^{vol-High}$ is 1 for days with high sector volume and 0 otherwise, based on a 30-day moving average $R_{m,t}$ is the the average value of sector return for each sector, $CSAD_{i,t}$ is the cross-sectional absolute deviation of returns for the market, α is the constant, γ_1, γ_2, γ_3, $\gamma_4$are coefficients and εt is

the error term at time t. The regression is estimated for the full sample and two sub-periods. The 1990 sample period covers 01/01/1990 to 18/10/2016, the 1996 sample period covers 01/01/1996 to 18/10/2016 and the 2011 sample period covers 01/01/2011 to 18/10/2016. The sub sample periods were split based on the percentage annual increase of the number of firms. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. *******, ****** and ***** represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5.9 Estimates of industry herding during periods of high and low volume in Chinese stock markets

Panel A: Shenzhen Stock Exchange

			1990			
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Auto	0.0064	0.7875	0.7900	-0.1966	-0.1903	91.51 %
	(16.95) ***	(43.35) ***	(60.09) ***	(-3.79) ***	(-5.37) ***	
Banks	0.0011	0.0990	0.0747	-0.6626	-0.4550	4.15 %
	(15.93) ***	(10.72) ***	(9.89) ***	(-9.31) ***	(-5.94) ***	
Basic Resources	0.0102	0.3117	0.2408	-1.2390	-1.0924	17.20 %
	(60.59) ***	(14.84) ***	(13.92) ***	(-4.77) ***	(-5.00) ***	
Chemicals	0.0111	0.2665	0.1168	-0.9570	-0.0065	18.00 %
	(41.11) ***	(8.50) ***	(2.43) **	(-2.36) **	(1.25)	
Construct	0.0106	0.3705	0.2837	-0.3764	-0.4034	30.00 %
	(62.94) ***	(26.35) ***	(11.93) ***	(-2.52) **	(-0.87)	
Financials	0.0100	0.1991	-0.0474	0.2804	3.6845	30.59 %
	(17.68) ***	(4.07) ***	(-0.45)	(0.35)	(2.16) **	
Food & Beverage	0.1238	11.7879	10.9312	-30.1174	-24.0091	29.54 %
	(14.71) ***	(11.06) ***	(10.16) ***	(-1.70) *	(-1.46)	
Healthcare	0.0105	0.2934	0.2458	-0.8895	-0.8205	14.50 %
	(28.32) ***	(5.20) ***	(4.07) ***	(-0.97)	(-0.75)	
Industrial Goods	0.0106	0.4110	0.3226	-0.4066	0.1435	35.82 %
	(51.19) ***	(18.28) ***	(8.96) ***	(-1.15)	(0.19)	
Media	0.0089	0.2214	0.1950	-1.1690	-1.0443	5.51 %
	(38.89) ***	(7.56) ***	(9.19) ***	(-3.35) ***	(-2.84) ***	
Oil & Gas	0.0084	0.4615	0.3371	-2.9329	-1.8040	16.16 %
	(34.29) ***	(12.41) ***	(13.27) ***	(-4.90) ***	(-4.41) ***	
Personal& Household	0.0104	0.4120	0.3289	0.9188	-0.9441	35.57 %
	(28.63) ***	(8.28) ***	(3.97) ***	(0.82)	(0.51)	

Real Estate	0.0010	0.4322	0.3544	-0.4631	-0.9298	40.82 %
	(56.23) ***	(21.53) ***	(13.86) ***	(-1.47)	(-1.93) *	
Retail	0.0108	0.3178	0.2420	-0.6080	-0.7551	18.76 %
	(44.87) ***	(12.26) ***	(6.21) ***	(-1.69) *	(-1.12)	
Tech	0.0109	0.3176	0.2202	-0.9949	-0.9535	17.02 %
	(52.04) ***	(16.95) ***	(8.16) ***	(-4.80) ***	(-2.42) **	
Telecom	0.0067	0.5614	0.5062	-5.7870	-4.8525	13.28 %
	(19.42) ***	(16.00) ***	(14.13) ***	(-12.01) ***	(-9.47) ***	
Travel & Leisure	0.0106	0.1806	0.1360	-0.8047	1.599	12.90 %
	(29.15) ***	(6.96) ***	(1.68)	(-2.98) ***	(1.01)	
Utilities	0.0095	0.3604	0.2771	-1.1548	-0.6333	25.29 %
	(51.09) ***	(16.51) ***	(9.10) ***	(-3.71) ***	(-1.11)	

		1996				
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Auto	0.0081	0.7360	0.7402	0.2333	0.1362	88.03 %
	(31.22) ***	(59.68) ***	(47.08) ***	(3.51) ***	(1.50)	
Banks	0.0012	0.1391	0.1120	-1.0119	-0.8513	5.78 %
	(12.85) ***	(9.61) ***	(9.95) ***	(-5.76) ***	(-5.17) ***	
Basic Resources	0.0093	0.4839	0.4360	-3.2408	-3.5301	27.30 %
	(38.62) ***	(9.22) ***	(18.31) ***	(-2.82) ***	(-9.09) ***	
Chemicals	0.0097	0.5254	0.4057	-4.0556	-2.6265	30.54 %
	(59.48) ***	(25.75) ***	(18.67) ***	(-10.19) ***	(-6.13) ***	
Construct	0.0103	0.5327	0.4353	-4.4220	-3.4135	26.59 %
	(58.44) ***	(26.98) ***	(21.34) ***	(-12.24) ***	(-9.44) ***	
Financials	0.0105	0.1957	-0.0960	0.9061	5.2354	43.40 %
	(23.39) ***	(2.59) ***	(-1.84) *	(0.68)	(6.27) ***	
Food & Beverage	0.1238	11.7879	10.9312	-30.1174	-24.0091	29.54 %
	(14.71) ***	(11.06) ***	(10.16) ***	(-1.70) *	(-1.46)	
Healthcare	0.0097	0.5505	0.4734	-4.2058	-3.6014	31.02 %
	(57.49) ***	(23.46) ***	(21.66) ***	(-8.66) ***	(-8.64) ***	
Industrial Goods	0.0104	0.5215	0.4414	-3.5397	-3.2310	31.63 %
	(54.86) ***	(15.99) ***	(19.74) ***	(-4.15) ***	(-7.47) ***	
Media	0.0089	0.3829	0.3377	-2.3136	-1.9138	13.03 %
	(15.30) ***	(7.98) ***	(2.65) ***	(-3.14) ***	(-0.74)	

Oil & Gas	0.0080	0.6623	0.4887	-5.8438	-3.1086	16.16 %
	(27.54) ***	(23.39) ***	(7.81) ***	(-11.97) ***	(-2.41) **	
Personal& Household	0.0098	0.5633	0.4500	-3.8514	-2.7998	30.66 %
	(50.08) ***	(16.92) ***	(14.35) ***	(-4.51) ***	(-3.87) ***	
Real Estate	0.0097	0.5570	0.4945	-3.4865	-3.6935	34.41 %
	(53.88) ***	(18.67) ***	(21.59) ***	(-4.39) ***	(-8.01) ***	
Retail	0.0010	0.5211	0.4534	-3.3898	-3.6849	26.15 %
	(55.17) ***	(19.47) ***	(20.71) ***	(-5.60) ***	(-9.38) ***	
Tech	0.0104	0.4083	0.4283	-1.0435	-3.2952	29.35 %
	(35.84) ***	(6.71) ***	(15.65) ***	(-0.77)	(-7.41) ***	
Telecom	0.0067	0.5614	0.5062	-5.7870	-4.8525	13.28 %
	(19.42) ***	(16.00) ***	(14.13) ***	(-12.01) ***	(-9.47) ***	
Travel & Leisure	0.0097	0.4731	0.4191	-3.0221	-3.2717	24.00 %
	(45.92) ***	(12.61) ***	(17.79) ***	(-3.70) ***	(-7.45) ***	
Utilities	0.0086	0.5655	0.4145	-4.6831	-2.5246	30.45 %
	(51.70) ***	(26.73) ***	(15.64) ***	(-11.58) ***	(-4.53) ***	

2011

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Auto	0.0095	0.6968	0.6591	-0.4515	-0.1455	69.10 %
	(19.63) ***	(15.66) ***	(13.38) ***	(-0.71)	(-0.20)	
Banks	0.0020	0.2815	0.2264	-1.9814	-1.6268	20.81 %
	(12.34) ***	(8.80) ***	(10.60) ***	(-3.72) ***	(-4.40) ***	
Basic Resources	0.0094	0.4419	0.3517	-1.3787	0.3814	43.93 %
	(35.04) ***	(13.76) ***	(9.64) ***	(-2.47) **	(0.59)	
Chemicals	0.0104	0.4162	0.3545	-1.7610	-0.5829	38.70 %
	(37.10) ***	(12.91) ***	(9.57) ***	(-2.85) ***	(-0.98)	
Construct	0.0106	0.4484	0.3730	-2.5964	-1.0458	35.77 %
	(35.57) ***	(12.96) ***	(9.71) ***	(-3.88) ***	(-0.87)	
Financials	0.0085	0.4594	0.4747	-2.8481	-4.0895	26.19 %
	(25.80) ***	(11.78) ***	(13.63) ***	(-4.33) ***	(-7.06) ***	
Food & Beverage	0.0856	4.4774	4.8963	-42.8481	-22.5140	12.33 %
	(19.57) ***	(8.57) ***	(6.47) ***	(-4.16) ***	(-1.64) *	
Healthcare	0.0096	0.4470	0.3959	-1.8722	-0.9799	41.57 %
	(34.56) ***	(12.14) ***	(11.33) ***	(-2.28) **	(-1.73) *	

Industrial Goods	0.0105	0.4524	0.3781	-2.2624	-0.3484	41.49 %
	(35.04) ***	(12.69) ***	(9.25) ***	(-3.07) ***	(-0.44)	
Media	0.0104	0.6076	0.1393	-4.6786	7.2605	51.52 %
	(16.85) ***	(10.93) ***	(0.97)	(-4.86) ***	(2.16) ***	
Oil & Gas	0.0109	0.3951	0.1383	-2.0865	4.9146	32.14 %
	(13.16) ***	(5.77) ***	(0.60)	(-1.99) **	(0.85)	
Personal& Household	0.0100	0.4640	0.3914	-1.3175	0.2186	42.45 %
	(34.59) ***	(11.39) ***	(9.35) ***	(-1.35)	(0.27)	
Real Estate	0.0087	0.5315	0.4501	-2.9816	-1.2313	42.53 %
	(30.62) ***	(15.29) ***	(11.17) ***	(-4.75) ***	(-1.50)	
Retail	0.0091	0.5092	0.4840	-2.4846	-2.7779	35.79 %
	(29.99) ***	(12.43) ***	(9.44) ***	(-2.75) ***	(-2.47) **	
Tech	0.0106	0.45156	0.4124	-1.8512	-1.2398	41.13 %
	(31.86) ***	(13.14) ***	(10.83) ***	(-2.75) ***	(-1.98) **	
Telecom	0.0073	0.5845	0.6316	-3.8211	-4.8446	28.22 %
	(15.87) ***	(11.55) ***	(12.09) ***	(-4.46) ***	(-5.50) ***	
Travel & Leisure	0.0086	0.5202	0.4527	-2.3706	-1.3729	40.07 %
Utilities	(31.37) ***	(13.71) ***	(11.82) ***	(-2.95) ***	(-2.14) **	
	0.0081	0.5215	0.3818	-3.4010	-1.2877	36.70 %

Panel B: Shanghai Stock Exchange

	1990					
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Automobile	0.0106	0.3687	0.2689	-0.7914	0.1745	29.55 %
	(55.39) ***	(15.53) ***	(10.35) ***	(-2.38) **	(0.34)	
Banks	0.0026	0.3434	0.2490	-2.7719	-1.0867	23.51 %
	(21.61) ***	(18.01) ***	(8.97) ***	(-8.43) ***	(-1.38)	
Basic Resources	0.0108	0.1990	0.2710	0.8746	-0.7713	57.48 %
	(48.35) ***	(8.87) ***	(9.99) ***	(16.96) ***	(-2.03) **	
Chemicals	0.0120	0.3670	0.2798	-0.6422	-0.0065	31.21 %
	(60.82) ***	(12.81) ***	(19.12) ***	(-1.31)	(-0.04)	
Construction	0.0105	0.3646	0.2915	-0.9425	-1.0951	22.94 %
	(42.60) ***	(13.24) ***	(7.04) ***	(-2.63) ***	(-1.48)	
Financials	0.0221	-1.1061	-1.8538	17.1084	27.9586	6.40 %
	(8.75) ***	(-2.94) ***	(-4.35) ***	(2.28) **	(2.94) ***	

Food & Beverage	0.0169	0.5929	0.6510	3.4985	2.0030	35.94 %
	(45.05) ***	(10.66) ***	(16.57) ***	(3.63) ***	(3.62) ***	
HealthCare	0.0098	0.4440	0.3530	-0.3285	0.8587	41.14 %
	(40.85) ***	(19.01) ***	(7.19) ***	(-1.12)	(0.93)	
Industrial Goods	0.0117	0.2319	0.1786	2.7258	1.9287	64.54 %
	(32.48) ***	(2.61) ***	(9.22) ***	(1.71) *	(19.36) ***	
Insurance	0.0036	0.2447	0.2128	-1.9743	-1.7515	15.38 %
	(24.09) ***	(12.24) ***	(12.28) ***	(-5.76) ***	(-6.41) ***	
Media	0.0093	0.3414	0.2235	-2.2099	-1.4148	11.37 %
	(40.69) ***	(11.68) ***	(8.95) ***	(-5.58) ***	(-4.21) ***	
Oil & Gas	0.0077	0.3516	0.2971	-2.3004	-3.5868	8.03 %
	(12.77) ***	(2.36) **	(6.69) ***	(-0.79)	(-7.40) ***	
Personal& Household	0.0107	0.3768	0.3415	-0.0264	-0.6340	35.42 %
	(61.81) ***	(17.63) ***	(14.32) ***	(-0.07)	(-1.46)	
Real Estate	0.0106	0.3035	0.2692	0.0365	-0.9516	40.88 %
	(26.89) ***	(6.85) ***	(9.18) ***	(1.06)	(-2.43) **	
Retail	0.0096	0.3177	0.2515	-1.0898	-0.8752	22.04 %
	(56.32) ***	(12.31) ***	(15.19) ***	(-3.45) ***	(-6.12) ***	
Technology	0.0109	0.2872	0.2032	-1.0029	-0.5741	12.88 %
	(53.95) ***	(12.70) ***	(11.52) ***	(-6.67) ***	(-5.74) ***	
Telecom	0.0028	0.2951	0.2908	-1.4891	-2.0697	9.47 %
	(12.21) ***	(10.87) ***	(8.61) ***	(-3.58) ***	(-4.20) ***	
Travel & Leisure	0.0090	0.5270	0.4277	-1.2986	0.3061	40.53 %
	(40.79) ***	(20.11) ***	(11.22) ***	(-3.57) ***	(0.38)	
Utilities	0.0101	0.3103	0.1709	-0.9622	1.1966	25.84 %
	(26.80) ***	(12.80) ***	(2.19) **	(-4.89) ***	(0.94)	

		1996				
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Automobile	0.0099	0.5338	0.3610	-4.5403	-1.8462	27.95
	(61.08) ***	(27.47) ***	(19.63) ***	(-11.93) ***	(-5.34) ***	
Banks	0.0026	0.3434	0.2490	-2.7719	-1.0867	23.51
	(21.61) ***	(18.01) ***	(8.97) ***	(-8.43) ***	(-1.38)	
Basic Resources	0.0097	0.5633	0.4508	-4.4559	-3.2369	28.70
	(53.90) ***	(19.89) ***	(20.54) ***	(-7.15) ***	(-8.52) ***	
Chemicals	0.0101	0.5382	0.39786	-4.4889	-2.2453	30.86
	(62.98) ***	(26.72) ***	(21.44) ***	(-11.24) ***	(-6.51) ***	

Construction	0.0095	0.5977	0.4471	-5.1091	-2.9275	29.63
	(56.76) ***	(27.86) ***	(23.54) ***	(-12.72) ***	(-9.58) ***	
Financials	0.0121	-0.5444	0.5609	18.5546	-10.3719	7.17
	(5.63) ***	(-1.27)	(1.49) ***	(2.14) **	(-1.33)	
Food & Beverage	0.0169	0.4912	0.4745	4.3994	4.7152	36.25
	(53.84) ***	(11.41) ***	(8.79) ***	(4.79) ***	(3.79) ***	
HealthCare	0.0095	0.5264	0.4388	-3.4679	-2.5841	33.42
	(53.52) ***	(15.97) ***	(20.53) ***	(-4.70) ***	(-6.28) ***	
Industrial Goods	0.0102	0.5676	0.4297	-4.8755	-2.8622	31.49
	(65.05) ***	(28.24) ***	(24.27) ***	(-12.19) ***	(-9.14) ***	
Insurance	0.0036	0.2447	0.2128	-1.9743	-1.7515	15.38
	(24.09) ***	(12.24) ***	(12.28) ***	(-5.76) ***	(-6.41) ***	
Media	0.0083	0.5480	0.4408	-4.8485	-3.7989	20.44
	(43.95) ***	(23.44) ***	(19.21) ***	(-11.05) ***	(-9.33) ***	
Oil & Gas	0.0077	0.3516	0.2971	-2.3004	-3.5868	8.03
	(12.77) ***	(2.36) **	(6.69) ***	(-0.79)	(-7.40) ***	
Personal& Household	0.0099	0.5686	0.4567	-4.5757	-3.1375	30.96
	(62.40) ***	(28.09) ***	(24.89) ***	(-13.11) ***	(-9.70) ***	
Real Estate	0.0097	0.5471	0.4267	-4.5650	-2.7460	32.91
	(60.81) ***	(27.15) ***	(21.66) ***	(-10.78) ***	(-7.08) ***	
Retail	0.0095	0.5200	0.3946	-4.3961	-2.7782	29.17
	(63.46) ***	(27.18) ***	(22.94) ***	(-11.92) ***	(-9.35) ***	
Technology	0.0100	0.5722	0.4602	-4.6363	-3.3567	29.58
	(57.20) ***	(28.05) ***	(21.58) ***	(-13.79) ***	(-8.42) ***	
Telecom	0.0025	0.3875	0.4195	-2.3298	-3.5872	12.44
	(4.56) ***	(3.03) ***	(10.63) ***	(-1.06)	(-8.46) ***	
Travel & Leisure	0.0082	0.7360	0.6109	-6.8272	-5.3715	34.49
	(52.04) ***	(33.21) ***	(30.73) ***	(-16.46) ***	(-14.52) ***	
Utilities	0.0088	0.5362	0.4091	-4.5100	-2.5482	30.18
	(61.28) ***	(26.25) ***	(23.81) ***	(-11.58) ***	(-8.77) ***	

		2011				
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Automobile	0.0099	0.4209	0.3330	-1.5682	-0.9023	34.28
	(33.39) ***	(11.98) ***	(8.76) ***	(-2.53) **	(-1.32)	
Banks	0.0031	0.3715	0.2555	-2.7835	-1.5982	34.07
	(20.27) ***	(11.42) ***	(10.50) ***	(-4.30) ***	(-2.57) **	

