Chinese stock market conditions and herd behaviour on the JSE: Evidence from idiosyncratic volatile stock portfolios and industry sectors

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LIST OF ACRONYMS

APT	arbitrary pricing theory
BRICS	Brazil, Russia, India, China, South Africa
CAPM	Capital asset pricing model
CSAD	cross-sectional absolute deviation
CSRC	China Security Regulatory Commission
CSSD	Cross-sectional standard deviation of stock returns
GDP	gross domestic product
JSE	Johannesburg Stock Exchange
Rmt	market return portfolio
CSI	Chinese stock index

Abstract

The intention of the study was to broaden the knowledge and understanding of herd mentality on the JSE 40. Herd behaviour has the potential to destabilise and deteriorate financial markets, and a better understanding of this behaviour could minimize investment loss. Therefore, the study examined herd behaviour in terms of various idiosyncratic volatile stocks and different industry sectors using a dispersion-based model.

The study also investigated whether or not Chinese market conditions influenced herd behaviour regarding those stock portfolios. The results suggest that fully and partly diversified portfolios tend to show evidence of herd behaviour. However, Chinese market conditions affect each stock portfolio differently. For example, the Industrial Portfolio Index was influenced by Chinese market conditions across all tranquil and turbulent periods. Meanwhile, other portfolios were only influenced by long tranquil or extreme volatile periods in the Chinese market. Interestingly, the Banking sector was the only stock portfolio that was not influenced by the Chinese market. Perhaps investors can use this knowledge to enhance their future portfolio returns.

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1 INTRODUCTION

1.1 CONTEXT TO THE STUDY

Dynamic movements in financial markets have always puzzled scholars and defy all standard financial theories, particularly in highly volatile periods. Many speculate that during highly volatile periods, traditional asset pricing theories (CAPM and APT) fail to explain the volatility of excess return in capital markets (Economou, Kostakis and Philippas, 2011; Huang, Lin, Yang, 2014; Phan and Vo, 2018). Therefore, there is growing interest in studying investor behaviour in terms of highly volatile stock markets. One of the most studied patterns of investment behaviour is herd behaviour, which is defined as the irrational behaviour of mutual imitation leading to the convergence of action. As suggested by Chiang and Zheng (2010), copying behaviour amongst investors is seen in both a single market and at the global level, i.e., across markets (Economou, Kostakis and Philippas, 2011).

Interestingly, this type of irrational behaviour amongst investors is more likely to occur during periods of financial distress because investors may not have enough time to analyse the information they gather from various sources (Fu and Lin, 2010); therefore, they may copy the behaviour of other investors or institutional investors. Empirical studies confirm that herd behaviour is more evident during rising and falling periods, high volatility periods and crisis periods (Economou, Kostakis and Philippas, 2011; Haung, Lin and Yanh, 2014; khan, Shah and Shah ,2017; Phan and Vo, 2018).

Similarly, idiosyncratic volatility is known to influence herd mentality. Studies done on both Vietnam and Taiwan found evidence that different herd behaviour patterns are seen in stock portfolios at different levels of idiosyncratic volatility (Huang, Lin and Yang, 2014; Vo and Phan, 2018). Hence, the total volatility of an individual stock is respectively decomposed into two segments: systematic volatility and non-systematic volatility (idiosyncratic volatility). Systematic volatility is the volatility that influences many assets and which cannot be eliminated through diversification. On the other hand, idiosyncratic or non-systematic volatility is the volatility associated with a small number of assets or a specific asset, and it can be eliminated through diversification (He, Liu and Qu, 2019).

The irrational choices or wealth constraints of many individual investors in terms of the stock markets limits them in terms of portfolio diversification. Phan and Vo (2018) suggest that undiversified investors tend to copy what they perceive other investors are doing, rather than doing their own analysis. Therefore, understanding the link between herd behaviour and idiosyncratic volatility is crucial, as herding behaviour has the tendency to misprice assets and increase risk of an asset price bubble. Consequently, herding generates highly volatile periods

and leads to market instability if the phenomenon continues (Phan and Vo, 2018). Therefore, herding studies help investment managers to tailor their models to accommodate the herd behaviour phenomenon and limit portfolio deterioration.