Basic Resources	0.0094	0.4419	0.3517	-1.3787	0.3814	43.93
	(35.04) ***	(13.76) ***	(9.64) ***	(-2.47) **	(0.55)	
Chemicals	0.0100	0.4049	0.3711	-1.8306	-1.3140	38.14
	(37.03) ***	(12.99) ***	(11.78) ***	(-3.17) ***	(-2.55) **	
Construction	0.0091	0.4756	0.3905	-2.8079	-1.6229	35.87
	(32.67) ***	(13.68) ***	(12.21) ***	(-4.15) ***	(-3.25) ***	
Financials	0.0058	0.4458	0.1818	0.6004	-0.5553	5.25
	(2.49) ***	(1.55) ***	(0.37)	(-0.06)	(-0.06)	
Food & Beverage	0.0152	0.4435	0.5320	6.2735	3.9055	39.89
	(26.21) ***	(6.15) ***	(4.50) ***	(4.30) ***	(1.37)	
HealthCare	0.0090	0.4657	0.4222	-2.2016	-1.7322	41.58
	(36.48) ***	(13.87) ***	(12.74) ***	(-3.41) ***	(-2.82) ***	
Industrial Goods	0.0094	0.4626	0.3567	-2.7303	-0.8654	38.43
	(35.20) ***	(13.69) ***	(10.45) ***	(-4.07) ***	(-1.51)	
Insurance	0.0034	0.2075	0.2231	-0.5667	-1.5774	24.48
	(19.29) ***	(6.30) ***	(10.17) ***	(-0.75)	(-4.51) ***	
Media	0.0070	0.5019	0.4154	-4.2674	-3.3492	28.44
	(24.84) ***	(16.53) ***	(13.13) ***	(-8.78) ***	(-6.32) ***	
Oil & Gas	0.0094	0.0916	0.3572	8.8380	-2.1185	51.08
	(17.39) ***	(0.70)	(6.87) ***	(2.69) ***	(-2.42) **	
Personal& Household	0.0103	0.4110	0.3308	-1.6473	-0.3000	36.50
	(36.22) ***	(12.22) ***	(9.47) ***	(-2.95) ***	(-0.53)	
Real Estate	0.0091	0.4762	0.4180	-2.6245	-1.4286	41.33
	(33.59) ***	(14.67) ***	(12.01) ***	(-4.20) ***	(-2.27) **	
Retail	0.0070	0.1983	0.1114	-0.4320	0.2549	13.90
	(19.74) ***	(6.04) ***	(2.11) **	(-1.84) *	(0.31)	
Technology	0.0098	0.5036	0.3840	-3.2316	-1.0709	39.38
	(33.00) ***	(15.83) ***	(11.57) ***	(-7.35) ***	(-1.88) *	
Telecom	0.0023	0.8261	0.7616	-7.5536	-6.6012	30.68
	(6.76) ***	(16.77) ***	(15.16) ***	(-14.15) ***	(-9.60) ***	
Travel & Leisure	0.0074	0.5566	0.47780	-3.2443	-1.1494	42.62
	(28.62) ***	(13.71) ***	(12.12) ***	(-3.74) ***	(-1.48)	
Utilities	0.0081	0.4335	0.3769	-1.7017	-1.1614	41.53
	(35.69) ***	(14.30) ***	(11.92) ***	(-3.43) ***	(-2.35) **	

Notes: Table 5.9 reports the estimates from the following equation:
$CSAD_t = \alpha + \gamma_1 D^{vol-High} \left|R_{m,t}\right| + \gamma_2 \left(1 - D^{vol-High}\right)\left|R_{m,t}\right| + \gamma_3 \ D^{vol-High} (R_{m.t})^2 + \gamma_4 \left(1 - D^{vol-High}\right)(R_{m.t})^2 + \varepsilon_t$

Where $D^{vol-High}$ is 1 for days with high sector volume and 0 otherwise, based on a 30-day moving average $R_{m,t}$ is the the average value of sector return for each sector, $CSAD_{i,t}$ is the cross-sectional absolute deviation of returns for the sector, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients and εt is the error term at time t. The regression is estimated for the full sample and two sub-periods. The 1990 sample period covers 01/01/1990 to 18/10/2016, the 1996 sample period covers 01/01/1996 to 18/10/2016 and the 2011 sample period covers 01/01/2011 to 18/10/2016.The sub sample periods were split based on the percentage annual increase of the number of firms. T-test statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses.*******, ****** and ***** represent statistical significance at the 1%, 5%, and 10% level, respectively.

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5.5.3.3.2 Results for industry sectors

Having found mixed evidence of herding in high and low volume for the aggregate market, we now focus on the industry sectors to examine whether the observed herding is concentrated in specific sectors. Table 5.9 provides the regression estimates for both markets. The results for SZSE across the three periods are reported in Panel A. For the full sample, the γ_3 coefficient is negative and significant when trading volume is high in all industries except the Financials, Healthcare, Industrial Goods, Personal and Household and Real Estate, indicating the presence of herd behaviour. This finding is different from the results is Table 5.8, which indicate no herding for the full sample. Our evidence supports the literature which suggests that investors are more likely to herd at the industry level. When we analyse the results for the 1996 sub-period, we observe that for high volume states, the γ_3 coefficient is negative and significant in all sectors except Automobile, Financials and Technology. This result suggests that herding is prevalent in most sectors, therefore herding affect the dispersion of returns when trading volume is high. It is interesting to note that the Healthcare, Industrial Goods, Personal and Household and Retail sectors herd in both high and low volume states. We also note that for the Automobile sector, 'negative' herding occurs when the trading volume is high, but it diminishes in low volume state. For the 2011 sub-period, we find that when trading volume is high, the γ_3 coefficient is negative and significant for all sectors except Automobile and Personal and Household.

For the full sample, when trading volume is low, the γ_4 coefficient is negative and significant in all industries except Chemicals, Construction, Food and Beverage, Healthcare, Financials, Industrial Goods, Personal and Household, Retail, Travel and Leisure and Utilities. This is evidence that during this period investors focusing on the same sector herd towards the industry consensus when trading volume is low.

For the 1996 sub-period, the γ_4 coefficient is negative and significant for all sectors except Automobile, Financials, Food and Beverage and Media, indicating the prevalence of herd behaviour. For the 2011 sub-period, when trading volume is low the γ_4 coefficient is negative and significant for all sectors except Automobile, Basic Resources, Chemicals, Construction, Industrial Goods, Oil and Gas, Personal and Household and Retail sectors. It is interesting to note that herding is absent in the Financial sector when the trading volume is high, whereas, the coefficient becomes positive and significant when the trading volume is low indicating 'negative' herding. It is possible that investors in the sector find it easier to decipher the information of others when the trading volume is low, thus causing them to largely ignore their personal industry information in favour of that of others. Once again, the results are different from the aggregate results in Table 5.8, where there is no evidence of herding in low volume states. Overall, for the SZSE herding issignificant when trading volume is high, which may imply that its liquidity-oriented investors herd around industries where they can make a quick profit.

The results for SHSE are reported in Panel B. During high volume periods, the γ_3 coefficient for the full sample is negative and significant in all industries except Basic Resources Chemicals, Financials, Food and Beverage, Industrial Goods, Healthcare, Oil and Gas, Personal and Household and Real Estate, which provides a limited evidence of herding in most industries when trading volume is high. A stronger evidence of herding is reported in the 1996 sub-period. When the trading volume is high, the γ_3 coefficient is negative and significant for all industries except Financials, Food and Beverage, Oil and Gas, and Telecommunications, indicating herd behaviour in most industries. For the 2011 sub-period, the strong level of herding across industries persists when the trading volume is high as we report negative and significant coefficients in all industries expect Financials, Food and Beverage and Insurance.

The evidence for low trading volume state for the full sample shows that the γ_4 coefficient is negative and significant for Basic Resources, Insurance, Media, Oil and Gas, Real Estate, Retail, Technology, and Telecommunications. Herding becomes stronger for the 1996 sub-period, the γ_4 coefficient is negative and significant for all sectors except Banks, Food and Beverage and Financials, indicating the presence of herd behaviour in most sectors. However, herding appears to dissipate in the 2011 sub-period when the trading volume is low, more sectors do not herd (Automobile, Basic Resources, Financials, Food and Beverage, Industrial Goods, Personal and Household, Retail and, Travel and Leisure), the γ_4 coefficient is negative and significant for all other sectors. We note that 'negative' herding exists in the Food and Beverage sector in both high and low trading volume conditions. This suggests that investors in this sector ignore the industry consensus as a group.

Our overall results indicate that there is a relationship between herding and trading volume in the Chinese stock market, which exhibits similar patterns in both stock exchanges over time. All industries across the sub-periods show that herding starts with massive increases then declines when the trading volume is low in the last sub-periods. We find the strongest evidence of herding during the 1996 sub-period, which may have links with the panic selling that occurred during the Asian crisis (the impact of the crisis on herding is examined in a later section). Specifically, this is consistent with hypothesis H2C; industry herding is contingent upon trading volume.

Our results are consistent with Zheng, et al., (2017) who show that industry herding in the Chinese market occurs in only six out of ten industries when trading volume is high. On the other hand, when trading volume is low, more than five industries exhibit herd behaviour. They explain that investors tend to herd when markets are illiquid, thus when trading volume is low, public and private information is scarce and induces herding.

5.5.4 Herding and market stress

Christie and Huang (1995) suggest that herding is more likely to occur during periods of market stress. However, later studies report conflicting results on the impact on herding during crises. For example, regarding the effect of the Asian Crisis (AC thereafter) on the Chinese market, Demirer and Kutan (2006) and Tan, et al., (2008) do not find evidence of herding during the crisis, while Zheng, et al., (2017) confirm herd behaviour during the crisis. Consequently, in this section, we investigate the effect of the AC and GFC on market and sector level herding.

5.5.4.1 The Asian Crisis

The East Asian crisis that occurred in July 1997 has been cited as one of the major foreign currency crises of the 1990s (Goldstein, 1998). The crisis started in Thailand and resulted in a contagion that spread to other parts of Asia. Although the cause of the crisis has been disputed, academics argue that it was caused by the loss of confidence and panic of investors. According to Corsetti, et al., (1998) the exchange rate plummeted because of the overreaction of the market and herding.

While studies on the impact of the crisis on herding focus on the countries that were directly affected by the crisis (For example, Kim and Wei, 2002; Bowe and Domuta, 2004 and Chiang and Zheng, 2010), we set out to examine the impact of the crisis on herding the Chinese market and sectors. Few studies examine the impact of the AC on the herding on the Chinese market (See Demirer and Kutan, 2006; Tan, et al., 2008; Zheng, et al., 2017). Thus, this investigation enhances the existing literature.

To examine the impact of the AC on herding, we run the regression with the base model in equation 2. The regression is run using this equation for the three sub-periods.

5.5.4.1.1 Results for the overall market

Table 5.10 presents the results for the impact of the AC on herding in the Chinese market estimated using Eqn. (2) for the three sub-periods. The results for the SZSE are shown in Panel A. The γ_2 coefficient is negative and significant pre, during and post crisis, suggesting the presence of herd behaviour. Indeed, this means that investors in the SZSE appear to herd regardless of the state of the market. This agrees with the literature on contagion effect, given the Chinese market was not directly affected by the crisis. Interestingly, the nonlinear coefficient is most negative during the post-crisis period, which implies that the crisis revealed the new fundamentals and gave rise to a new market consensus on which the investors herded.

We observe interesting results when we examine the results for the SHSE reported in panel B. We find evidence of herding pre and after the crisis but not during the crisis. A possible explanation for the observed herding is that investors in this market tend to herd during tranquil times as it is easier to view the trade of others. This herd formation is consistent with the theory that herding is generated by information asymmetry as investors infer that their peers possess relevant information that they do not. Therefore, they are driven by the intent to herd regardless of their personal information. In contrast, at the onset of the crises, investors preferred to focus on their information and thus, ignored the market consensus because of the crisis (Calvo and Mendoza, 1997). Further, we conjecture that the Chinese investors may have been optimistic and exhibited the overconfidence bias because of the governments' fiscal policy and pro-active risk prevention measures it took before the crisis. Thus this reduced the tendency to herd. Consequently, investors preferred to trade based on their private information.

To summarise, our results are in favour of herding in the Chinese markets; we obtain evidence consistent with herding across all sub-periods except during the crisis period for the SHSE. Our results are largely in line with the prediction of H3 that herding is stronger during the AC, which is particularly interesting given that the Chinese market was seen to be immune from the effects of the crisis. In comparison to previous studies, our results differ from Demirer and Kutan (2006) who find no evidence of herding in SZSE and SHSE during the AC. However, the herding measure they employ in their study focuses on measuring herding during extreme market movement and may not detect herding during tranquil periods. In the same vein, our results are also in contrast with those of Tan, et al (2008), do not find evidence that herd behaviour is affected by the AC in SZSE and SHSE. The difference may be due to the herding measure employed, the period and the crisis sub-period specification. However, our results are like those obtained for other emerging markets affected by the crisis. Bowe and Domuta (2004) investigate herding among foreign and domestic investors in the Jakarta Stock Exchange and find evidence that both herd pre, during and post-crisis. Chiang and Zheng (2010) find evidence of herd behaviour during the crisis in the all the neighbouring markets (US, Indonesia, Korea and Singapore) examined except Malaysia. Hwang and Salmon (2004) reach an opposite conclusion, they find that herding behaviour in the Korean market during the AC helped to reduce herd behaviour. Having obtained evidence for the aggregate market, we examine the impact of the crisis on sectors.

Table 5.10 Regression estimates for herd behaviour for the Asian Crisis

Panel A: Shenzhen Stock Exchange

Period	α	γ_1	γ_2	Adj. R^2
Pre- crisis	0.0091	0.4438	-0.5406	52.50%
	(26.84) ***	(19.47) ***	(-3.45) ***	
Crisis	0.0130	0.5571	-5.4481	27.51%
	(24.48) ***	(12.37) ***	(-9.85) ***	
Post- crisis	0.0103	0.4696	-3.0602	34.47%
	(59.67) ***	(24.93) ***	(-8.55) ***	

Panel B: Shanghai stock exchange

Period	α	γ_1	γ_2	Adj. R^2
Pre- crisis	0.0135	0.2552	-0.3987	5.57%
	(23.74) ***	(5.31) ***	(-4.31) ***	
Crisis	0.0157	0.1786	-1.3897	4.49%
	(26.69) ***	(2.61) ***	(-1.02)	
Post- crisis	0.0116	0.3046	-1.9887	14.85%
	(67.04) ***	(14.73) ***	(-4.88) ***	

Notes: Table 5.10 reports the estimates from the following equation:

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

where $R_{m,t}$is the cross-sectional average of the N market returns in each sector at time t, the squared market return $R_{m,t}^2$ is used to capture the nonlinearity in the relationship, $CSAD_t$ is the cross-sectional absolute deviation of returns for the market, α is the constant, γ_1, and γ_2 are coefficients, and ε_t is the error term at time t. The model is run for the separately for the pre-crisis, crisis and post-crisis periods. Pre-crisis refers to the period between 1/01/1993 and 01/07/1997. Crisis refers to the period between 02/07/1997 and 30/12/1997. Post-crisis refers to the period between 01/01/1998 and 10/09/2001. T-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.4.1.2 Results for industry sectors

Regression results for the sectors during the AC estimated using Eqn. (2) are presented in Table 5.11. Panel A reports the results for the SZSE across the three sub-crisis periods. During the pre-crisis period we find strong evidence of herding, the γ_2 coefficents are negative and significant for all sectors except Chemicals, Healthcare, Media, Personal and Household, Retail, and Travel and Leisure sectors. The results for the crisis period show that investors herd significantly, the γ_2 coefficient is negative and significant for all sectors except the Automobile and Healthcare sectors. A similar level of herd behaviour persists post-crisis with all sectors except Automobile, Financials, Media and Real Estate sectors showing negative and significant γ_2 coefficients. We note that the coefficients for the Automobile and Financials sectors are positive and significant, indicating that during this period, investors in these sectors exhibited 'negative' herding, they largely ignore the industry consensus in favour of their private information. These results are consistent with the herd behaviour across all the crisis periods we report in Table 5.10.

The evidence of herding during the AC is further confirmed in Panel B which presents the results for the SHSE. During, the pre-crisis period all the γ_2 coefficients are negative and significant in all sectors but Basic Resources, Chemicals, Construction, Financials, Food and Beverage, Industrial Goods, Healthcare, Personal and Household, and Real Estate indicating the presence of herd behaviour in more than half of the sectors. However, we report positive and significant γ_2 coefficients for Basic Resources, Financials, Food and Beverage, Industrial Goods and Real Estate sectors, indicating the presence of 'negative' herding. It is important to point out the Oil and Gas sector and Food and Beverage were in excluded in the analysis for the pre-crisis and crisis periods due to insufficient data. For the crisis period, all the γ_2 coefficients are negative and statistically significant in all but the Food and Beverage sector, suggesting that almost all sectors display greater correlation in returns during the crisis due to herding. Therefore, during the crisis investors may have been loss averse, fearing potential loss and hence more inclined to herd. For the post-crisis period we report negative and significant γ_2 coefficients in all but the Construction, Financials, Food and Beverage and Oil and Gas sectors. From these results, we note that the investors in the Food and Beverage sector herd negatively across all crisis sub-periods, suggesting localised herding. Consequently, investors in this sector may have moved as a group into the sector resulting in an increased dispersion of returns. The results we obtain for the pre-and post-crisis periods are consistent with those in Table 5.10, while the results for the crisis period is inconsistent, as herding absent in the aggregate market becomes evident in the sector results.

Overall the evidence of the impact of the AC on industry herding indicates that it triggered herding in the Chinese market, pre, during and post-crisis, with the strongest level of herding exhibited in the SHSE during the crisis period. Our evidence is in contrast the literature that herding occurs during periods of market stress (Christie and Huang, 1995). On the contrary, we find that herding occurs in the industry sectors regardless of whether or not the market is in stress, which is consistent with H3. Possible explanations for the observed herding are like those provided in the previous section. Our findings are somewhat consistent with those obtained by Zheng, et al., (2017). They find herding in 8 out of 10 industries examined (Oil and Gas, Basic Materials, Industrial Goods, Consumer Goods, Healthcare, Consumer Services, Financials and Technology) during crises periods in their study which includes the AC. They report stronger levels of herding during tranquil periods, all the industries herd, probably due to prevailing pessimistic investor sentiment.

Table 5.11 Regression estimates for industry herd behaviour for the Asian Crisis

Panel A: Shenzhen Stock Exchange

	Pre-crisis				Crisis				Post Crisis			
Industry	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj.R^2
Automobile	-0.0002	0.8064	-0.2043	94.08%	0.0098	0.7082	0.3466	88.14%	0.0085	0.7113	0.3870	84.86%
	(-0.20)	(38.38) ***	(-5.22) ***		(10.83) ***	(15.14) ***	(1.20)		(31.66) ***	(52.86) **	(4.37) ***	
Banks	Insufficient data	For the sample period							0.0012	0.1590	-1.2418	7.30%
									(12.43) ***	(13.48) ***	(-8.09) ***	
Basic Resources	0.0089	0.1459	-0.5438	3.96%	0.0121	0.2066	-1.5503	7.49%	0.0091	0.4754	-3.5301	32.07%
	(17.41) ***	(5.48) ***	(-4.89) ***		(20.72) ***	(3.87) ***	(-2.05) **		(54.84) ***	(26.29) ***	(-10.69) ***	
Chemicals	0.0078	0.1424	-0.0241	10.14%	0.0129	0.2567	-2.9565	7.48%	0.0096	0.4601	-3.0436	33.21%
	(16.22) ***	(5.58) ***	(-0.09)		(22.21) ***	(5.08) ***	(-4.21) ***		(58.22) ***	(25.58) ***	(-9.40) ***	
Construction	0.0075	0.4284	-0.5654	38.60%	0.0139	0.2482	-1.2634	11.36%	0.0102	0.4477	-3.2980	26.57%
	(17.78) ***	(15.20) ***	(-3.42) ***		(20.12) ***	(3.79) ***	(-1.20)		(56.10) ***	(24.63) ***	(-10.66) ***	
Financials	0.0046	0.1170	-0.2526	9.08%	0.0111	0.1999	-2.3625	2.76%	0.0109	-0.0292	5.5833	66.14%
	(13.37) ***	(5.69) ***	(-2.18) **		(14.82) ***	(3.19) ***	(-2.99) ***		(45.54) ***	(-1.21)	(16.40) ***	
Food & Beverage	Insufficient data for	sample period							0.1241	11.3738	-27.7877	29.55%
									(14.73) ***	(12.70) ***	(-2.12) **	
Healthcare	0.0085	0.1501	0.0376	7.87%	0.0148	0.2401	-1.5144	9.83%	0.0096	0.4576	-2.9056	32.91%

	(11.75) ***	(2.15) **	(0.05)		(20.09) ***	(3.59) ***	(-1.29)		(57.03) ***	(23.76) ***	(-8.10) ***	
Industrial Goods	0.0081	0.5350	-0.7722	43.17%	0.0146	0.2970	-1.9074	15.74%	0.0101	0.4689	-3.2694	32.88%
	(16.27) ***	(12.93) ***	(-2.09) ***		(22.84) ***	(4.74) ***	(-1.75) *		(58.79) ***	(25.21) ***	(-9.36) ***	
Media	0.0007	0.0035	-0.0323	0.007%	0.0069	0.2932	-2.5017	5.82%	0.0090	0.3966	-0.1256	27.61%
	(4.37) ***	(0.69)	(-1.44)		(8.10) ***	(4.25) ***	(-2.76) ***		(9.10) ***	(2.39) **	(-0.04)	
Oil & Gas	0.0035	0.2314	-1.2500	6.56%	0.0061	0.6836	-5.0932	24.62%	0.0085	0.5259	-3.8482	23.05%
	(7.44) ***	(5.82) ***	(-4.76) ***		(6.32) ***	(6.99) ***	(-3.18) ***		(21.26) ***	(8.01) ***	(-2.67) ***	
Personal & Household	0.0087	0.6028	0.4628	48.89%	0.0146	0.2566	-1.8779	11.26%	0.0094	0.5003	-2.7480	36.52%
	(13.97) ***	(7.29) ***	(0.33)		(18.39) ***	(4.50) ***	(-2.46) **		(51.38) ***	(20.56) ***	(-4.67) ***	
Real Estate	0.0080	0.4140	-0.4579	48.48%	0.0144	0.5738	-3.6434	58.70%	0.0093	0.4303	-1.1606	38.57%
	(22.49) ***	(16.30) ***	(-1.71) *		(22.84) ***	(10.73) ***	(-4.61) ***		(33.88) ***	(11.55) ***	(-1.23)	
Retail	0.0093	0.2277	-0.1693	14.58%	0.0146	0.2680	-2.2418	14.58%	0.0097	0.4606	-3.3493	26.44%
	(17.67) ***	(6.34) ***	(-0.63)		(23.08) ***	(4.86) ***	(-2.68) ***		(54.67) ***	(23.95) ***	(-9.59) ***	
Technology	0.0078	0.1725	-0.4073	7.74%	0.0136	0.3523	-3.4156	9.57%	0.0098	0.4756	-3.2024	32.63%
	(15.80) ***	(6.72) ***	(-4.52) ***		(17.61) ***	(4.92) ***	(-3.35) ***		(52.50) ***	(25.08) ***	(-9.29) ***	
Telecom	Insufficien t data for	sample period							0.0066	0.5334	-5.3161	13.27%
									(19.45) ***	(18.18) ***	(-14.03) ***	
Travel & Leisure	0.0055	0.1225	0.0939	8.11%	0.0130	0.2562	-2.1597	7.66%	0.0094	0.4593	-3.1198	26.50%
	(10.59) ***	(2.81) ***	(0.17)		(18.12) ***	(4.28) ***	(-2.56) **		(50.76) ***	(22.34) ***	(-7.92) ***	
Utilities	0.0089	0.2898	-0.6903	19.69%	0.0125	0.2760	-2.0946	11.90%	0.0084	0.4653	-3.2799	30.41%
	(19.95) ***	(9.96) ***	(-4.13) ***		(20.33) ***	(4.66) ***	(-2.14) **		(52.91) ***	(26.52) ***	(-10.88) ***	

Panel B: Shanghai Stock Exchange

	Pre-crisis				Crisis				Post Crisis			
Industry	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj.R^2
Automobile	0.0099	0.3707	-0.4456	32.60%	0.0129	0.3497	-3.0168	13.59%	0.0096	0.4519	-3.3027	27.93%
	(20.12) ***	(11.33) ***	(-2.06) ***		(21.37) ***	(5.38) ***	(-2.96) ***		(56.53) ***	(26.16) ***	(-10.93) ***	
Banks	Insufficient data for	sample period							0.0026	0.2952	-1.9460	22.92%
									(22.45) ***	(16.06) ***	(-4.73) ***	
Basic Resources	0.0101	0.0914	0.9936	68.64%	0.0125	0.6959	-6.8244	25.22%	0.0093	0.4915	-3.6136	30.69%
	(20.31) ***	(2.96) ***	(13.57) ***		(17.46) ***	(8.88) ***	(-6.24) ***		(54.93) ***	(27.11) ***	(-11.94) ***	
Chemicals	0.0115	0.3332	-0.2637	28.48%	0.0136	0.4341	-4.9866	14.14%	0.0098	0.4580	-3.0843	32.58%
	(22.12) ***	(8.54) ***	(-0.72)		(20.46) ***	(5.30) ***	(-2.78) ***		(58.48) ***	(25.87) ***	(-3.87) ***	
Construction	0.0105	0.2109	-0.2056	16.64%	0.0115	0.6590	-5.6015	29.78%	0.0093	0.4780	-2.3238	1.71%
	(19.93) ***	(5.31) ***	(-0.63)		(16.58) ***	(8.37) ***	(-3.93) ***		(52.45) ***	(1.64)	(-0.40)	
Financials	0.0238	-2.5492	26.4547	7.70%	0.0069	2.0373	-55.0429	9.25%	0.0080	0.4436	-2.9349	2.39%
	(1.99) **	(-2.77) ***	(3.83) ***		(1.96) **	(2.75) ***	(-2.84) ***		(4.56) ***	(1.13)	(-0.41)	
Food & Beverage	0.0247	0.7173	1.9686	32.41%	0.0164	-0.4524	5.6378	37.88%	0.0167	0.4381	4.9760	36.30%
	(16.74) ***	(7.81) ***	(2.67) ***		(21.34) ***	(5.10) ***	(4.47) ***		(49.75) ***	(9.95) ***	(5.29) ***	
Healthcare	0.0085	0.5983	-0.7188	48.87%	0.0117	0.5092	-4.2817	23.44%	0.0091	0.5136	-3.7627	35.11%
	(17.91) ***	(14.62) ***	(-1.61)		(17.88) ***	(6.20) ***	(-2.69) ***		(58.23) ***	(28.50) ***	(-11.60) ***	
Industrial Goods	0.0105	0.3194	1.7366	74.73%	0.0146	0.4803	-4.7105	20.90%	0.0098	0.4794	-3.5654	20.90%
	(15.26) ***	(6.75) ***	(32.29) ***		(21.45) ***	(6.45) ***	(-3.07) ***		(60.54) ***	(28.22) ***	(-12.23) ***	

Insurance									0.0036	0.2272	-1.8410	15.21%
									(24.07) ***	(14.61) ***	(-7.68) ***	
Media	0.0053	0.0810	-0.5141	1.20%	0.0123	0.5195	-5.5860	11.23%	0.0079	0.5149	-4.5716	23.91%
	(10.32) ***	(2.99) ***	(-3.64) ***		(12.65) ***	(4.61) ***	(-2.21) **		(42.66) ***	(28.61) ***	(-16.61) ***	
Oil & Gas	Insufficient data for	sample period							0.0080	0.4170	-3.5508	11.42%
									(9.86) ***	(3.28) ***	(-1.57)	
Personal & Household	0.0111	0.4046	-0.1756	41.21%	0.0140	0.5216	-5.6871	18.82%	0.0095	0.4909	-3.5173	32.85%
	(23.51) ***	(10.87) ***	(-0.51)		(19.42) ***	(6.10) ***	(-2.93) ***		(58.47) ***	(28.95) ***	(-12.88) ***	
Real Estate	0.0089	0.2324	0.1076	46.91%	0.0134	0.2970	-2.7151	11.07%	0.0095	0.4868	-3.3301	34.98%
	(9.45) ***	(4.33) ***	(2.42) ***		(21.50) ***	(4.10) ***	(-1.78) *		(56.69) ***	(27.53) ***	(-10.30) ***	
Retail	0.0064	0.2627	-0.8122	22.67%	0.0127	0.2454	-2.7848	7.14%	0.0092	0.4636	-3.3202	30.78%
	(23.04) ***	(12.77) ***	(-6.34) ***		(22.23) ***	(3.86) ***	(-2.25) **		(57.90) ***	(27.16) ***	(-11.52) ***	
Technology	0.0080	0.1720	-0.4799	6.57%	0.0128	0.6207	-6.6998	21.72%	0.0096	0.5011	-3.8669	31.36%
	(19.34) ***	(6.42) ***	(-5.14) ***		(17.37) ***	(7.15) ***	(-3.99) ***		(55.24) ***	(29.50) ***	(-14.40) ***	
Telecom									0.0032	0.4548	-3.3115	14.91%
									(3.84) ***	(4.14) ***	(-1.91) *	
Travel & Leisure	0.0063	0.7323	-1.6316	56.06%	0.0130	0.7395	-7.5611	25.54%	0.0080	0.6370	-5.6692	34.79%
	(13.19) ***	(20.70) ***	(-4.87) ***		(14.11) ***	(6.91) ***	(-3.02) ***		(49.33) ***	(34.34) ***	(-17.82) ***	
Utilities	0.0099	0.3707	-0.4456	32.60%	0.0124	0.3375	-2.1611	14.54%	0.0084	0.4507	-3.2143	31.30%
	(20.12) ***	(11.33) ***	(-2.06) **		(19.87) ***	(5.00) ***	(-1.90) ***		(57.27) ***	(26.67) ***	(-11.09) ***	

Notes: Table 5.11 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 \ R_{m,t}^2 + \varepsilon_t$$

where $R_{m,t}$ is the cross-sectional average of the N market returns in each sector, at time t, the squared market return $R_{m,t}^2$ is used to capture the nonlinearity in the relationship, $CSAD_t$ is the cross-sectional absolute deviation of returns for the sectors, α is the constant, γ_1, and γ_2 are coefficients, and ε_t is the error term at time t. The model is run for the separately for the pre-crisis, crisis and post-crisis periods. Pre-crisis refers to the period between 1/01/1993 and 01/07/1997. Crisis refers to the period between 02/07/1997 and 30/12/1997. Post-crisis refers to the period between 01/01/1998 and 10/09/2001. T-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.4.2 Global Financial Crisis

Research has documented that co-movements during crises spread through contagion (Gebka and Wohar, 2013). Indeed, there is evidence of high levels of linkages between developed and emerging markets (For example, Gallo and Otranto, 2005). This linkage also results in the spread of crises beyond its country of origin to neighbouring markets and the world at large. The GFC which originated from the US spread internationally to economies and sectors of both developed and emerging markets. As a result, more finance researchers have focused their attention on the negative effect of these linkages on herding (For example Chiang and Zheng, 2010 and Yao, et al., 2014). Given the significant trade relationship between the US and China, we examine the impact of the GFC on Chinese stock markets. Therefore, we investigate the GFC related herding behaviour by dividing the daily data into sub-samples as follows: Pre-crisis (01/05/2002- 31/07/2007), Crisis (01/08/2007 - 30/03/2009) and Post-crisis: (01/04/2009 - 18/10/2016). The results for the aggregate market and sectors are discussed in the sections below.

5.5.4.2.1. Results for the aggregate market

Table 5.12 contains the regression estimates for both markets. Regressions are estimated for the three sub-samples using Equation (2). The results for the SZSE are reported in Panel A. Herding is observed across all the crisis phases, all the γ_2 coefficients are negative and significant. This result implies that these investors herded regardless of whether the market was in a tranquil or crisis state. It also provides evidence of the effect of greater financial integration and linkages via exports as earlier discussed. This effect is particularly pronounced in the SZSE because of its export-oriented nature which makes its investors informed of developments in international markets (Demirer and Kutan, 2006).

The results for the SHSE are reported in Panel B. The evidence suggests that herding occurs before the crisis and during the crisis, the γ_2 coefficients are negative and significant. However, the observed herding diminished after the crisis. We interpret this to mean that as tranquillity returned to the market, investors preferred to follow their own private information rather than that of the market.

The observed herding is of interest given that the crisis originated in the US and further demonstrates how its effect was amplified in the Chinese markets. These investors may have been driven to herd due to the contagion during the GFC (Chiang and Zheng, 2010). Our results of herding during the crisis is consistent with the literature that the uncertainty in periods of market stress such as crises drives investors to herd, thus confirms the predictions of H4. The herding we report pre-crisis is consistent with Hwang and Salmon's (2004) argument that herding is more prevalent during tranquil market condition. During such periods investors can respond quickly to the release of news by adjusting their investment decisions in line with the aggregate market.

Our results are consistent with those reported by Laih and Liau (2013) who provide evidence of herding in pre and post-crisis periods in the Chinese market during the GFC. Our results are also in line with Chiang and Zheng (2010) and Lao and Singh (2011) who find that herd behaviour is more prevalent in the Chinese market during the GFC. We report results that are in contrast with Yao, et al., (2014) who find no evidence the Chinese markets herd during the GFC. The differences in result may be due to sample and crisis period specifications.

Table 5.12 Regression estimates for herd behaviour in the Chinese markets around the Global Financial Crisis

Panel A: Shenzhen Stock Exchange

Period	α	γ_1	γ_2	Adj. R^2
Pre- crisis	0.0102	0.4763	-2.9739	31.82%
	(31.00) ***	(12.78) ***	(-3.65) ***	
Crisis	0.0137	0.3945	-2.9609	32.97%
	(17.47) ***	(7.16) ***	(-4.09) ***	
Post- crisis	0.0110	0.3925	-1.1851	38.48%
	(41.75) ***	(13.76) ***	(-2.27) **	

Panel B: Shanghai Stock Exchange

Period	α	γ_1	γ_2	Adj. R^2
Pre- crisis	0.1171	0.3163	-1.8103	14.51%
	(33.84) ***	(7.47) ***	(-1.88) *	
Crisis	0.0173	0.1834	-2.0167	3.43%
	(20.42) ***	(2.90) ***	(-2.34) **	
Post- crisis	0.0119	0.2194	-0.2716	16.71%
	(47.17) ***	(7.03) ***	(-0.42)	

Notes: Table 5.12 reports the estimates from the following equation:

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

where $R_{m,t}$ is the cross-sectional average of the N market returns at time t, the squared market return $R_{m,t}^2$ is used to capture the nonlinearity in the relationship, $CSAD_t$ is the cross-sectional absolute deviation of returns for the market, α is the constant, γ_1, and γ_2 are coefficients, and ε_t is the error term at time t. The model is run separately for the pre-crisis, crisis and post-crisis periods. Pre-crisis refers to the period between 01/05/2002 and 31/07/2007. Crisis period refers to the period between 01/08/2007 and 30/03/2009. Post-crisis refers to the period between 01/04/2009 and 18/10/2016. T-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.4.2.2. Results for industry sectors

Regression results for the industry sectors during the GFC estimated using Eqn. (2) are presented in Table 5.13. Panel A reports the results for the SZSE across the 3 sub-crisis periods. During the pre-crisis period we find strong evidence of herding, the γ_2 coefficents are negative and significant for all sectors except the Automobile, Banks, Food & Beverage, Financials, and Travel and Leisure sectors. Noticeably, we find evidence of 'negative' herding in the Financials sector as the γ_2 coefficient is positive and significant, indicating that the return dispersion is higher than the predictions of rational asset pricing models. This behaviour can be described as localised herding where investors move simultaneously in (out) of sectors resulting in increased return dispersion (Gebka and Wohar, 2013). Herd behaviour is more pronounced during the crisis period, the γ_2 coefficient is negative and significant in all sectors except the Automobile, Financials and Oil and Gas sectors where we observe positive and significant coefficients. The prevalence of industry herding during this period may be due to the reduced confidence and increased loss aversion of the investors. Another possible reason is that the crisis resulted in a 'flight to safety' whereby investors rebalance their portfolios with less risky assets during periods of uncertainty. The observed herd behaviour persists post-crisis as majority of the sectors except Automobile, Financials, Personal and Households, Real Estate, Media, Food and Beverage, and Oil and Gas show negative and significant γ_2 coefficients. The above results further confirms herding across all the crisis periods we find in Table 5.12.

We obtain similar results for the SHSE reported in Panel B. The results for the pre-crisis period show strong evidence of herding in most cases, the γ_2 coefficient is negative and significant in all sectors except Financials and Telecommunications. Evidence of herding becomes stronger during the crisis, the γ_2 coefficient is negative and significant in all sectors except the Food and Beverage sector. Again, the herding persists post-crisis, γ_2 coefficients are negative and significant in all sectors except the Financials, Food and Beverage and Oil and Gas sectors. The results we obtain for the pre-crisis and crisis periods are consistent with those in Table 5.12. However, the results for the post-crisis period is at odds with those in Table 5.12, the herding absent in the aggregate market becomes evident in the sector results.

Given that China is the world's leading consumer of food and beverage products[62], it is important to point out that its sector is strongly driven by 'negative' herding. We report positive and significant γ_2 coefficients for all the crisis sub-periods examined. This suggests that investors in the sector herd together against industry consensus regardless of whether the market is in a tranquil or crisis state. A possible explanation of this herd behaviour may be due to the sophistication of the investors in this sector which increases their reluctance to make losses and hence results in the homogeneity of their investment decisions.

The overall results for industry herd behaviour during the GFC reveal that investors in the Chinese market herd significantly pre, during and post-crisis, consistent with H4. Evidently, the GFC triggered herding activity as a result of a strong contagion effect. The findings for the crisis phase characterise the presence of intentional herding, where due to the uncertainty in the markets investors are motivated by an intent to invest in the same sectors as their peers. In contrast herding during the pre and post-crisis period may have been driven by the overconfidence bias stemming from their optimistic outlook of the market. Moreover, our results are somewhat consistent with those obtained by Zheng, et al., (2017). They find herding in 9 out of 10 industries examined (Oil and Gas, Basic Materials, Industrial Goods, Consumer Goods, Healthcare, Consumer services, Financials and Technology) during crises periods in their study which includes the GFC. They report stronger levels of herding during

[62] Source: Report: The Food & Beverage Market in China, EU SME

tranquil periods, all the industries herd, probably due to prevailing pessimistic investor sentiment. From an international context, our results are like that of BenSaida (2017) who provides evidence of herding in 10 out of 12 sectors of all the domestic US firms during the GFC.