1.2 BACKGROUND TO THE STUDY

The Chinese stock market turbulence in 2016 was caused by an increasing volume of margin trading accounts from both traditional borrowers and shadow banks during 2014. On 12 June 2015, the China Security Regulatory Commission (CSRC) banned investors from borrowing money from unregulated lenders (Kellard, Lambercy and Yan, 2019). This immediately drained the liquidity in Chinese markets and caused the Chinese stock market to tumble during the period June 2015 to February 2016 (Kellard, Lambercy and Yan, 2019). Similarly, the on 6 July 2018, a 25 % tariff was imposed on Chinese shipments entering the US, which resulted in the Chinese stock markets becoming very volatile. Figure 1.1 shows the high volatility periods in the Chinese stock market during the periods 12 June 2015 to 12 February 2016 and 6 July 2018 to 14 June 2019. Note, the periods outside the red circles were known as tranquil periods.

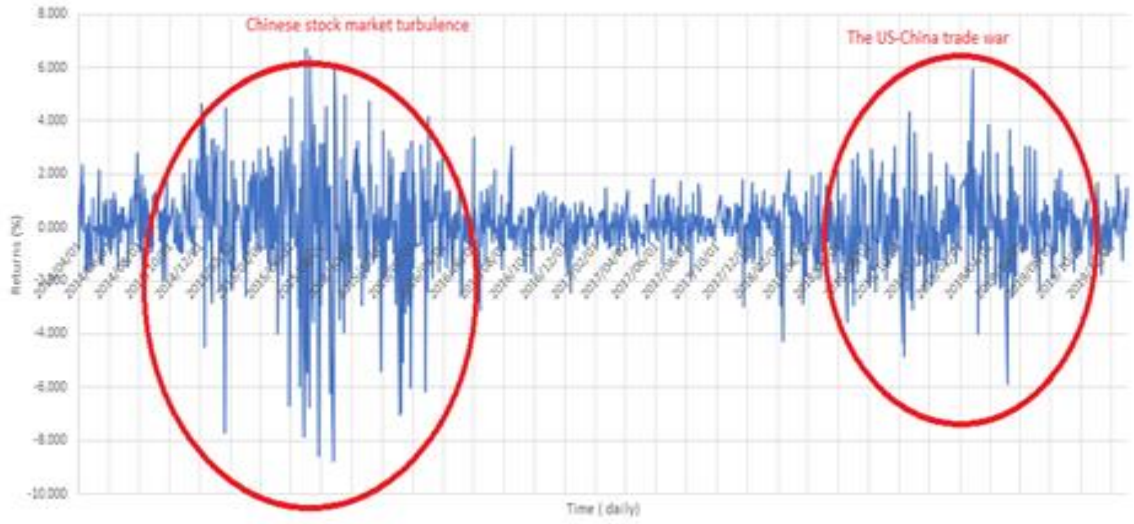

Figure 2.1: CSI 300 index returns

The Chinese stock market turbulence and the US-China trade war did not cause significant volatility in the Chinese stock market compared to other historical events. However, considering that financials markets and investors are constantly changing at a fast pace, it is important to use recent events in herd behaviour studies because the investors of a decade ago were different to investors today (and we know that herd behaviour is driven by investors).

Interestingly, herd behaviour among the Chinese was more intense during turbulent periods (Bany-Ariffin, Chong, Matemilola, & Mcgowan, 2019), and it was established that herd

behaviour on the JSE was influenced by Chinese market conditions (Bany-Ariffin, Chong, Matemilola, & Mcgowan, 2019). In contrast, Mekwa (2017) established that there was no evidence of herd behaviour on the JSE or any of its sectors between 2003 and 2015.