Table 5.13 Regression estimates for industry herd behaviour in the Chinese markets around the Global Financial Crisis

Panel A: Shenzhen Stock Exchange

	Pre-crisis				Crisis				Post Crisis			
Industry	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj. R^2
Automobile	0.0071	0.7799	0.1079	89.49%	0.0157	0.4876	1.0207	69.95%	0.0340	0.0100	0.6423	73.82%
	(15.02)***	(37.27)***	(0.78)		(9.61)***	(6.93)***	(2.29)**		(4.08)***	(25.17)***	(25.39)***	
Banks	0.0035	0.0163	-0.1113	00.09%	0.0051	0.3057	-3.0369	9.34%	0.0024	0.2353	-1.6800	16.77%
	(2.82)***	(1.47)	(-0.91)		(7.09)***	(6.13)***	(-5.67)***		(15.71)***	(12.46)***	(-5.64)***	
Basic Resources	0.0091	0.5174	-4.3293	27.56%	0.0132	0.4075	-3.6194	23.78%	0.0098	0.3832	-1.1760	37.71%
	(27.74)***	(15.50)***	(-7.52)***		(14.66)***	(7.21)***	(-5.15)***		(40.02)***	(14.00)***	(-2.31)**	
Chemicals	0.0092	0.4891	-2.9449	32.71%	0.0134	0.4402	-3.5786	30.66%	0.0109	0.3584	-1.0489	35.34%
	(30.04)***	(14.61)***	(-4.60)***		(15.75)***	(7.67)***	(-4.85)***		(43.21)***	(13.89)***	(-2.47)**	
Construction	0.0101	0.4520	-3.1220	25.58%	0.0160	0.4687	-1.6193	12.36%	0.0110	0.3909	-1.9067	31.84%
	(28.64)***	(12.02)***	(-4.15)***		(13.16)***	(5.73)***	(-4.26)***		(40.88)***	(14.15)***	(-4.02)***	
Financials	0.0100	0.2318	4.7954	70.05%	0.0120	-0.1745	6.6353	91.13%	0.1202	7.9997	10.0742	22.10%
	(21.26)***	(5.29)***	(18.53)***		(16.17)***	(-4.73)***	(22.37)***		(13.90)***	(7.20)***	(0.46)	
Food & Beverage	0.4640	22.8677	-47.2278	33.62%	0.2885	13.7133	-81.3592	40.18%	0.0057	0.0203	0.1842	17.66%
	(3.10)***	(2.16)**	(-0.50)		(12.66)***	(9.59)***	(-4.92)***		(48.17)***	(2.61)***	(7.55)***	
Healthcare	0.0091	0.5076	-2.9896	30.29%	0.0125	0.3505	-2.2355	33.62%	0.0100	0.3867	-1.1735	38.61%
	(26.24)***	(11.40)***	(-3.13)***		(16.29)***	(6.71)***	(-3.44)***		(41.13)***	(14.48)***	(-2.38)**	

Industrial Goods	0.0101	0.4958	-3.7152	31.08%	0.0128	0.3812	-2.9641	29.34%	0.0109	0.3818	-1.2150	36.88%
	(30.62) ***	(13.78) ***	(-5.09) ***		(16.44) ***	(6.86) ***	(-3.99) ***		(40.72) ***	(13.30) ***	(-2.29) **	
Media	0.0084	0.4171	-2.4632	17.83%	0.0120	0.4908	-4.8549	13.89%	0.0111	0.2385	1.3591	24.32%
	(17.79) ***	(7.96) ***	(-2.33) **		(10.55) ***	(6.59) ***	(-5.55) ***		(12.60) ***	(1.55)	(0.38)	
Oil & Gas	0.0066	0.7108	-6.3095	27.01%	0.0106	-0.0080	0.1961	42.94%	0.0077	0.0082	0.2207	25.89%
	(16.24) ***	(15.67) ***	(-8.37) ***		(23.34) ***	(-1.16)	(8.98) ***		(47.83) ***	(1.55)	(12.52) ***	
Personal & Household	0.0089	0.5000	-4.0793	28.76%	0.0120	0.4908	-4.8549	13.89%	0.0104	0.3785	-0.3547	37.59%
	(28.75) ***	(15.12) ***	(-7.02) ***		(10.55) ***	(6.59) ***	(-5.55) ***		(40.27) ***	(12.26) ***	(-0.56)	
Real Estate	0.0102	0.5251	-3.1966	32.70%	0.0113	0.5738	-3.6434	58.70%	0.0093	0.4303	-1.1606	38.57%
	(27.05) ***	(10.21) ***	(-2.26) **		(16.03) ***	(10.73) ***	(-4.61) ***		(33.88) ***	(11.55) ***	(-1.23)	
Retail	0.0098	0.4305	-2.6555	23.60%	0.0137	0.3229	-2.7099	14.74%	0.0096	0.4405	-2.3568	31.39%
	(26.63) ***	(10.55) ***	(-3.22) ***		(14.63) ***	(5.18) ***	(-3.55) ***		(35.17) ***	(12.44) ***	(-3.16) ***	
Technology	0.0010	0.4345	-2.6179	26.70%	0.0131	0.4098	-3.6636	23.37%	0.0109	0.4830	-1.4311	38.40%
	(27.50) ***	(11.51) ***	(-3.32) ***		(15.34) ***	(7.04) ***	(-4.98) ***		(37.00) ***	(15.03) ***	(-3.12) ***	
Telecom	Insufficie nt data for	sample period			0.0029	0.1805	-1.9963	2.52%	0.0074	0.5643	-4.3738	22.44%
					(4.28) ***	(3.65) ***	(-4.15) ***		(18.42) ***	(14.22) ***	(-6.84) ***	
Travel & Leisure	0.0102	0.3878	-1.0514	22.75%	0.0142	0.3290	-3.1535	12.70%	0.0093	0.4229	-11.8062	32.19%
	(21.73) ***	(5.39) **	(-0.54)		(15.91) ***	(5.17) ***	(-4.07) ***		(36.85) ***	(15.14) ***	(-3.71) ***	
Utilities	0.0086	0.4607	-3.2151	27.67%	0.0116	0.4331	-3.6256	25.59%	0.0087	0.4072	-1.9726	32.77%
	(28.39) ***	(13.35) ****	(-4.97) ***		(13.84) ***	(7.50) ***	(-4.96) ***		(35.71) ***	(15.51) ***	(-4.35) ***	

Panel B: Shanghai Stock Exchange

	Pre-crisis				Crisis				Post Crisis			
Industry	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj. R^2	α	γ_1	γ_2	Adj.R^2
Automobile	0.0100	0.4743	-3.4118	24.15%	0.0131	0.3006	-2.3751	17.49%	0.0104	0.3632	-1.3605	30.23%
	(27.84) ***	(13.47) ***	(-4.98) ***		(15.17) ***	(5.48) ***	(-3.61) ***		(38.64) ***	(12.92) ***	(-2.76) ***	
Banks	0.0034	0.2718	-0.7842	22.11%	0.058	0.3429	-3.1925	25.46%	0.0032	0.2889	-1.8972	32.65%
	(9.36) ***	(4.08) ***	(-0.46)		(11.15) ***	(9.55) ***	(-6.98) ***		(23.41) ***	(13.40) ***	(-4.00) ***	
Basic Resources	0.0097	0.5110	-4.0561	28.37%	0.0140	0.3815	-3.4097	23.03%	0.0094	0.3822	-1.6799	34.97%
	(29.20) ***	(13.88) ***	(-5.47) ***		(15.72) ***	(6.74) ***	(-4.95) ***		(40.01) ***	(16.65) ***	(-4.48) ***	
Chemicals	0.0096	0.4684	-2.9773	30.10%	0.0141	0.3897	-2.9773	28.49%	0.0104	0.3713	-1.5074	35.77%
	(30.35) ***	(13.65) ***	(-4.24) ***		(15.75) ***	(6.48) ***	(-4.24) ***		(42.95) ***	(15.64) ***	(-3.87) ***	
Construction	0.0096	0.4431	-2.1274	28.76%	0.0135	0.4523	-4.2778	18.50%	0.0096	0.3938	-1.9705	32.33%
	(27.11) ***	(11.10) ***	(-2.41) **		(15.54) ***	(6.67) ***	(-5.20) ***		(39.19) ***	(15.95) ***	(-4.95) ***	
Financials	0.0136	-0.8420	16.3147	6.72%	0.0092	1.1135	-17.8326	1.60%	0.0052	0.4436	-2.9349	2.39%
	(4.75) ***	(-0.16)	(1.25)		(2.63) **	(2.10) **	(-1.84) *		(2.04) **	(1.13)	(-0.41)	
Food & Beverage	0.0177	0.3090	7.1979	31.88%	0.0303	-0.0017	7.6359	27.57%	0.0162	0.4068	6.1587	37.62%
	(31.54) ***	(4.83) ***	(5.96) ***		(14.79) ***	(-0.01)	(2.75) ***		(30.64) ***	(5.52) ***	(3.73) ***	
Healthcare	0.0096	0.5306	-3.8444	35.10%	0.0134	0.3592	-2.7955	26.04%	0.0095	0.4018	-1.7188	37.67%
	(31.48) ***	(15.68) ***	(-5.52) ***		(15.54) ***	(6.10) ***	(-3.79) ***		(42.85) ***	(16.37) ***	(-3.91) ***	

Industrial Goods	0.0102	0.4959	-3.8416	29.86%	0.0133	0.4057	-3.6542	26.73%	0.0010	0.3696	-1.5150	34.09%
	(32.20) ***	(15.38) ***	(-6.48) ***		(16.56) ***	(7.54) ***	(-5.16) ***		(41.76) ***	(14.67) ***	(-3.56) ***	
Insurance	0.0042	0.1754	-1.9321	3.31%	0.0051	0.2180	-2.2841	6.72%	0.0035	0.1964	-0.8696	21.19%
	(5.88) ***	(3.21) ***	(-3.13) ***		(7.82) ***	(5.22) ***	(-5.17) ***		(22.40) ***	(9.56) ***	(-2.12) ***	
Media	0.0082	0.5605	-4.6707	24.84%	0.0108	0.5700	-5.7538	23.24%	0.0075	0.4409	-3.7243	25.15%
	(20.74) ***	(11.96)	(-4.99) ***		(11.78) ***	(-9.59) ***	(-8.38) ***		(29.23) ***	(18.48) ***	(-10.11) ***	
Oil & Gas	0.0083	0.6018	-5.3649	23.42%	0.0121	0.5427	-5.7910	19.80%	0.0098	0.1596	4.6784	36.85%
	(22.51) ***	(14.84) ***	(-8.63) ***		(13.40) ***	(8.00) ***	(-6.50) ***		(8.30) ***	(0.77)	(1.01)	
Personal & Household	0.0089	0.5245	-3.8176	31.37%	0.0131	0.35711	-3.0048	23.88%	0.0105	0.3565	-1.0187	34.11%
	(29.34) ***	(15.92) ***	(-6.91) ***		(16.28) ***	(7.06) ***	(-5.11) ***		(41.91) ***	(14.04) ***	(-2.61) **	
Real Estate	0.0104	0.4900	-3.2947	29.82%	0.0131	0.4512	-3.4872	37.96%	0.0094	0.4059	-1.7700	38.36%
	(28.26) ***	(11.26) ***	(-3.13) ***		(15.95) ***	(8.08) ***	(-4.77) ***		(39.71) ***	(16.73) ***	(-14.35) ***	
Retail	0.0093	0.5343	-4.0173	28.94%	0.0136	0.3504	-2.8732	22.89%	0.0096	0.4405	-2.3568	31.39%
	(28.05) ***	(14.28) ***	(-5.79) ***		(16.49) ***	(6.37) ***	(-4.14) ***		(35.17) ***	(12.44) ***	(-3.16) ***	
Technology	0.0099	0.4559	-3.457	28.22%	0.0135	0.3155	-2.9276	14.49%	0.0102	0.3994	-1.8250	38.40%
	(29.32) ***	(14.79) ***	(-6.50) ***		(15.89) ***	(5.92) ***	(-4.75) ***		(39.20) ***	(16.49) ***	(-4.90) ***	
Telecom	0.0049	0.3748	0.6467	28.53%	0.0050	0.6078	-5.6271	16.18%	0.0030	0.7142	-6.1897	27.45%
	(5.00) ***	(2.72) ***	(0.25)		(4.85) ***	(8.03) ***	(-7.00) ***		(9.58) ***	(19.87) ***	(-14.03) ***	
Travel & Leisure	0.0089	0.6016	-5.2418	33.68%	0.0119	0.4528	-4.5965	21.43%	0.0079	0.4647	-2.0667	37.67%

	(28.52) ***	(17.69) ***	(-7.29) ***		(14.22) ***	(8.78) ***	(-7.71) ***		(33.88) ***	(15.66) ***	(-3.48) ***	
Utilities	0.0083	0.4636	-3.4451	31.25%	0.0113	0.4194	-3.8480	27.41%	0.0084	0.3763	-1.3324	35.45%
	(30.72) ***	(16.57) ***	(-7.95) ***		(15.17) ***	(8.63) ***	(-6.62) ***		(39.32) ***	(14.73) ***	(-3.57) ***	

Notes: Table 5.13 reports the estimates from the following equation:

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

where $R_{m,t}$ is the cross-sectional average of the N sector returns at time t, the squared market return $R_{m,t}^2$ is used to capture the nonlinearity in the relationship, $CSAD_t$ is the cross-sectional absolute deviation of returns for the sectors, α is the constant, γ_1, and γ_2 are coefficients, and ε_t is the error term at time t. The model is run for the separately for the pre-crisis, crisis and post-crisis periods. Pre-crisis refers to the period between 01/05/2002 and 31/07/2007. Crisis period refers to the period between 01/08/2007 and 30/03/2009. Post-crisis refers to the period between 01/04/2009 and 18/10/2016. T-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.5 Impact of the US market on herding in the Chinese Market

In the last two decades, there has been a substantial increase in global financial integration. Along with the benefits of integration such as growth capital flows between industrial and developing economies comes the adverse effects of financial contagion (Prasad, Rogoff, Wei and Kose, 2005). Chiang and Zheng (2010) point out that herd behaviour in a country can be influenced by herd behaviour in neighbouring and or global markets. Indeed, they provide evidence that investors herd around the US market. Accordingly, we investigate the impact of the US market on herding in the Chinese markets and sectors using data from the SZSE and SHSE. This investigation is important given that U.S. exports to China increased by 491% between 2002 and 2017[63]. Therefore, we include the US market (sector) return squared and CSAD as shown in equation 6. We analyse the results in the sections below.

5.5.5.1 Results for the aggregate market

Table 5.14 presents the results of the regression estimated for both markets across our sub-periods. From the results for the SZSE reported in Panel A, we observe that across the periods herd behaviour is absent as reflected by the negative but not statistically significant γ_4 coefficients. Thus, the evidence suggests that the SZSE does not herd with the US market. Interestingly, the results for the SHSE reported in Panel B contrast with these results. The γ_4 coefficients are negative and significant across all the sub-periods, indicating a dominant impact of the US return dispersion in the SHSE. Consequently, fluctuations in the US market returns induces herd behaviour in the SHSE.

We conjecture that investor composition is a reasonable explanation for the differences in the results we obtain for both markets. Chen, Nofsinger and Rui (2004) suggest that because major Chinese firms and choice universities are in Shanghai, the investors are likely to more

[63] Source: China-U.S. Trade Issues

sophisticated and informed than most parts of China. As a result, these investors may be more informed about global markets such as the US which increases the tendency to herd with these markets. In addition, the difference in size of the firms in both exchanges can provide another explanation for the differences in the results. The SHSE consists of mainly larger firms while SZSE consists of smaller firms. Larger firms are more likely involved in international trade and are therefore more prone to herd with the markets where these firms are located. Furthermore, the results can be explained by the increased trading relationship between the US and China: the imports from China to the US increased by 80% between 2000 and 2017 (United States Census Bureau, 2018), making China the top trading partner of the US. This rapidly developing relationship further increases the tendency to herd.

Overall, our results are in line with the predictions of H5; US returns play a role in herding in the Chinese markets. Our results for the SHSE are consistent with those reported by Luo and Schinckus (2015), they find the US has positive influence on herding in the Shanghai A-share market. Similarly, our results partly consistent with those of Chiang and Zheng (2010) who provide evidence that US returns influence herding in the Chinese stock market. Having obtained evidence from the aggregate market, we examine the sector results in the next section.

Table 5.14 Analysis of the impact of the US market on herding behaviour in the Chinese markets

Panel A: Shenzhen Stock Exchange

Year	1990	1996	2011
α	0.0108	0.0104	0.0106
	(76.01) ***	(59.69)***	(36.58)***
γ_1	0.0005	-0.5025	-0.0723
	(0.14)	(-11.59) ***	(-8.84)***
γ_2	0.3600	0.5034	0.4233
	(29.15) ***	(24.57) ***	(12.61)***
γ_3	-0.2848	-3.6938	-1.2826
	(-1.76) *	(-9.21) ***	(-2.13) **
γ_4	-0.0083	-0.0079	-0.0019
	(-1.21)	(-1.18)	(-0.14)
Adj. R^2	40.74 %	33.03%	42.28%

Panel B: Shanghai Stock Exchange

Year	1990	1996	2011
α	0.0122	0.0121	0.0118
	(66.86)***	(74.69)***	(42.65)***
γ_1	0.2601	0.2651	0.1765
	(18.46) ***	(15.30)***	(5.28)***
γ_2	-0.3371	-0.9223	1.0676
	(-14.23) ***	(-2.88) ***	(1.59)
γ_3	-0.3847	-0.6555	1.5562
	(-9.53) ***	(-2.66)***	(3.40)***
γ_4	-0.0211	-0.0225	-0.0280
	(-2.62) ***	(-2.95)***	(-1.84)*
Adj. R^2	10.15 %	17.30%	22.25%

Notes: Table 5.14 reports the estimates from the following equation:
$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 \ R_{m,t}^2 + \gamma_3 \ CSAD_{US,t} + \gamma_4 \ R_{US,m,t}^2 + \ \varepsilon_t$

where $R_{m,t}$is the cross-sectional average of the N market returns at time t, the squared market return $R_{m,t}^2$ is used to capture the nonlinearity in the relationship, $CSAD_{US,t}$ is the cross-sectional absolute deviation of returns for the US market and $R_{US,m,t}$is the return for the US market, α is the constant, γ_1, and γ_2 are coefficients, and ε_t is the error term at time t. The model is run for the whole period and the 1996 and 2011 sub-periods. T-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.4.5.2. Results for industry sectors

In this section we analyse sector results to investigate the impact of US sector returns on herd behaviour in corresponding Chinese sectors. Due to the close trading relationship between the US and China it is more likely to observe imitative behaviour especially in industries that trade heavily with the US[64]. To this end, we conduct similar tests using sector data.

Table 5.15 presents the regression results for Eq. (6). The results for the SZSE across the sub-periods are reported in Panel A. For the full sample, we observe negative and significant γ_3 coefficients in only the Banks, Industrial Goods, Personal and Household, Technology and Telecommunications sectors, indicating that investors in these sectors herd with their US counterparts. In addition, the results suggest 'negative' herd behaviour in Basic Resources, Chemicals, Food and Beverage, Media, Oil and Gas, and Real Estate, with positive and significant coefficients. This suggests that investors in these six sectors simultaneously herd away from the industry consensus of their US counterparts resulting a in increased dispersion in returns than that predicted by asset pricing models. For the 1996 sub-period, we obtain negative and significant γ_3 coefficients in only the Automobile, Construction, Financials, Industrial Goods, Technology and Telecommunications, implying that investors in these sectors strongly follow the analyses and information of their

[64] According to the United States International Trade Commission from 2013-2016 the top 5 China in sectors that traded with the US are Agriculture, Transportation equipment, electronic products, chemical and related products, minerals and metals.

corresponding US sectors. The herding coefficient γ_3 is significant and positive in Banks, Food and Beverage and Real Estate sectors. This indicates that during this period, investors make investment decisions based on their private information rather than the trading behaviour or sector news of US investors in corresponding sectors. The results for the 2011 sub-period suggests that herding occurs in almost half of the sectors: Automobile, Chemicals, Construction, Financials, Industrial Good, Media, Personal and Households, Technology and Travel and Leisure sectors. From our results we find that the technology sector in China herds with that of the U.S. across all sub-periods. This could be due to the significant amount of computer equipment imports from China, the second of the top five U.S. import from China[65]. Overall these results are in contrast those in the reported in Table 5.14, where we find no evidence of herding, which is consistent with the argument that herding is more likely to occur at the sector level.

The evidence for SHSE is reported in Panel B. There is limited evidence of herd behaviour during the 1990 period, as shown by the negative and significant γ_3 coefficients in the Automobile, Telecommunications and Travel and Leisure sectors. However, we find 'negative' herding in the Banks, Basic Resources, Media, Oil and Gas, Real Estate and Retail sectors. A few more industries herd during the 1996 sub-period, we report negative and significant coefficients in the Automobile, Industrial Good, Oil and Gas, Personal and Households and Technology sector while the we find 'negative' herding in the Banks sector. Herd behaviour further increases during the 2011 sub-period where we find negative and significant γ_3 coefficients in the Automobile, Chemicals, Construction, Financials, Industrial Goods, Oil and Gas and Technology sectors. We note that herding occurs in the Automobile sector across all sub-periods, this is interesting because according to the US

[65] Source: China- U.S. Trade Issues

Census Bureau, China imports substantial auto parts from the US which has increased by almost 90% between 2002 and 2016 (US Census Bureau, 2016). Similarly, US annual auto trade with China increased by almost 100% during the same period (US Census Bureau, 2016). The significant increase in auto trade between both countries is a possible explanation for the persistent herd behaviour we find.

In summary, our results for the impact of U.S. sectors on herding in Chinese sectors provide limited evidence of herding. Further, we find that more sectors in SZSE exhibit herd behaviour compared to the SHSE. In addition, a few sectors herd 'negatively' with the U.S. sectors. We observe this as evidence that investors in the Chinese sectors seem to mimic the trading decisions of their U.S. counterparts, particularly in sectors where there is significant trade between both countries. Furthermore, there is limited evidence in support of H5. Our results are somewhat like those of Zheng, et al., (2017) that show that Chinese industries do not follow the US market closely.

Table 5.15 Analysis of impact of the US market on industry herding behaviour in the Chinese markets

Panel A: Shenzhen Stock Exchange

			1990			
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2 (%)
Auto	0.0066	0.7885	-0.1925	0.0094	-0.4024	91.51
	(17.77) ***	(64.98) ***	(-6.26) ***	(4.12) ***	(-1.24)	
Banks	0.0010	0.0847	-0.5506	0.0020	-0.3201	5.72
	(13.90) ***	(12.53) ***	(-9.94) ***	(0.89)	(4.48) ***	
Basic Resources	0.0101	0.2725	-1.1357	0.0008	0.3066	16.66
	(59.29) ***	(16.45) ***	(-5.96) ***	(0.19)	(4.39) ***	
Chemicals	0.0107	0.2372	-0.5897	0.0023	0.4544	15.66

	(61.27) ***	(12.95) ***	(-2.03) **	(0.54)	(3.06) ***	
Construct	0.0106	0.3225	-0.2990	0.0003	-0.1206	28.89
	(65.46) ***	(23.39) ***	(-1.64)	(0.07)	(-0.96)	
Financials	0.0094	0.1246	1.3113	0.0582	0.0330	23.03
	(14.06) ***	(1.54)	(1.16)	(9.55) ***	(-0.39)	
Food & Beverage	0.1214	11.2548	-27.6944	0.5037	45.7895	29.69
	(14.37) ***	(12.51) ***	(-2.11) **	(2.25) **	(2.88) ***	
Healthcare	0.0105	0.2682	-0.8234	-0.0169	0.0978	14.22
	(27.74) ***	(5.40) ***	(-1.08)	(-3.56) ***	(0.42)	
Industrial Goods	0.0107	0.3712	-0.1813	0.0026	-0.4153	35.37
	(56.04) ***	(17.41) ***	(-0.53)	(0.57)	(-1.98) **	
Media	0.0088	0.2085	-1.1153	0.0078	0.4722	5.55
	(32.81) ***	(8.74) ***	(-4.18) ***	(1.47)	(2.60) ***	
Oil & Gas	0.0083	0.3976	-2.3785	0.0102	0.2606	15.54
	(32.21) ***	(14.16) ***	(-5.93) ***	(1.82) *	(3.38) ***	
Personal& Household	0.0104	0.3707	0.9610	0.0130	-0.7953	35.08
	(30.71) ***	(6.80) ***	(0.85)	(2.40) **	(-2.93) ***	
Real Estate	0.0099	0.3783	-0.4208	0.0113	0.1489	39.20
	(63.22) ***	(23.95) ***	(-1.67) *	(2.80) ***	(3.13) ***	
Retail	0.0108	0.2724	-0.5477	0.0010	0.2637	17.70
	(47.51) ***	(10.87) ***	(-1.58)	(0.21)	(1.22)	
Tech	0.0110	0.2659	-0.9241	0.0051	-0.2481	15.40
	(53.03) ***	(14.70) ***	(-4.45) ***	(1.18)	(-2.70) ***	
Telecom	0.0068	0.5335	-5.2911	-0.0032	-0.8755	13.47
	(19.48) ***	(18.18) ***	(-13.92) ***	(-0.39)	(-2.56) **	
Travel & Leisure	0.0102	0.2096	-0.5642	0.0118	0.3767	9.61
	(47.79) ***	(8.03) ***	(-1.24)	(2.44) **	(0.02)	
Utilities	0.0094	0.3232	-0.9882	0.0029	0.0094	26.93
	(56.06) ***	(17.83) ***	(-3.80) ***	(0.60)	(0.66)	

			1996			
Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2 (%)
Auto	0.0082	0.7418	0.1566	0.0162	-0.7437	88.04
	(28.26) ***	(56.36) ***	(2.14) **	(5.50) ***	(-2.31) **	
Banks	0.0011	0.1212	-0.8988	0.0027	0.2759	6.90
	(11.12) ***	(11.20) ***	(-6.72) ***	(0.95)	(4.17) ***	
Basic Resources	0.0093	0.4602	-3.4206	-0.0181	0.0782	26.71
	(34.27) ***	(11.49) ***	(-4.50) ***	(-3.93) ***	(1.25)	
Chemicals	0.0097	0.4700	-3.3944	-0.0398	0.0113	29.83
	(59.14) ***	(26.13) ***	(-10.67) ***	(-8.87) ***	(0.08)	
Construct	0.0103	0.4887	-3.9656	-0.0500	-0.2413	26.13
	(58.14) ***	(27.77) ***	(-13.59) ***	(-10.34) ***	(-2.01) **	
Financials	0.0100	0.1082	2.2778	0.0704	-0.2148	34.07
	(10.53) ***	(0.93)	(1.38)	(11.10) ***	(-2.25) **	
Food & Beverage	0.1214	11.2548	-27.6944	0.5037	45.7895	29.69
	(14.37) ***	(12.51) ***	(-2.11) **	(2.25) **	(2.88) ***	
Healthcare	0.0097	0.5165	-3.9707	-0.0396	-0.0842	30.60
	(57.08) ***	(26.45) ***	(-11.38) ***	(-8.22) ***	(0.41)	
Industrial Goods	0.0104	0.4883	-3.4854	-0.0443	-0.3854	30.98
	(55.11) ***	(20.66) ***	(-7.24) ***	(-9.57) ***	(-2.04) **	
Media	0.0089	0.3648	-2.2043	-0.002	0.0089	12.95
	(26.58) ***	(8.42) ***	(-2.78) ***	(-0.04)	(0.24)	
Oil & Gas	0.0080	0.5656	-4.2447	-0.0070	-0.0096	23.30
	(24.41) ***	(11.36) ***	(-4.03) ***	(-1.15)	(-0.13)	
Personal& Household	0.0098	0.5093	-3.3633	-0.0288	-0.3575	30.02
	(49.47) ***	(18.60) ***	(-5.56) ***	(-5.57) ***	(-1.63)	
Real Estate	0.0096	0.5293	-3.7016	-0.0308	0.1037	33.72
	(52.80) ***	(22.91) ***	(-7.42) ***	(-6.47) ***	(1.94) *	
Retail	0.0099	0.5041	-3.8918	-0.0375	-0.1038	25.32

	(54.51) ***	(24.09) ***	(-10.11) ***	(-7.06) ***	(-0.45)	
Tech	0.0107	0.4156	-2.1125	-0.0146	-0.4995	27.95
	(27.84) ***	(7.44) ***	(-1.95) *	(28.68) ***	(-4.92) ***	
Telecom	0.0068	0.5335	-5.2911	-0.0032	-0.8755	13.47
	(19.48) ***	(18.18) ***	(-13.92) ***	(-0.39)	(-2.56) ***	
Travel & Leisure	0.0097	0.4441	-3.1086	-0.0112	0.0722	23.38
	(42.87) ***	(14.91) ***	(-5.38) ***	(-2.24) **	(1.14)	
Utilities	0.0087	0.4881	-3.5424	-0.0295	-0.0116	26.56
	(50.19) ***	(22.57) ***	(-8.61) ***	(-6.15) ***	(-0.06)	

2011

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2 (%)
Auto	0.0098	0.6773	-0.2868	0.0527	-1.5505	69.20
	(18.87) ***	(17.21) ***	(-0.55)	(6.98) ***	(-1.71) *	
Banks	0.0021	0.2514	-1.7655	0.0203	-0.1665	20.29
	(-0.74)	(11.55) ***	(-5.27) ***	(3.58) ***	(-0.74)	
Basic Resources	0.0094	0.3962	-0.4895	-0.0463	-01212	43.79
	(33.84) ***	(13.16) ***	(-0.98)	(-5.38) ***	(-0.41)	
Chemicals	0.0105	0.3849	-0.5290	-0.0630	-0.5290	38.71
	(36.26) ***	(12.67) ***	(-1.64) ***	(-7.42) ***	(-1.64) **	
Construct	0.0108	0.4134	-1.8137	-0.0743	-1.0617	35.93
	(58.14) ***	(12.75) ***	(-3.32) ***	(-8.63) ***	(-3.01) **	
Financials	0.0086	0.4794	-3.7216	-0.0065	-1.3396	26.39

	(25.55) ***	(14.36) ***	(-6.95) ***	(-0.76)	(-4.04) ***	
Food & Beverage	0.0863	4.3954	-23.1741	-0.6085	4.4042	11.54
	(19.53) ***	(8.25) ***	(-2.28) ***	(-3.45) ***	(0.29)	
Healthcare	0.0097	0.4215	-1.4255	-0.0524	-0.0285	41.48
	(33.83) ***	(13.44) ***	(-2.60) ***	(-6.34) ***	(0.97)	
Industrial Goods	0.0106	0.4155	-1.2299	-0.0694	-0.9904	41.39
	(34.57) ***	(12.21) ***	(-1.99) **	(-8.18) ***	(-2.45) **	
Media	0.0112	0.2321	4.5491	0.0447	-0.9258	44.52
	(9.48) ***	(1.17)	(1.05) **	(4.23) ***	(-2.01) **	
Oil & Gas	0.0111	0.2513	1.9043	0.0399	-0.5426	28.98
	(10.52) ***	(1.42)	(0.47)	(3.53) ***	(-1.48)	
Personal& Household	0.0102	0.4273	-0.4603	-0.0652	-1.4024	42.58
	(34.12) ***	(11.63) ***	(-0.63)	(-6.73) ***	(-3.15) ***	
Real Estate	0.0089	0.4943	-2.1740	-0.0516	-0.5185	42.40
	(30.52) ***	(15.30) ***	(-3.90) ***	(-5.69) ***	(-1.19)	
Retail	0.0091	0.5018	-2.7427	-0.0631	-0.3354	35.68
	(28.19) ***	(11.59) ***	(-3.10) ***	(-6.33) ***	(-0.49)	
Tech	0.0108	0.4341	-1.5478	-0.0505	-0.8667	41.20
	(31.55) ***	(13.82) ***	(-3.01) ***	(-6.19) ***	(-1.88) *	
Telecom	0.0073	0.6132	-4.4512	0.0073	-0.6420	28.13

	(14.88) ***	(13.16) ***	(-5.91) ***	(0.71)	(-0.71)	
Travel & Leisure	0.0088	0.4837	-1.7916	-0.0376	-0.8612	40.13
	(30.77) ***	(14.81) ***	(3.32) ***	(-3.76) ***	(2.23) **	
Utilities	0.0082	0.4480	-2.2876	-0.0449	0.0919	35.98
	(29.27) ***	(14.61) ***	(-4.56) ***	(-4.92) ***	(0.13)	

Panel B: Shanghai Stock Exchange

1990

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2 (%)
Automobile	0.0106	0.3212	-0.3697	0.0144	-0.2519	28.96
	(66.14) ***	(22.52) ***	(-1.91) *	(3.27) ***	(-2.04) **	
Banks	0.0026	0.2945	-1.9525	0.0055	0.0829	23.00
	(22.10) ***	(15.99) ***	(-4.73) ***	(1.38)	(2.52) **	
Basic Resources	0.0114	0.1518	0.8902	-0.0112	0.3534	54.75
	(45.75) ***	(7.48) ***	(9.48) ***	(-2.44) **	(4.63) ***	
Chemicals	0.0110	0.3226	-0.3323	0.0141	-0.0445	29.66
	(58.62) ***	(15.30) ***	(-0.97)	(3.18) ***	(-0.28)	
Construction	0.0106	0.3108	-0.8168	0.0102	0.0313	21.88
	(47.41) ***	(12.44) ***	(-2.39) **	(2.21) **	(0.26)	

Financials	0.0197	-1.2901	19.8914	3.8317	1.5310	6.06
	(7.33) ***	(-3.65) ***	(3.08) ***	(7.01) ***	(1.76) *	
Food & Beverage	0.0170	0.6057	3.0236	0.0002	0.3660	35.83
	(43.14) ***	(13.94) ***	(4.43) ***	(0.02)	(0.32)	
Health Care	0.0097	0.4103	0.0764	-0.0035	0.1506	40.78
	(51.32) ***	(17.44) ***	(0.21)	(-0.71)	(0.55)	
Industrial Goods	0.0114	0.2431	1.8703	-0.0293	-0.3746	63.50
	(45.97) ***	(12.73) ***	(20.70) ***	(-6.32) ***	(-1.55)	
Insurance	0.0036	0.2264	-1.8431	0.0100	0.1011	15.26
	(23.63) ***	(14.58) ***	(-7.70) ***	(2.49) **	(1.50)	
Media	0.0092	0.2773	-1.7801	0.0074	0.3809	10.44
	(38.70) ***	(11.74) ***	(-6.11) ***	(1.56)	(2.22) **	
Oil & Gas	0.0076	0.3106	-2.7860	-0.0216	0.3624	6.20
	(10.63) ***	(2.85) ***	(-1.47)	(-3.53) ***	(4.91) ***	
Personal& Household	0.0108	0.3465	-0.1203	0.0060	-0.2681	34.68
	(60.23) ***	(16.84) ***	(-0.35)	(1.32)	(-1.18)	
Real Estate	0.0109	0.2463	0.0891	-0.0071	0.2943	39.32
	(29.17) ***	(8.56) ***	(4.42) ***	(-1.66)	(5.07) ***	
Retail	0.0096	0.2826	-0.9663	-0.0025	0.3927	21.54
	(59.22) ***	(18.02) ***	(-6.66) ***	(-0.65)	(2.12) **	

Technology	0.0109	0.2340	-0.7089	0.0038	0.1360	12.18
	(47.54) ***	(12.02) ***	(-5.85) ***	(0.92)	(1.31)	
Telecom	0.0030	0.2791	-0.5252	0.0079	-0.5252	9.13
	(13.56) ***	(11.12) ***	(-4.52) ***	(1.60)	(-2.90) ***	
Travel & Leisure	0.0089	0.4983	-0.8175	0.0255	-0.3117	40.12
	(48.62) ***	(24.90) ***	(-2.41) **	(4.97) ***	(2.31) **	
Utilities	0.0100	0.2599	-0.1347	-0.0326	0.1001	21.19
	(29.64) ***	(5.91) ***	(-0.21)	(-6.67) ***	(0.54)	

1996

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2 (%)
Automobile	0.0099	0.4533	-3.3343	-0.0414	-0.2414	26.82
	(59.90) ***	(26.43) ***	(-10.86) ***	(-8.77) ***	(-2.12) **	
Banks	0.0026	0.2945	-1.9525	0.0055	0.0829	23.00
	(22.10) ***	(15.99) ***	(-4.73) ***	(1.38)	(2.52) **	
Basic Resources	0.0097	0.5039	-3.8278	-0.0204	0.0607	28.10
	(54.28) ***	(24.23) ***	(-10.17) ***	(-4.14) ***	(0.83)	
Chemicals	0.0101	0.4698	-3.4062	-0.0516	0.0097	30.08
	(61.82) ***	(27.27) ***	(-11.18) ***	(-11.27) ***	(0.06)	

Construction	0.0096	0.5163	-3.8973	-0.0312	-0.1478	28.85
	(56.62) ***	(29.68) ***	(-14.16) ***	(-6.26) ***	(-1.26)	
Financials	0.0152	-0.4006	10.9240	2.1507	0.3073	2.91
	(4.14) ***	(-0.73)	(1.10)	(13.83) ***	(0.42)	
Food & Beverage	0.0154	0.4820	5.1561	-0.0017	-1.0129	39.80
	(26.24) ***	(5.81) ***	(2.87) ***	(-0.17)	(-0.49)	
Health Care	0.0090	0.4456	-1.9760	-0.0374	-0.6136	41.53
	(35.06) ***	(15.40) ***	(-4.01) ***	(-7.94) ***	(0.85)	
Industrial Goods	0.0096	0.4075	-1.6758	-0.0462	-1.3843	38.37
	(34.99) ***	(13.60) ***	(-3.43) ***	(-9.98) ***	(-3.61) ***	
Insurance	0.0034	0.2149	-1.0550	-0.0897	-0.0103	23.74
	(19.27) ***	(9.57) ***	(-2.41) ***	(-2.06) **	(-0.04)	
Media	0.0071	0.4580	-3.7920	-0.0109	-0.5475	28.04
	(24.74) ***	(17.33) ***	(-9.58) ***	(-2.08) **	(-1.07)	
Oil & Gas	0.0104	0.1184	5.3332	-0.0216	-0.9641	38.89
	(7.87) ***	(0.54)	(1.13)	(-3.53) ***	(-2.12) **	
Personal& Household	0.0105	0.3702	-0.9171	-0.0386	-0.9576	36.41
	(35.93) ***	(12.30) ***	(-2.06) **	(-7.83) ***	(-1.94) *	
Real Estate	0.0091	0.4442	-1.9388	-0.0484	-0.2684	41.27
	(33.40) ***	(15.21) ***	(-4.00) ***	(-10.97) ***	(-0.55)	

Retail	0.0086	0.4354	-2.2025	-0.0373	0.3194	39.44
	(32.44) ***	(14.52) ***	(-4.32) ***	(-8.32) ***	(0.46)	
Technology	0.0100	0.4431	-2.1035	-0.0341	-1.3583	39.20
	(32.71) ***	(15.68) ***	(-5.20) ***	(-7.06) ***	(-2.92) ***	
Telecom	0.0024	0.7932	-7.0820	-0.0008	-0.9618	30.69
	(6.85) ***	(19.54) ***	(-15.41) ***	(-0.15)	(-1.27)	
Travel & Leisure	0.0074	0.5206	-2.2043	-0.0305	-0.7500	42.47
	(26.81) ***	(14.15) ***	(-3.07) ***	(-5.72) ***	(-1.53)	
Utilities	0.0081	0.4040	-1.4760	-0.0279	0.7204	41.45
	(35.04) ***	(14.92) ***	(-3.64) ***	(-5.99) ***	(1.10)	

2011

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2 (%)
Automobile	0.0100	0.3796	-1.3071	-0.0502	-0.8641	34.03
	(33.40) ***	(11.58) ***	(-2.37) ***	(-5.72) ***	(-3.67) ***	
Banks	0.0031	0.3083	-2.0586	0.0191	-0.1512	32.43
	(19.46) ***	(12.16) ***	(-3.88) ***	(3.24) ***	(-1.11)	
Basic Resources	0.0089	0.4017	-1.4230	-0.0321	-0.2658	39.72
	(33.58) ***	(14.86) ***	(-3.28) ***	(-3.91) ***	(-1.08)	