Since herd behaviour has the potential to destabilise markets, it is important for investors to have access to reliable herd behaviour studies. This study hopes to update existing studies and obtain further insight into how herd behaviour in terms of different stock portfolios (various idiosyncratic volatility stocks and different industry stocks on the JSE) were influenced by Chinese market conditions. This will help policymakers to identify various volatile stocks or sectors of the JSE that are strongly influenced by Chinese market conditions, which will help policymakers to formulate appropriate policies to reduce herd behaviour on the JSE (i.e. policy makers would need to incorporate regulations in their policies).

1.3 STATEMENT OF THE PROBLEM

The South African markets exhibit both high risk and high return on investment (high volatility) compared to developed markets. The latter has drawn many foreign investors into the South African market, as they provide an attractive opportunity for international portfolio diversification (Jabalameli and Rasoulinezhadr,2018). However, herd behaviour can result in numerous negative consequences and in capital markets on the JSE deteriorating. One study that addressed this concern suggests that Chinese market conditions generally influence herd behaviour on the JSE (Bany-Ariffin, Chong, Matemilola, & Mcgowan, 2019). However, the study only investigated herding behaviour at a market level, as the bulk study was focused on the European and American markets.

Ababio and Mwamba (2017) suggested that testing for herding only at a market level will not provide a full understanding of the true behaviour dynamics of South African investors. This makes it difficult for investment managers, traders and undiversified investors to use these studies to enhance hedging strategies. Herding behaviour at an industry or idiosyncratic volatility level might reveal a different herding pattern compared to herding behaviour in the entire market and it might be influenced more or less by Chinese market conditions.

1.4 RESEARCH QUESTIONS

In light of the previous discussion, and the gaps identified in the literature, this study seeks to answer the following questions:

Is there evidence of herd behaviour in different sectors or various idiosyncratic volatility stock portfolios in South African stock market?

Is herding behaviour in the South African stock market influenced by market movements and herding behaviour in China?

1.5 OBJECTIVE OF THE STUDY

The objectives of the study are:

To investigate herd behaviour in various stock portfolios using a dispersion-based model.

To investigate the impact of Chinese market conditions (tranquil and turbulent) on herding behaviour in various stock portfolios on the JSE.

1.6 JUSTIFICATION FOR THE RESEARCH

Over ZAR 100 million worth of all equities were traded on the South African market almost every day. This represents more than 10 % of the annual GDP of South Africa. Reported studies have suggested that herd behaviour has the potential to cause mispricing (the value of an asset is greater or less than the intrinsic value of the asset) of about 5% (Economou, Kostakis and Philippas, 2011). Hence, both South African and international investors could lose an estimated value of ZAR 365 million per year.

Therefore, it is extremely important for investors to acknowledge the value of herd behaviour studies. Hence, these studies can follow up with thorough policies decisions that can reduce herd behaviour within financial markets. Although, many authors have studied the behaviour of herd mentality both at an index and industry sector level. These studies were published in 2017 and considering financial markets move at a fast pace. These studies were considered dated.

Therefore, this study builds on the understanding of herding by updating the results obtained from previous studies and testing whether Chinese market condition tie in with the explanation of herd behaviour in the JSE. Lastly, the study also sheds light on idiosyncratic volatility (this is a foreign topic to many investors). Hence, the more different corridors of herd behaviour studies available to market participants. Thus, market participants will have a better understanding of how herd behaviour affects them and hopefully minimize the investment wealth loss in South Africa.

1.7 LIMITATIONS OF THE STUDY

The first limitation of the study is that because of the size of the study subject, this study focused only on the major stock portfolios. Hence, the conclusions drawn from the results obtained in this study, can only be applied to the major stock portfolios on the JSE. The second limitation is that herd behaviour is driven by irrational behaviour amongst market participants, therefore, the study cannot fully explain some anomalies in the results.