Chemicals	0.0102	0.3871	-1.5337	-0.0641	-0.4537	38.20
	(36.90) ***	(14.10) ***	(-3.60) ***	(-8.13) ***	(-1.70) *	
Construction	0.0093	0.4310	-2.1665	-0.0402	-1.0875	35.93
	(32.54) ***	(14.84) ***	(-4.82) ***	(-4.78) ***	(-3.60) ***	
Financials	0.0061	0.3754	-1.1825	1.0841	-4.7448	4.05
	(2.22) **	(0.89)	(-0.16)	(13.92) ***	(-3.36) ***	
Food & Beverage	0.0154	0.4820	5.1561	0.0224	-1.0129	39.80
	(26.24) ***	(5.81) ***	(2.87) ***	(1.10)	(-0.49)	
Health Care	0.0090	0.4456	-1.9760	-0.0538	-0.6136	41.53
	(35.06) ***	(15.40) ***	(-4.01) ***	(-6.51) ***	(-0.85)	
Industrial Goods	0.0096	0.4075	-1.6758	-0.0538	-1.3843	38.37
	(34.99) ***	(13.60) ***	(-3.43) ***	(-6.47) ***	(-3.61) ***	
Insurance	0.0034	0.2149	-1.0550	-0.0014	-0.0103	23.74
	(19.27) ***	(9.57) ***	(-2.41) **	(-0.95)	(-0.04)	
Media	0.0071	0.4580	-3.7920	-0.0100	-0.5475	28.04
	(24.74) ***	(17.33) ***	(-9.58) ***	(-1.35)	(-1.07)	
Oil & Gas	0.0104	0.1184	5.3332	0.0703	-0.9641	38.89
	(7.87) ***	(0.54)	(1.13)	(6.04) ***	(-2.12) **	
Personal& Household	0.0105	0.3702	-0.9171	-0.0664	-0.9576	36.41
	(35.93) ***	(12.30) ***	(-2.06) ***	(-7.57) ***	(-1.94)	

Real Estate	0.0091	0.4442	-1.9388	-0.0552	-0.2684	41.27
	(33.40) ***	(15.21) ***	(-4.00) ***	(-6.64) ***	(-0.55)	
Retail	0.0086	0.4354	-2.2025	-0.0404	0.3194	39.44
	(32.44) ***	(14.52) ***	(-4.32) ***	(-4.92) ***	(0.46)	
Technology	0.0100	0.4431	-2.1035	-0.0419	-1.3583	39.20
	(32.71) ***	(15.68) ***	(-5.20) ***	(5.11) ***	(-2.92) ***	
Telecom	0.0024	0.7932	-7.8020	0.0058	-0.9288	30.69
	(6.85) ***	(19.64) ***	(-15.41) ***	(0.53)	(-1.27)	
Travel & Leisure	0.0074	0.5206	-2.2043	-0.0206	-0.7500	42.47
	(26.81) ***	(14.15) ***	(-3.07) ***	(-2.07) **	(-1.53)	
Utilities	0.0081	0.4040	-1.4760	-0.0536	0.7204	41.45
	(35.04) ***	(14.92) ***	(-3.64) ***	(-6.78) ***	(1.10)	

Notes: Table 5.15 reports the estimates from the following equation:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 \; R^2_{m,t} + CSAD_{US,t} + R_{US,m,t} + \; \varepsilon_t$$

where $R_{m,t}$is the cross-sectional average of the N sector returns at time t, the squared market return $R^2_{m,t}$ is used to capture the nonlinearity in the relationship, $CSAD_{US,t}$ is the cross-sectional absolute deviation of returns for the US sectors and $R_{US,m,t}$is the return for the US sectors, α is the constant, γ_1, and γ_2 are coefficients, and ε_t is the error term at time t. The model is run for the whole period and the 1996 and 2011 sub-periods. T-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5.16 Summary of Results for herding in Chinese markets

<table>
<tr><td>Test</td><td>Shenzhen Stock Exchange</td><td>Shanghai Stock Exchange</td></tr>
<tr><td>Market herding</td><td>Yes (all periods)</td><td>Yes (Whole sample and 2nd sub-period)</td></tr>
<tr><td>Industry herding</td><td>Whole period: Automobile, Banks, Basic Resources, Chemicals, Food and Beverage, Media, Oil and Gas, Real Estate, Technology, Telecommunication, and Utilities.

1st sub-period: all except Automobile and Financials.

2nd sub-period: Banks, Chemicals, Construction, Financials, Food and Beverage, Industrial Goods, Real Estate, Retail, Technology, Telecommunications, and Travel & Leisure, and Utilities.</td><td>Whole period: except for Basic Resources, Financials, Food and Beverage, Health Care, Industrial Goods, Oil & Gas, Personal Holding, Real Estate and Utilities.

1st sub-period: all except for Financials, and Food & Beverage.

2nd sub-period: all except for Food and Beverage, and Oil and Gas</td></tr>
<tr><td>Herding: rising (declining) market returns

Market level</td><td>Rising market: Yes (only in the 1st sub-period).

Declining market: Yes (all periods).</td><td>Rising market: Yes (only in the 1st sub-period).

Declining market: Yes (only in the 1st sub-period).</td></tr>
<tr><td>Herding: rising (declining) market returns

Sector level</td><td>Whole period
Rising market: Automobile, Banks, Basic Resources, Media, Oil and Gas, Personal and Household, Real Estate, Retail, Technology, Telecommunications, & Utilities.

Declining market: all except Personal and Household.

1st sub-period:
Rising market: the all s except for Financials, Food and Beverage, Oil and Gas, and Real Estate

Declining market: all except Automobile, Personal & Household.

2nd sub-period:
Rising market: all except for Healthcare, Media, Oil and Gas, Personal and Household, Travel and Leisure and Utilities.</td><td>Whole period
Rising market: Banks, Construction, Insurance, Media, Oil & Gas, Retail, Technology, & Telecommunications.

Declining market: all except for Banks, Food and Beverage, Industrial Goods, Real Estate, Telecommunications & Utilities.

1st sub-period:
Rising market: all except for Financials, Food & Beverage, & Personal & Household.

Declining market: Bank, Financials, Telecommunications.

2nd sub-period:
Rising market: Automobile, Banks, Construction, Industrial Goods, Media, Insurance, Real Estate,</td></tr>
</table>

	Declining market: all	Technology, Telecommunication & Utilities Declining market: all except for Bank, Food & Beverage, & Insurance.
Herding: high (low) volatility Market level	High volatility: Yes (1st sub-period). Low volatility: Yes (whole period & 2nd sub-period).	High volatility: Yes (whole period & 1st sub-period). Low volatility: Yes (2nd sub-period).
Herding: high (low) volatility Sector level	**Whole period** High volatility: all except for Chemicals, Financials, Food and Beverage, Healthcare, Industrial Goods, Personal & Household, Real Estate, and Travel & Leisure Low volatility: all **1st sub-period**: High volatility: all except for Automobile, Financials, Food and Beverage and Technology Low volatility: all except for Automobile, & Telecommunication. **2nd sub-period**: High volatility: all expect for Automobile, Chemicals, Construction, Healthcare, Industrial Goods, Media, Oil & Gas, & Technology. Low volatility: Automobile, Banks, Financials, Telecommunications, & Utilities.	**Whole period** High volatility: all except Automobile, Chemicals, Healthcare, Personal & Household, Oil & Gas, & Utilities. Low volatility: all except Basic Resources and Technology. **1st sub-period**: High volatility: all except Financials, Insurance, Industrial Good, and Oil & Gas Low volatility: all except Financials and Telecommunications. **2nd sub-period**: High volatility: Bank, Construction, Healthcare, Media, Real Estate, Retail, Technology, Telecommunications, Travel & Leisure. Low volatility: Banks, Basic Resources, Chemicals, Media, Oil & Gas, Personal & Household, Real Estate, Retail, Technology and Telecommunications.
Herding: high (low) volume Market level	High volume: Yes (1st and 2nd sub-periods). Low volume: Nil	High volume: Yes (whole period & 1st sub-period). Low volume: Yes (whole period & 1st sub-period)
Herding: high (low) volume Sector level	**Whole period** High volume: all except Financials, Healthcare, Industrial Goods, Personal & Household, & Real Estate.	**Whole period** High volume: all except Basic Resources Chemicals, Financials, Food & Beverage, Industrial Goods, Healthcare, Oil and Gas,

	Low volume: all except Chemicals, Construction, Food & Beverage, Healthcare, Financials, Industrial Goods, Personal & Household, Retail, Travel & Leisure & Utilities. **1st sub-period**: High volume: all except Automobile, Financials & Technology. Low volume: all except Automobile, Financials, Food and Beverage and Media. **2nd sub-period**: High volume: all except Automobile, & Personal & Household. Low volume: all except Automobile, Basic Resources, Chemicals, Construction, Industrial Goods, Oil and Gas, Personal & Household & Retail.	Personal & Household & Real Estate. Low volume: Basic Resources, Insurance, Media, Oil & Gas, Real Estate, Retail, Technology, & Telecommunications **1st sub-period**: High volume: all except Financials, Food & Beverage, Oil & Gas, & Telecommunications. Low volume: all except Banks, Food and Beverage and Financials. **2nd sub-period**: High volume: all except Financials, Food & Beverage, and Insurance. Low volume: all except Automobile, Basic Resources, Financials, Food & Beverage, Industrial Goods, Personal & Household, Retail, & Travel & Leisure.
Asian Crisis Market level	Yes (all crisis phases)	Yes (pre and post-crisis)
Asian Crisis Sector level	**Pre-crisis:** all except Chemicals, Healthcare, Media, Personal & Household, Retail, Travel & Leisure. **Crisis:** all except Automobile, & Healthcare. **Post-crisis:** all except Automobile, Financials, Media, & Real Estate.	**Pre-crisis:** all except Basic Resources, Chemicals, Construction, Financials, Food & Beverage, Industrial Goods, Healthcare, Personal & Household, & Real Estate . **Crisis:** all except Food & Beverage **Post-crisis:** all except Construction, Financials, Food & Beverage, & Oil & Gas.
GFC Market level	Yes (all crisis phases)	Yes (pre and during the crisis)
GFC Sector level	**Pre-crisis:** all except Automobile, Banks, Food & Beverage, Financials, Travel & Leisure. **Crisis:** all except Automobile, Financials & Oil & Gas.	**Pre-crisis:** all except, Financials, & Telecommunication **Crisis:** all except Food & Beverage **Post-crisis:** all except Financials, Food & Beverage, & Oil & Gas.

	Post-crisis: all except Automobile, Financials, Personal & Households, Real Estate, Media, Food & Beverage, and Oil & Gas.	
Impact of US returns Market level	Nil (all periods)	Yes (all periods)
Sector level	**Whole period**: Banks, Industrial Goods, Personal and Household, Technology, &Telecommunications. **1st sub-period**: Automobile, Construction, Financials, Industrial Goods, Technology & Telecommunications. **2nd sub-period**: Automobile, Chemicals, Construction, Financials, Industrial Goods, Media, Personal and Households, Technology and Travel and Leisure	**Whole period**: Automobile, Telecommunication, Travel & Leisure. **1st sub-period**: Automobile, Industrial Goods, Oil & Gas, Personal & Household, & Technology. **2nd sub-period**: Automobile, Chemicals, Construction, Financials, Industrial Goods, Oil & Gas, & Technology.

5.6. Summary and Conclusion

In this chapter, we extended the investigation of industry herding to Chinese markets using individual data of 1,481 Shenzhen firms and 978 Shanghai firms classified into 19 sectors. Specifically, we investigate whether herd behaviour is contingent upon high (low) market return, days with high (low) volatility and, trading volume. Also, we examine the impact of the AC and GFC on herding. Furthermore, we examine the role the US market plays on market (industry) level herding in the Chinese markets. We test for herding using the CSAD model proposed by Tan, et al., (2008) on our sample from January 1990 to October 2016.

Our findings are summarised in Table 5.16. We find evidence of herding at both the market level and industry level in China, although herding was more pronounced in SZSE. This is in line with the argument of Demirer and Kutan (2006) who point out that SZSE is more likely to herd because it consists of small firms and exporting firms and is seen to be less informed than SHSE. Regarding asymmetry, we find that industry herding is more prevalent in the SZSE when the market is declining, particularly in sectors like Banks, Chemicals, Construction, Food and Beverage and Industrial Goods. Regarding volatility, we find that investors in SZSE herd more when volatility is low. However, in SHSE, herding is more prevalent on days with high volatility.

We also report that SZSE market only herds on days with high trading volume at the market level. However, herding is more prevalent at the industry level and is strongest in the 1st sub-period with all sectors herding except Automobile, and Telecommunication. When we examine the effect of the Asian crisis on herding, we find that the SZSE herds pre, during, and post-crisis at both the market and industry level. During the Global Financial Crisis, we find a similar herding trend, SZSE herded during all the crisis phases, for both stock exchanges there is strong evidence of herding in most sectors. On the role of the US market, we that at the market level, US returns only has an impact on herding in the SHSE. However, we find limited evidence of its impact on industry herding in both stock exchanges.

The findings in this chapter have important policy implications. First, the finding implies that participants in the Chinese stock markets (sectors) maybe irrational when they make investment decisions. Policy makers and/or regulators should therefore consider the irrationality of Chinese market participants in their rule-making process and in their market reforms. Second, policy makers and/or regulators should be concerned of the potential for herding to destabilise the stock market. Three, market segmentation is a barrier for the efficient flow of price information because there are differences in the level of information available to market participants in the two markets. Four, another implication of our findings is that due to the co-movement of stocks, investors require a larger number of stocks to achieve diversification. Additionally, the Chinese market may be impacted by future crises due to contagion, as our findings show that the Chinese market was impacted by the Asian crisis and the global financial crisis. Fifth, stricter stock market regulations may be required in the Chinese markets to curtail industry herd behaviour. Finally, the results on the impact of US returns on herding in the Chinese markets (sectors) imply that the trade relationship between both countries facilitates the transition of information between both markets. Therefore, policymakers should monitor this relationship and place restrictions where necessary.

Future herding research can examine a few issues. First, future research can examine industry herding in Chinese A and B shares. Previous studies (Dermirer and Kutan, 2006 and Yao, et al., 2014), have reported differences in herding between both shares investors, this research can be extended by investigating if these differences affect industry herding. Second, our analysis employs the CSAD model since herding has time-varying properties. Future studies can employ dynamic herding models which uses approaches such as Markov switching. Such models examine industry herding by differentiating market states, volatility and trading volume when herding may or may not take place (for example, Blasco, et al., 2012 and Balcilar, Demirer, and Hammoudeh, 2013). Third, our study employs daily data. Future studies can investigate industry herding in Chinese using high-frequency intraday data to provide more precise insights of herding (see, for example, Gleason, et al., 2004). Fourth, future work may consider herding during Chinese market crises (for example the 2015-16 Chinese market turbulence). Finally, future studies can examine cross-market herding with other Asian markets like Hong Kong.

Chapter 6 Summary and Suggestion for Future Research

6.1. Introduction

In this thesis we provide empirical evidence on the determinants of industry herding for the US and the Chinese markets. In this chapter, we reiterate our key findings and conclusions. It is organised as follows:

Section 6.2 summarises the findings presented in the each empirical chapter in relation to the relevant hypotheses. The summary is structured to link the empirical evidence to the tested hypotheses and provide a conclusion of whether it has been accepted or rejected.

Section 6.3 discusses the potential implications of the empirical evidence.

Section 6.4 discusses the limitations of the empirical evidence.

Section 6.5 discusses the recommendations for further research.

6.2. Summary of findings

6.1.1. The determinants of Industry herding in the US stock market

The first empirical focuses on the first research question, which is investigating whether US investors herd towards the market (industry) consensus contingent upon the market return, trading volume and volatility. We also investigate the effect of the Dot Com Bubble and the GFC on herding at the market and sector level.

By utilising stock prices for the S&P 500 index spanning from January 1990 to October 2016, we measure herding with the well-known CSAD model. The first hypothesis was stated assumed that there is no herding effect in the US market/ industry.

Our results show that market wide herding is absent in the US market. Therefore we accept the null hypothesis H1 of no herding in the US market. This finding indicates that at the market level, US investors do not ignore their beliefs in factor of the market consensus. It can be thus deduced that these investors may be overconfident and optimistic in their beliefs and information. From an EMH perspective, it can be argued that US investors are rational and the market is informationally efficient.

However, limited evidence of herding becomes visible at the sector level, especially in the Healthcare, Industrial good and Oil and Gas sectors. Therefore, we reject the null hypothesis that there is no herding in the US industry. This finding suggests that the herding absent at the market level surfaces at the sector level, which is consistent with Bikhchandani and Sharma's (2001) suggestion that investors follow each other in and out of the same industry, commonly termed as 'flight to quality'.

At the market level, hypothesis H2a (i.e. Industry herding is contingent upon market/sector returns was rejected because there was no evidence of herding. Hence, there is no evidence that herding is stronger (weaker) on days with rising (declining) market prices. In contrast, herding becomes evident at the industry level, hence the null hypothesis is accepted.

Hypothesis H2b states industry herding is contingent upon market /sector volatility. At the market level, the hypothesis could not be accepted as investors only herd in periods of low volatility. Similarly, the hypothesis could not be accepted at the industry level, as there was limited evidence of herding.

Hypothesis H2C postulates that industry herding is contingent upon market/sector volume. The rejection of the hypothesis at the both the market and industry level, therefore there is no relationship between herding and high (low) trading volume.

Overall, there is a simultaneous acceptance of hypotheses H3 and H4 (i.e. herd behaviour is stronger during the Dot com (GFC) period) at both the market (industry) level. Specifically, that the US investors herd during the pre-bubble and bubble periods, however herding is manifested in various sectors during and after the bubble. During the GFC crisis we find that the US market only herds during the pre-crisis period, although herding is clear across sectors during and after the GFC.

6.1.2. The determinants of Industry herding in the Chinese stock markets

The second empirical chapter focuses on the second research question, which is investigating determinants of market and industry herding in the Chinese markets. We also investigate the effect of the AC and GFC on herding at the market and sector level. Furthermore, we examine the role the US market plays on market (industry) level herding in the Chinese markets.

We test for herding using the CSAD model on our sample all firms listed on the SZSE and SHSE.

Hypothesis H1 postulates that herding exists in Chinese markets/industry. This is accepted because since there is evidence of herding at both the market level and industry level, although it is more pronounced in SZSE.

Hypothesis H2a has been accepted (i.e. market/ industry herding is contingent upon market or sector returns), industry herding is more prevalent in the SZSE when the market is declining, particularly in sectors like Banks, Chemicals, Construction, Food and Beverage and Industrial Goods.

Furthermore, there while SZSE herds more when volatility is low, SHSE herds more on days when volatility is high. Consequently, hypothesis H2b has been accepted as market (industry) herding is contingent upon market/sector volatility. There is also evidence that SZSE market only herds on days with high trading volume at the market level. Therefore, hypothesis H2c is accepted: market (industry) herding is contingent upon market (sector) volume.

Hypotheses H3 and H4 (i.e. herd behaviour is stronger during the Asian crisis (GFC) period) at both the market (industry) level are accepted. There is evidence that the SZSE herds pre, during post-crisis the AC at both the market and industry level. During the GFC we find a similar herding trend, SZSE herded during all the crisis phases.

On the role of the US market, we find that at the market level, US returns only has an impact on herding in the SHSE. Therefore, hypothesis H5, i.e. US returns impact herding in the Chinese markets (sectors) is accepted. However, we find limited evidence of its impact on industry herding in both stock exchanges.

6.3. Implications of the study

Our findings have important implications for US financial market investors and stock market regulatory authorities. From the investors' perspective, it is important to know the impact of industry herding as it could potentially affect their investment strategies, especially those interested in investing in specific sectors. For the regulatory authorities, our evidence suggests that it would be useful to encourage investors to diversify their sector investments. They can achieve this by providing information on the correlation between correlations of different markets and sectors to the public. This information will give investors a better insight on intensity of institutional herding and thus inform their investment decisions.

The results may help provide greater insight into the co-movement in Chinese industry returns, which is different from the predictions of traditional models. Under the traditional view, co-movement in stocks is either driven by changes in cash flows or discount rates.

An important implication of our findings is that due to the co-movement of stocks, investors require a larger number of stocks to achieve diversification. It is also important to point out that although the Chinese markets have been subject to various reforms recently, our results imply that more stringent market regulations are required to curtail industry herd behaviour. A possible implication of the evidence of herding during the AC and GFC is that the Chinese markets may be impacted by contagion. Our results on the impact of US returns on herding in the Chinese markets (sectors) imply that the trade relationship between both countries facilitates the transition of information between both markets. Therefore, policymakers should monitor this relationship and place restrictions where necessary.

6.4. Limitations of the study

This section gives a brief summary of the limitations of this thesis. As earlier stated, this study is being carried out on the US and China stock market. For the US market we used the S&P500 index as a proxy in line with previous studies. It is therefore assumed that this sample is representative of the firms on the US stock market. Regarding the time frame of 1999 -2016 which has been selected to include, recent crises periods, it is assumed that the specific time periods for these which are selected based on previous research sufficiently capture the effect of herding during these periods.

As this research is confined to the analyses of herding towards the market consensus, the review of literature suggests that there is a wide range of other arears and issues that could be explored and potentially have an impact on herding. There are other contexts such as institutional investor herding (see for example Lakonishok et al., (1992), herding in financial analyst recommendations and newsletters (see for example Graham (1999) and herding in other markets such as commodity, derivative and real estate markets. To keep this study within manageable proportions, the focus is be restricted to only the issues raised in the research questions. Also, due to time, data and resource constraints this study focuses on herding using aggregate data from the stock market rather than considering other contexts aforementioned.

Our investigation considers, herding in the US and Chinese financial market at the market and industry level. Theoretical arguments against the EMH, regarding the rationality and the independence of investor decision making have provided the basis towards testing its validity in the presence of an anomaly such as herding. Inferences from empirical research indicates that some investors are not rational and mimic other investors. While research on herding has received attention from psychology and other fields in the social science, this study focuses on the field of behavioural finance. In addition, this study consolidates on pertinent past research my employing similar methods.

6.5. Further research

We suggest some issues that future studies on the US market can examine. First, we employ the CSAD model to measure herding. It would be interesting to see whether other models like CAMP-based models produce similar results especially at the sector level. Second, we find that herding is prevalent in the Healthcare and Oil and Gas sectors respectively. Future studies can conduct an in-depth investigation on these sectors to provide empirical evidence on the subsectors that herd in these sectors. Third, we use the S&P 500 index as a proxy for the US market, future studies can provide recent evidence using all data from all the listed firms in the US market. Finally, it would be interesting to examine cross-sector herding interactions.

For the Chinese market, future herding research can examine a few issues. First, our research only focuses on herding in SZSE and SHSE; future research can also examine industry herding in Chinese A and B shares. As earlier stated, few studies have reported differences in herding between both share investors. Hence this research can be extended by investigating if these differences affect industry herding. Second, our analysis employs the CSAD model, since herding has time-varying properties, future studies can employ dynamic herding models which uses approaches such as Markov switching. Such models examine industry herding by differentiating market states, volatility and trading volume when herding may or may not take place. (For example, Blasco, et al., 2012 and Balcilar, Demirer, and Hammoudeh, 2013). Third, our study employs daily data future studies can investigate industry herding in Chinese using high-frequency intraday data to provide more precise insights of herding (see, for example, Gleason, et al., 2004). Fourth, since we find evidence that Chinese market herd during crises that originate from other markets, future work may consider herding during Chinese market crises (for example the 2015-16 Chinese market turbulence). Finally, our research provides limited evidence of the impact of the US markets; future studies can examine cross-market herding with other Asian markets like Hong Kong.

References

Abreu, D. and Brunnermeier, M.K., 2003. Bubbles and crashes. *Econometrica*, *71*(1), pp.173-204.

Allais, M., 1953. L'extension des théories de l'équilibre économique général et du rendement social au cas du risque. *Econometrica, Journal of the Econometric Society*, pp.269-290.

Allen, F. and Karjalainen, R., 1999. Using genetic algorithms to find technical trading rules1. *Journal of Financial Economics*, *51*(2), pp.245-271.

Amir, E., Guan, Y., and Oswald, D. (2010). The effect of pension accounting on corporate pension asset allocation. *Review of Accounting Studies*, *15(2)*, pp.345–366.

Ardalan, K. (2008). *On the role of paradigms in finance*. 1st ed. Aldershot, England: Ashgate Pub.

Autor, D., Dorn, D. and Hanson, G., 2013. The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review*, *103*(6), pp.2121-68.

Avery, C. and Zemsky, P., 1998. Multidimensional uncertainty and herd behavior in financial markets. *American economic review*, pp.724-748.

Avgouleas, E., 2009. The global financial crisis, behavioural finance and financial regulation: in search of a new orthodoxy. *Journal of Corporate Law Studies*, *9*(1), pp.23-59.

Ball, R., 2009. The global financial crisis and the efficient market hypothesis: What have we learned?. *Journal of Applied Corporate Finance*, 21(4), pp.8-16.

Banerjee, A.V., 1992. A simple model of herd behavior. *The Quarterly Journal of Economics*, *107*(3), pp.797-817.

Barber, B.M. and Odean, T., 1999. The courage of misguided convictions. *Financial Analysts Journal*, *55*(6), pp.41-55.

Barber, B.M. and Odean, T., 2001. The internet and the investor. *Journal of Economic Perspectives*, *15*(1), pp.41-54.

Barber, B.M. and Odean, T., 2002. Online investors: do the slow die first?. *The Review of Financial Studies*, *15*(2), pp.455-488.

Barber, B.M., Odean, T. and Zhu, N., 2009a. Systematic noise. *Journal of Financial Markets*, *12*(4), pp.547-569.

Barber, B. M., Odean, T. and Zhu, N., 2009b. Do Retail Trades Move Markets?, *Review of Financial Studies*, *22(1)*, pp. 151–186.

Barberis, N. and Huang, M., 2008. Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review*, *98*(5), pp.2066-2100.

Barberis, N. and Thaler, R., 2003. A survey of behavioral finance. *Handbook of the Economics of Finance*, 1, pp.1053-1128.

Barberis, N., Shleifer, A. and Vishny, R., 1998. A model of investor sentiment1. *Journal of Financial Economics*, *49*(3), pp.307-343.

Barberis, N., Shleifer, A. and Wurgler, J., 2005. Comovement. *Journal of Financial Economics*, *75*(2), pp.283-317.

Baytas, A., Cakici, N., 1999. "Do markets overreact? International evidence", Journal of Banking and Finance, 23, 1121-1144

Beltratti, A. and Stulz, R.M., 2012. The credit crisis around the globe: Why did some banks perform better?. *Journal of Financial Economics*, *105*(1), pp.1-17.

BenMabrouk, H., 2018. Cross-herding behavior between the stock market and the crude oil market during financial distress: Evidence from the New York stock exchange. *Managerial Finance*, *44*(4), pp.439-458.

BenSaïda, A., 2017. Herding effect on idiosyncratic volatility in US industries. *Finance Research Letters*, 23, pp.121-132.

BenSaïda, A., 2017. Herding effect on idiosyncratic volatility in US industries. *Finance Research Letters*, *23*, pp.121-132.
BenSaïda, A., Jlassi, M. and Litimi, H., 2015. Volume–herding interaction in the American market. *American Journal of Finance and Accounting*, *4*(1), pp.50-69.
Bernardo, A.E. and Welch, I., 2001. On the evolution of overconfidence and entrepreneurs. *Journal of Economics & Management Strategy*, *10*(3), pp.301-330.
Bikhchandani S., Sharma S. 2001. Herd behavior in financial markets: A review. IMF Staff Papers, *47*, pp. 279-310.
Bikhchandani, S., Hirshleifer, D. and Welch, I., 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, *100*(5), pp.992-1026.
Biais, B., and Weber, M. 2009. Hindsight bias, risk perception, and investment performance. Management Science, *55(6)*, pp.1018–1029.
BIS, 2009. The International Financial Crisis: Timeline, Impact and Policy Responses in Asia and the Pacific. *Bank for International Settlements.*
Blasco, N., Corredor, P. and Ferreruela, S., 2012. Does herding affect volatility? Implications for the Spanish stock market. *Quantitative Finance*, *12*(2), pp.311-327.
Blake, Sarno, and Zinna, 2017. The market for lemmings: The herding behavior of pension funds, *Journal of Financial Markets*, *36(C)*, pp.17-39.
Blaxter, L., Hughes, C. and Tight, M. (2006). *How to research*. 1st ed. Milton Keynes: Open University Press.
Bohl, M.T., Branger, N. and Trede, M., 2017. The case for herding is stronger than you think. *Journal of Banking & Finance*, *85*, pp.30-40.
Bohl, M.T., Klein, A.C. and Siklos, P.L., 2013. Are short sellers positive feedback traders? Evidence from the global financial crisis. *Journal of Financial Stability*, *9*(3), pp.337-346.
Bowe, M. and Domuta, D., 2004. Investor herding during financial crisis: A clinical study of the Jakarta Stock Exchange. *Pacific-Basin Finance Journal*, *12*(4), pp.387-418.
Boyd, N.E., Büyükşahin, B., Haigh, M.S. and Harris, J.H., 2016. The prevalence, sources, and effects of herding. *Journal of Futures Markets*, *36*(7), pp.671-694.
Brunnermeier, M., Sockin, M. and Xiong, W., 2017. China’s model of managing the financial system. *Unpublished Working Paper*.
Brunnermeier, M.K. and Parker, J.A., 2005. Optimal expectations. *American Economic Review*, *95*(4), pp.1092-1118.
Caballero, R.J., Farhi, E. and Gourinchas, P.O., 2008. An equilibrium model of" global imbalances" and low interest rates. *American Economic Review*, *98*(1), pp.358-93.
Carhart, M.M., 1997. On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), pp.57-82.
Calvo, G.A. and Mendoza, E.G., 2000. Capital-markets crises and economic collapse in emerging markets: An informational-frictions approach. *American Economic Review*, *90*(2), pp.59-64.
Campbell, J.Y. and Kyle, A.S., 1993. Smart money, noise trading and stock price behaviour. *The Review of Economic Studies*, *60*(1), pp.1-34.
Carpenter, J. N., Lu, F., and Whitelaw, R. F., 2014. The real value of China’s stock market. New York: Mimeo, New York University.
Carpenter, J.N. and Whitelaw, R.F., 2017. The development of China's stock market and stakes for the global economy. *Annual Review of Financial Economics*, *9*, pp.233-257.
Chang, C., 2010. Herding and the role of foreign institutions in emerging equity markets. *Pacific-Basin Finance Journal*, *18*(2), pp.175-185.

Chang, C.H. and 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 & Finance*, *37*, pp.380-392.
Chang, E.C., Cheng, J.W. and Khorana, A., 2000. An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, *24*(10), pp.1651-1679.
Chen, G., Kim, K.A., Nofsinger, J.R. and Rui, O.M., 2007. Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of Behavioral Decision Making*, *20*(4), pp.425-451.
Chen, J., Hong, H. and Stein, J.C., 2001. Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, *61*(3), pp.345-381.
Chen, J., Hong, H. and Stein, J.C., 2002. Breadth of ownership and stock returns. *Journal of Financial Economics*, *66*(2-3), pp.171-205.
Chen, T., 2013. Do investors herd in global stock markets?. *Journal of Behavioral Finance*, *14*(3), pp.230-239.
Chi, L., Zhuang, X. and Song, D., 2012. Investor sentiment in the Chinese stock market: an empirical analysis. *Applied Economics Letters*, *19*(4), pp.345-348.
Chiang, T. C., and Zheng, D., 2010. An empirical analysis of herding behaviour in global stock markets. Journal of Banking and Finance, 34(8), 1911–1921
Chiang, T. C., Tan, L., Li, J., and Nelling, E. 2013. Dynamic herding behavior in Pacific-Basin markets: evidence and implications. *Multinational Finance Journal*. *17*. pp. 165-200.
Chiang, T.C., Li, J. and Tan, L., 2012. Does herding behavior in Chinese markets react to global markets?. *International Review of Accounting, Banking & Finance*, *4*(1).
Choe, H., Kho, B.C. and Stulz, R.M., 1999. Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial Economics*, *54*(2), pp.227-264.
Choi, N. and Sias, R.W., 2009. Institutional industry herding. *Journal of Financial Economics*, *94*(3), pp.469-491.
Choi, N. and Skiba, H., 2015. Institutional herding in international markets. *Journal of Banking & Finance*, *55*, pp.246-259.
Chong, T.T.L., Lam, T.H. and Yan, I.K.M., 2012. Is the Chinese stock market really inefficient?. *China Economic Review*, *23*(1), pp.122-137.
Chong, T.T.L., Liu, X. and Zhu, C., 2017. What explains herd behavior in the Chinese stock market?. *Journal of Behavioral Finance*, *18*(4), pp.448-456.
Christie, W.G. and Huang, R.D., 1995. Following the pied piper: Do individual returns herd around the market?. *Financial Analysts Journal*, pp.31-37.
Cipriani, M. and Guarino, A., 2005. Herd behavior in a laboratory financial market. *American Economic Review*, *95*(5), pp.1427-1443.
Claessens, S., Demirgüç-Kunt, A. and Moshirian, F., 2009. Global financial crisis, risk analysis and risk measurement, *Journal of Banking & Finance*, *33*(11), pp. 1949 – 1952.
Clements, A., Hurn, S. and Shi, S., 2017. An empirical investigation of herding in the US stock market. *Economic Modelling*, *67*, pp.184-192.
Conlisk, J., 1996. Why bounded rationality?. *Journal of Economic Literature*, *34*(2), pp.669-700.
Cooper, M.J., Dimitrov, O. and Rau, P.R., 2001. A rose. com by any other name. *The Journal of Finance*, *56*(6), pp.2371-2388.
Corsetti, G., Pericoli, M. and Sbracia, M., 2005. Some contagion, some interdependence: More pitfalls in tests of financial contagion. *Journal of International Money and Finance*, *24*(8), pp.1177-1199.

Daniel, K., Hirshleifer, D. and Subrahmanyam, A., 1998. Investor psychology and security market under-and overreactions. *The Journal of Finance*, *53*(6), pp.1839-1885.
De Bondt, W.F. and Thaler, R., 1985. Does the stock market overreact?. *The Journal of Finance*, *40*(3), pp.793-805.
De Bondt, W.F. and Thaler, R.H., 1989. Anomalies: A mean-reverting walk down Wall Street. *Journal of Economic Perspectives*, *3*(1), pp.189-202.
De Long, J.B. and Magin, K., 2006. A short note on the size of the dot-com bubble, *NBER Working paper,* No. 8630
DeLong, J.B., Shleifer, A., Summers, L.H. and Waldmann, R.J., 1990. Noise trader risk in financial markets. *Journal of Political Economy*, *98*(4), pp.703-738.
Demirer, R. and Kutan, A.M., 2006. Does herding behavior exist in Chinese stock markets?. *Journal of International Financial Markets, Institutions and Money*, *16*(2), pp.123-142.
Demirer, R., Kutan, A.M. and Chen, C.D., 2010. Do investors herd in emerging stock markets?, Evidence from the Taiwanese market. *Journal of Economic Behavior & Organization*, *76*(2), pp.283-295.
Deng, Y. and Xu, Y., 2011. Do institutional investors have superior stock selection ability in China?. *China Journal of Accounting Research*, *4*(3), pp.107-119.
Dequech, D., 2001. Bounded rationality, institutions, and uncertainty. *Journal of Economic Issues*, *35*(4), pp.911-929.
Devenow, A. and Welch, I., 1996. Rational herding in financial economics. *European Economic Review*, *40*(3-5), pp.603-615.
Economou, F., Gavriilidis, K., Goyal, A. and Kallinterakis, V., 2015. Herding dynamics in exchange groups: Evidence from Euronext. *Journal of International Financial Markets, Institutions and Money,* 34, pp.228-244.
Economou, F., Kostakis, A. and Philippas, N., 2011. Cross-country effects in herding behaviour: Evidence from four south European markets. *Journal of International Financial Markets, Institutions and Money*, *21*(3), pp.443-460.
Economou, F., Gavriilidis, K., Kallinterakis, V. and Yordanov, N., 2015. Do fund managers herd in frontier markets—and why?. *International Review of Financial Analysis*, *40*, pp.76-87.
Ellsberg, D., 1961. Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, pp.643-669.
Falkenstein, E.G., 1996. Preferences for stock characteristics as revealed by mutual fund portfolio holdings. *The Journal of Finance*, *51*(1), pp.111-135.
Fama, E. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance, 25*(2), pp.383-417.
Fama, E., 1965. The behavior of stock-market prices. *The Journal of Business, 38*(1), pp.34-105.
Fischhoff, B. 1975. Hindsight is not equal to foresight: The effect of outcome knowledge on judgment under uncertainty. Journal of Experimental Psychology: Human Perception and Performance, 1(3), 288-299.
Fernald, J. G., and Babson, O. D. 1999. Why has China survived the Asia crisis so well? What risks remain? *International Finance Discussion Papers*, Board of Governors of the Federal Reserve System, Washington, DC.
Festinger, L., 1957. *A theory of cognitive dissonance,* Stanford University Press.
Financial Crisis Inquiry Commission and United States. Financial Crisis Inquiry Commission, 2011. *The financial crisis inquiry report, authorized edition: Final report of the National Commission on the Causes of the Financial and Economic Crisis in the United States*. Public Affairs.