1.8 ORGANISATION OF THE STUDY

The study report is divided into five chapters. Chapter one is the introduction to the study (background, problem statement, research question and objective of the study). Chapter two draws information from previous studies to identify gaps in the literature or motivate the purpose of the study. Chapter three explains how the study measured herd behaviour. Chapter four tallies the results into different tables and provides a comprehensive interpretation of the results. Lastly, chapter five discusses the key findings and concludes the study.

2 LITERATURE REVIEW

2.1 INTRODUCTION

This chapter reviews the literature on herd behaviour and idiosyncratic volatility. It outlines two strands of literature: theoretical literature and empirical literature. Theoretical literature focuses on the seminal works on herding behaviour, idiosyncratic volatility, and the theoretical explanations. The second stream of the literature explains previous empirical studies and reports on the methodology used in the studies. Lastly, the chapter gives additional background on the formation of BRICS. This could possibly aggravate the effects of herding on the JSE.

2.2 HERD BEHAVIOUR AND IDIOSYNCRATIC VOLATILITY

This sub-section focuses on the explanations of herd behaviour in financial markets: information-driven herding; psychology-related herding; and principal-agent relationship herding (Chen, Demirera and Kutan, 2010). The consequences of herd behaviour and the seminal studies on idiosyncratic volatility are also briefly dealt with in this sub-section.

2.2.1 Different types of herding behaviour

Ordinary investors do not have access to all the information gathered from institutional investors (Tirole, 2006). Therefore, they tend to ignore their own analysis, and instead observe and follow the action of professional investors, in order to compensate for the lack of information. Therefore, herd behaviour is driven by information. The information-related herding theory states that action of professional investors is considered useful information to ordinary investors in the market (Banerjee, 1992). Bikhchandani et al. and Sharma (2000) found evidence that ordinary investors ignore their own analysis and follow decisions made by institutional investors, which are perceived to be superior decision makers. This is known as information-driven herd behaviour.

It has also been observed that people are psychologically pressurised into making decisions and join the bandwagon of their peers, but which decisions do not necessarily maximise their utility. For example, the media has a strong influence on decisions made by individuals, as people tend to purchase similar items of clothing as that worn by models. Similarly, popular cars are not favoured for their fuel efficiency or speed; rather, they are popular because certain role models drive the car. Individuals adjust their decisions after observing the behaviour of other people in their social environment. This phenomenon is also observed within financial markets and is more intense during stressful events or periods of excess volatility (Phan and Vo, 2018).

Financial markets serve both ordinary and professional investors. Ordinary investors can be either optimistic or pessimistic and are pressurised and influenced by the optimism or negativity of sophisticated investors. This is known as psychology-related herding.

Another type of herding is known as principal-agent relationship herding. To prevent agency problems within firms, management team members are offered incentive contracts to motivate them to work hard and engage in careful decision making. It is believed that managers who hold a stake in a company (shares or options) act in the best interest of its shareholders. This allows investment managers to promote herd behaviour within financial markets. Hence, they purchase over-priced assets that they believe will go up due to herding behaviour, which guarantees that they receive a bonus at the end of the year. This is known as ride herding. However, the stock has been inflated by irrational ideas and not because of the value of the firm. This delivers an asset price bubble. This abnormal and unpredictable irrational investment behaviour convinces managers to short-sell overpriced security (i.e. trading against the herd), which they believe that they suffer a loss on when prices rationalise. This type of behaviour is extremely dangerous for investors and it distorts the risk-reward ratio for investors (Scharfstein and Stein, 1990).

2.2.2 The problems of herding behaviour

Irrational investment behaviour can distort asset prices and cause an asset price bubble. These bubbles are inflated based on irrational ideas and are not supported by the value of the asset, which can cause a sudden collapse in the market (Lux, 2015). This was confirmed by BenSaïdab, Bouraoui and Litimi (2016), who found evidence that herd behaviour within the US markets contributed to asset price bubbles and other financial crises, e.g., Black Monday in 1987 and the global financial crisis in late 2007. Similarly, another study found evidence that herd behaviour by US institutional investors created temporary asset price offsets and inflated asset bubbles (Singh, 2013). Previous studies that looked at herd behaviour in German and Indian stock markets suggested that, in the short run, institutional herding can destabilise stock prices (Garg et al., 2013). These findings indicate that herding is a practice that deteriorates markets and weakens a country's economy.