Findlay, M. and Williams, E. (1981). Financial Theory and Political Reality under Fundamental Uncertainty. *Journal of Post Keynesian Economics*, 3(4), pp.528-544.
Frankfurter G. and Mcgoun E. (1999). Ideology and the theory of financial economics. *Journal of Economic Behaviour & Organization, Vol.*39, Iss. 2, pp.159-177.
Froot, K.A. and Dabora, E.M., 1999. How are stock prices affected by the location of trade?. *Journal of Financial Economics*, *53*(2), pp.189-216.
Froot, K.A., Scharfstein, D.S. and Stein, J.C., 1992. Herd on the street: Informational inefficiencies in a market with short-term speculation. *The Journal of Finance*, *47*(4), pp.1461-1484.
Froot, K. and Teo, M., 2008. Style investing and institutional investors. *Journal of Financial and Quantitative Analysis*, *43*(4), pp.883-906.
Fu, T., and Lin. M., 2010. Herding in China equity market. *International journal of economics and finance*, *2*(2), p.148.
Galariotis, E.C., Krokida, S.I. and Spyrou, S.I., 2016. Herd behavior and equity market liquidity: Evidence from major markets. *International Review of Financial Analysis*, *48*, pp.140-149.
Galariotis, E.C., Rong, W. and Spyrou, S.I., 2015. Herding on fundamental information: A comparative study. *Journal of Banking & Finance*, *50*, pp.589-598.
Galbraith, J.K., 1994. *A short history of financial euphoria*. Penguin.
Gallo, G.M. and Otranto, E., 2007. Volatility transmission across markets: a Multichain Markov Switching model. *Applied Financial Economics*, *17*(8), pp.659-670.
García-Herrero, A., Gavilá, S. and Santabárbara, D., 2009. What explains the low profitability of Chinese banks?. *Journal of Banking & Finance*, *33*(11), pp.2080-2092.
Gavriilidis, K., Kallinterakis, V. and Ferreira, M.P.L., 2013. Institutional industry herding: Intentional or spurious? *Journal of International Financial Markets, Institutions and Money*, 26, pp.192-214.
Gębka, B. and Wohar, M.E., 2013. International herding: Does it differ across sectors? *Journal of International Financial Markets, Institutions and Money*, 23, pp.55-84.
Gigerenzer, G. and Gaissmaier, W., 2011. Heuristic decision making. *Annual Review of Psychology*, *62*, pp.451-482.
Goetzmann, W.N. and Peles, N., 1997. Cognitive dissonance and mutual fund investors. *Journal of Financial Research*, *20*(2), pp.145-158.
Goldstein, M., 1998. The Asian financial crisis: Causes, cures, and systemic implications. *Policy Analyses in International Economics*, *55*, Institute for International Economics, Washington, DC.
Gong, P. and Dai, J., 2018. Herding on lottery-type stocks: evidence from the Chinese stock market. *Applied Economics Letters*, *25*(10), pp.659-662.
Goodfellow, C., Bohl, M.T. and Gebka, B., 2009. Together we invest? Individual and institutional investors' trading behaviour in Poland. *International Review of Financial Analysis*, *18*(4), pp.212-221.
Goodnight, G.T. and Green, S., 2010. Rhetoric, risk, and markets: The dot-com bubble. *Quarterly Journal of Speech*, *96*(2), pp.115-140.
Green, S., 2003. *China's stock market: a guide to its progress, players and prospects* (Vol. 4). John Wiley & Sons.
Grinblatt, M. and Han, B., 2002. *The disposition effect and momentum* (No. w8734). National Bureau of Economic Research.
Grinblatt, M. and Han, B., 2005. Prospect theory, mental accounting, and momentum. Journal of financial economics, 78(2), pp.311-339.
Guba, E. G., and Lincoln, Y. S. (1996). *Competing Paradigms in Qualitative Research*. In Denzin & Lincoln (Eds.), Handbook of Qualitative Research. USA. Sage Publishers.

Guney, Y., Kallinterakis, V. and Komba, G., 2017. Herding in frontier markets: Evidence from African stock exchanges. *Journal of International Financial Markets, Institutions and Money*, *47*, pp.152-175.
Henker, J. and Henker, T., Mitsios A., 2006. Do investors herd intraday in Australian Equities? *International Journal of Managerial Finance*, *2*(3), pp.196-219.
Hilliard, J. and Zhang, H., 2015, Size and price-to-book e↵ects: Evidence from the Chinese stock markets, *Pacific-Basin Finance Journal 32*, pp.40–55.
Hirshleifer, D. and Hong Teoh, S., 2003. Herd behaviour and cascading in capital markets: A review and synthesis. *European Financial Management*, *9*(1), pp.25-66.
Hirshleifer, D., 2001. Investor psychology and asset pricing. *The Journal of Finance*, *56*(4), pp.1533-1597.
Hirshleifer, D., Subrahmanyam, A. and Titman, S., 1994. Security analysis and trading patterns when some investors receive information before others. *The Journal of Finance*, *49*(5), pp.1665-1698.
Hoitash, R. and Krishnan, M.M., 2008. Herding, momentum and investor over-reaction. *Review of Quantitative Finance and Accounting*, *30*(1), pp.25-47.
Holmes, P., Kallinterakis, V. and Ferreira, M.L., 2013. Herding in a concentrated market: a question of intent. *European Financial Management*, *19*(3), pp.497-520.
Hwang, S. and Salmon, M., 2004. Market stress and herding. *Journal of Empirical Finance*, *11*(4), pp.585-616.
Javaira, Z. and Hassan, A., 2015. An examination of herding behavior in Pakistani stock market. *International journal of Emerging Markets*, *10*(3), pp.474-490.
Jegadeesh, N. and Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, *48*(1), pp.65-91.
Jegadeesh, N. and Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance*, *56*(2), pp.699-720.
Jegadeesh, N. and Titman, S., 1995. Overreaction, delayed reaction, and contrarian profits. *The Review of Financial Studies*, *8*(4), pp.973-993.
Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. *The Journal of Finance*, *45*(3), pp.881-898.
Johansen, A., Sornette, D. and Ledoit, O., 1999. Predicting financial crashes using discrete scale invariance. *Journal of Risk*, *1*(4) (1999) 5-32.
Jones, C.M., Kaul, G. and Lipson, M.L., 1994. Transactions, volume, and volatility. *The Review of Financial Studies*, *7*(4), pp.631-651.
Kabir, M. H., 2018. Did investors herd during the financial crisis? Evidence from the US financial industry. *International Review of Finance*, *18 (1)*, pp. 59–90.
Kahneman, D. and Riepe, M.W., 1998. Aspects of investor psychology. *Journal of Portfolio Management*, *24*(4), pp.52 – 65.
Kahneman, D. and Tversky, A., 1972. Subjective probability: A judgment of representativeness. *The Concept of Probability in Psychological Experiments*, pp. 25-48. Springer, Dordrecht.
Kahneman, D. and Tversky, A., 1973. On the psychology of prediction. *Psychological Review*, *80*(4), p.237.
Kahneman, D. and Tversky, A., 1996. On the reality of cognitive illusions, *Psychological Review*, 103 (3), pp. 582 – 591.
Kaniel, R., Saar, G. and Titman, S., 2008. Individual investor trading and stock returns. *The Journal of Finance*, *63*(1), pp.273-310.
Kaminsky, G., 1999. *What triggers market jitters? A chronicle of the Asian crisis*. The World Bank.

Keynes, J. M. (1936). *The general theory of employment, interest and money*. London: Macmillan.
Kolb, R.W. (2010), *Ethical Implications of Finance*, in J.R. Boatright (ed.), *Finance Ethics: critical issues in theory and practice*, New Jersey: John Wiley and Sons, pp. 23-44.
Kothari, C. (2004). *Research methodology*. 1st ed. New Delhi: New Age International (P) Ltd.
Laih, Y.W. and Liau, Y.S., 2013. Herding behavior during the subprime mortgage crisis: Evidence from six Asia-Pacific stock markets. *International Journal of Economics and Finance*, *5*(7), p.71.
Lakonishok, J., Shleifer, A. and Vishny, R.W., 1992. The impact of institutional trading on stock prices. *Journal of Financial Economics*, *32*(1), pp.23-43.
Lakshman, M.V., Basu, S. and Vaidyanathan, R., 2013. Market-wide herding and the impact of institutional investors in the Indian capital market. *Journal of Emerging Market Finance*, *12*(2), pp.197-237.
Lam, K.S. and Qiao, Z., 2015. Herding and fundamental factors: The Hong Kong experience. *Pacific-Basin Finance Journal*, *32*, pp.160-188.
Lan, Q.Q. and Lai, R.N., 2011. *Herding and trading volume*. SSRN, 1914208.
Langer, E. J., 1975. "The Illusion of Control.". Journal of Personality and Social Psychology, *32*: pp.311–328.
Lao, P. and Singh, H., 2011. Herding behaviour in the Chinese and Indian stock markets. *Journal of Asian economics*, *22*(6), pp.495-506.
Le Bon, G., 1947. The Crowd: A Study of the Popular Mind, London: Ernest Benn.
Lee, 2017, Herd behaviour of the overall market: Evidence based on the cross-sectional comovement of returns, *The North American Journal of Economics and Finance,* 42, pp. 266-284.
Lee, C.C., Chen, M.P. and Hsieh, K.M., 2013. Industry herding and market states: evidence from Chinese stock markets. *Quantitative Finance*, *13*(7), pp.1091-1113.
Lee, J.W. and McKibbin, W.J., 2018. Service sector productivity and economic growth in Asia. *Economic Modelling*, *74*, pp. 247-263.
Li, G., 2008. China's stock market: Inefficiencies and institutional implications. *China & World Economy*, *16*(6), pp.81-96.
Li, H., Liu, Y. and Park, S.Y., 2017. Time-Varying Investor Herding in Chinese Stock Markets. *International Review of Finance*.
Li, W., Rhee, G. and Wang, S.S., 2017. Differences in herding: Individual vs. institutional investors. *Pacific-Basin Finance Journal*, *45*, pp.174-185.
Lichtenstein, S., Fischhoff, B. and Phillips, L., 1982. Calibration of probabilities: The state of the art to 1980. D. Kahneman, P. Slovic, and A. Tverski (Eds.) Judgement under uncertainty: Heuristics and biases.
Litimi, H., BenSaïda, A. and Bouraoui, O., 2016. Herding and excessive risk in the American stock market: A sectoral analysis. *Research in International Business and Finance*, *38*, pp.6-21.
Liu, Q. and Lu, Z.J., 2007. Corporate governance and earnings management in the Chinese listed companies: A tunneling perspective. *Journal of Corporate Finance*, *13*(5), pp.881-906.
Liu, Z. and Wang, S., 2017. Understanding the Chinese stock market: international comparison and policy implications. *Economic and Political Studies*, *5*(4), pp.441-455.
Lo, A.W. and MacKinlay, A.C., 1988. Stock market prices do not follow random walks: Evidence from a simple specification test. *The Review of Financial Studies*, *1*(1), pp.41-66.

Lo, A.W., Mamaysky, H. and Wang, J., 2000. Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *The Journal of Finance*, *55*(4), pp.1705-1765.
Lucey, Brian, M. (2000), Friday the 13th and the Philosophical Basis of Financial Economics, Journal of Economics and Finance, 24 (3), 294-301.
Luo, Z. and Schinckus, C., 2015. Herding behaviour in asymmetric and extreme situations: the case of China. *Applied Economics Letters*, *22*(11), pp.869-873.
Mahmud, S.F. and Tiniç, M., 2018. Herding in Chinese stock markets: a nonparametric approach. *Empirical Economics*, *55*(2), pp.679-711.
Maug, E. and Naik, N., 1995. Herding and Delegated Portfolio Management: The Impact of Relative Performance Evaluation on Asset Allocation, Working Paper.
Maug, E. and Naik, N., 1996. Herding and delegated portfolio management. *London Business School mimeo*.
McQueen, G., Pinegar, M. and Thorley, S., 1996. Delayed reaction to good news and the cross-autocorrelation of portfolio returns. *The Journal of Finance*, *51*(3), pp.889-919.
Mei, J. Scheinkman J. and Xiong W., 2009. "Speculative Trading and Stock Prices: Evidence from Chinese A-B Share Premia." *Annals of Economics and Finance, 10*(2), pp. 225-255
Merton, R.C., 1987. A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, *42*(3), pp.483-510.
Mobarek, A., Mollah, S. and Keasey, K., 2014. A cross-country analysis of herd behavior in Europe. *Journal of International Financial Markets, Institutions and Money*, 32, pp.107-127.
Nagaraj, R., 2017. Economic Reforms and Manufacturing Sector Growth. *Economic & Political Weekly*, *52*(2), p.61-68.
Nofsinger, J.R. and Sias, R.W., 1999. Herding and feedback trading by institutional and individual investors. *The Journal of Finance*, *54*(6), pp.2263-2295.
Nofsinger, J.R., 2001. The impact of public information on investors. *Journal of Banking & Finance*, *25*(7), pp.1339-1366.
Odean, T., 1998. Volume, volatility, price, and profit when all traders are above average. *The Journal of Finance*, *53*(6), pp.1887-1934.
Overholt, W. 2010. China in the Global Financial Crisis: Rising Influence, Rising Challenges, *The Washington Quarterly*, *33(1)*, pp. 21-34.
Perlmuter, L.C. and Monty, R.A., 1977. The importance of perceived control: Fact or fantasy? Experiments with both humans and animals indicate that the mere illusion of control significantly improves performance in a variety of situations. *American Scientist*, *65*(6), pp.759-765.
Phillips, P.C. and Yu, J., 2011. Dating the timeline of financial bubbles during the subprime crisis. *Quantitative Economics*, 2(3), pp.455-491.
Prasad, E., Rogoff, K., Wei, S.J. and Kose, M.A., 2005. Effects of financial globalization on developing countries: some empirical evidence. In *India's and China's recent experience with reform and growth* (pp. 201-228). Palgrave Macmillan, London.
Rabin, M., 1998. Psychology and economics. *Journal of Economic Literature*, *36*(1), pp.11-46.
Rabin, M., 2002. Inference by believers in the law of small numbers. *The Quarterly Journal of Economics*, *117*(3), pp.775-816.
Rashes, M.S., 2001. Massively confused investors making conspicuously ignorant choices (mci–mcic). *The Journal of Finance*, *56*(5), pp.1911-1927.
Richard Thaler 1983, *Transaction utility theory*, in NA - Advances in Consumer Research Volume 10, eds. Richard P. Bagozzi and Alice M. Tybout, Ann Abor, MI: Association for Consumer Research, pp. 229-232.

Ritchie, J. and Lewis, J. (2003). *Qualitative research practice*. 1st ed. London: Sage Publications.
Rouwenhorst, K.G., 1998. International momentum strategies. *The Journal of Finance*, *53*(1), pp.267-284.
Santos, M.S. and Woodford, M., 1997. Rational asset pricing bubbles. *Econometrica*, *65* (1), pp.19-57.
Scharfstein, D.S. and Stein, J.C., 1990. Herd behavior and investment. *The American Economic Review*, pp.465-479.
Scheinkman, J.A. and Xiong, W., 2003. Overconfidence and speculative bubbles. *Journal of political Economy*, *111*(6), pp.1183-1220.
Schwert, G.W., 2003. Anomalies and market efficiency. *Handbook of the Economics of Finance*, *1*, pp.939-974.
Seiler, M.J. and Rom, W., 1997. A historical analysis of market efficiency: do historical returns follow a random walk?. *Journal of Financial and Strategic Decisions*, *10*(2), pp.49-57.
Shefrin, H. and Statman, M., 1985. The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, *40*(3), pp.777-790.
Shefrin, H. and Statman, M., 2000. Behavioral portfolio theory. *Journal of Financial and Quantitative Analysis*, *35*(2), pp.127-151.
Shiller, R.J., 1981. The use of volatility measures in assessing market efficiency. *The Journal of Finance*, *36*(2), pp.291-304.
Shiller, R.J., 1990. Speculative prices and popular models. *Journal of Economic Perspectives*, *4*(2), pp.55-65.
Shiller, R.J., 2003. From efficient markets theory to behavioral finance. *Journal of Economic Perspectives*, *17*(1), pp.83-104.
Shleifer, A., 2000. *Inefficient markets: An introduction to behavioural finance*. OUP Oxford.
Sias, R.W., 2004. Institutional herding. *The Review of Financial Studies*, *17*(1), pp.165-206.
Simon, H.A., 1997. *Models of bounded rationality: Empirically grounded economic reason* (Vol. 3). MIT press.
Sirri, E.R. and Tufano, P., 1998. Costly search and mutual fund flows. *The Journal of Finance*, *53*(5), pp.1589-1622.
Sjöö, B. and Zhang, J., 2000. Market segmentation and information diffusion in China's stock markets. *Journal of Multinational Financial Management*, *10*(3-4), pp.421-438.
Sornette, D., Woodard, R. and Zhou, W.X., 2009. The 2006–2008 oil bubble: Evidence of speculation, and prediction. *Physica A: Statistical Mechanics and its Applications*, *388*(8), pp.1571-1576.
Statman, M., Thorley, S., Vorkink, K., 2006. Investor overconfidence and trading volume. *Review of Financial Studies*, 19(4): 1531-1565.
Tan, L., Chiang, T.C., Mason, J.R. and Nelling, E., 2008. Herding behavior in Chinese stock markets: An examination of A and B shares. *Pacific-Basin Finance Journal*, *16*(1-2), pp.61-77.
Taylor, S.E. and Brown, J.D., 1988. Illusion and well-being: a social psychological perspective on mental health. *Psychological Bulletin*, *103*(2), p.193.
Terre Blanche, M., Durrheim, K. and Painter, D. (2006). *Research in practice*. 1st ed. Cape Town: UCT Press.
Thaler, R.H. and Johnson, E.J., 1990. Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science*, *36*(6), pp.643-660.
Thaler, R.H., 2000. From homo economicus to homo sapiens. *Journal of Economic Perspectives*, *14*(1), pp.133-141.

Tham, E., 2016. Unbearable lightness of expectations of the Chinese investor. *Handbook of Sentiment Analysis in Finance*, pp. 400–416.
Tian, S., Wu, E. and Wu, Q., 2018. Who exacerbates the extreme swings in the Chinese stock market?. *International Review of Financial Analysis*, *55*, pp.50-59.
Tregenna, F., 2009. The fat years: the structure and profitability of the US banking sector in the pre-crisis period. *Cambridge Journal of Economics*, *33*(4), pp.609-632.
Trueman, B., 1994. Analyst forecasts and herding behavior. *The Review of Financial Studies*, *7*(1), pp.97-124.
Tseng, J. and Li, S., 2012. Quantifying volatility clustering in financial time series. *International Review of Financial Analysis*. Vol.23, Iss.3, pp.11-19.
Tumarkin, R. and Whitelaw, R.F., 2001. News or noise? Internet postings and stock prices. *Financial Analysts Journal*, *57*(3), pp.41-51.
Tversky, A. and Kahneman, D., 1973. Availability: A heuristic for judging frequency and probability. *Cognitive Psychology*, *5*(2), pp.207-232.
Tversky, A. and Kahneman, D., 1991. Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics*, *106*(4), pp.1039-1061.
U.S. Census Bureau, 2016. *Automobile Manufacturing Economic Census, Manufacturing Industry series*
LaRocca, G. United States International Trade Commission, 2019, China.
Vieira, E.F.S. and Pereira, M.S.V., 2015. Herding behaviour and sentiment: Evidence in a small European market. *Revista de Contabilidad*, *18*(1), pp.78-86.
Wang, X.L., Shi, K. and Fan, H.X., 2006. Psychological mechanisms of investors in Chinese Stock Markets. *Journal of Economic Psychology*, *27*(6), pp.762-780.
Wang, Z., Kutan, A.M. and Yang, J., 2005. Information flows within and across sectors in Chinese stock markets. *The Quarterly Review of Economics and Finance*, *45*(4-5), pp.767-780.
Wei, S. 1996. Intra-national versus International Trade: How Stubborn Are Nations in Global Integration, *National Bureau of Economic Research* Working Paper No. 5531
Wermers, R., 1999. Mutual fund herding and the impact on stock prices. *The Journal of Finance*, *54*(2), pp.581-622.
Wermers, R., 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. *The Journal of Finance*, *55*(4), pp.1655-1695.
Wheale, P.R. and Amin, L.H., 2003. Bursting the dot. com" Bubble': A case study in investor behaviour. *Technology Analysis & Strategic Management*, *15*(1), pp.117-136.
World Bank National Accounts Data, 2017. *World Bank national accounts data, and OECD National Accounts data files.*
Wu. (2003) Deregulation and growth in China's energy sector: a review of recent development, *Energy Policy, 31*, pp. 1417-1425.
Xie, T., Xu, Y. and 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 & Finance*, *37*, pp.324-339.
Yao, J., Ma, C. and He, W.P., 2014. Investor herding behaviour of Chinese stock market. *International Review of Economics & Finance*, *29*, pp.12-29.
Zheng, D., Li, H. and Chiang, T.C., 2017. Herding within industries: Evidence from Asian stock markets. *International Review of Economics & Finance, 51*, pp.487-509.
Zwiebel, J., 1995. Corporate conservatism and relative compensation. *Journal of Political Economy*, *103*(1), pp.1-25.