Another study found evidence that irrational investment behaviour amongst short-term investors promotes price discovery and fundamentals and stated that stock prices are ignored when long-term investors exhibit herd behaviour (Yuksel, 2015). Overall, herd behaviour has a negative impact on the market and aggravates financial crises. Many scholars believe that herd behaviour studies can change investors' policies and eliminate the effects of herd behaviour.

Jitka and Haoran (2015) found evidence that herd behaviour in Chinese markets decreased after a consecutive number of stock-market regulations were enforced in 2006 by the CSRC. This implies that the effects of herd behaviour can be minimised with the introduction of appropriate policies, and it highlights the importance of herd behaviour studies.

2.2.3 Idiosyncratic volatility

There is a lack of literature on idiosyncratic volatility in emerging markets, as most previous studies have focused on the assumption that investors are rational, and they often overlook the significance of investors' behaviour (Phan and Vo, 2018). One of the main implications of CAPM is that only non-diversified risk is priced, while idiosyncratic risk is eliminated through diversification (He, Liu and Qu, 2019). It is sensible for investors to diversify their portfolio to eliminate this excess volatility. However, irrational choices or wealth constraints mean that many individual investors in the stock markets do not hold diversified portfolios. This gives scholars the opportunity to expand the theory of idiosyncratic volatility (Phan and Vo, 2018).

Levy and Merton (1987) suggest that undiversified investors expect a premium for taking on idiosyncratic volatility; therefore, idiosyncratic volatility should influence stock returns positively. Picard and Switzer (2015) found evidence that idiosyncratic volatility influenced stock returns positively in 13 emerging markets (including South Africa). In contrast, evidence was found that returns in developed markets are less influenced by idiosyncratic volatility (Picard & Switzer, 2015). In addition, Nartea, Ward and Yao (2010) found evidence that idiosyncratic volatility had a positive influence on stock returns in Malaysia, Singapore and Thailand.

Many volatility studies use the three factor Fama model to measure or capture the idiosyncratic volatile behaviour within stocks. However, Picard and Switzer (2015) suggested that the single factor Fama model or a GARCH model can be used to measure idiosyncratic volatility. Many recent idiosyncratic volatility studies have adopted these methods because of their simplicity and consistent results. Hence, the study used the single factor Fama model to measure the idiosyncratic volatility of each stock included in the study.

Furthermore, studies suggest that idiosyncratic volatility has a greater influence on emerging markets (Fazil and Ipek, 2012). One study performed the analysis to determine if the size of a stock in emerging markets influences idiosyncratic volatility behaviour. Surprisingly, the study found evidence that: idiosyncratic volatility was found to be the biggest component of total volatility (systematic and non-systematic volatility); both small and big stocks show the same idiosyncratic volatility behaviour (Fazil and Ipek, 2012). Interestingly, idiosyncratic volatility affects each emerging market differently.

2.3 HERD BEHAVIOUR AND IDIOSYNCRATIC VOLATILITY: EMPIRICAL STUDIES

After the global financial crisis, many scholars claimed that herd behaviour within markets aggravates market volatility and can even lead to instability - hence, empirical studies on herding started to become more popular. This sub-section focuses on the empirical studies that are relevant to the current study and studies that outline the methods used to measure herd behaviour and idiosyncratic volatility in financial markets.

2.3.1 Chinese market conditions and herd behaviour in other markets

A previous study was done using the stock market data for the period January 2010 to June 2019 to investigate whether or not turbulence periods (US-China trade war in 2018) and tranquil periods in China's economy influences herding behaviour among traders in other markets. The results showed that herd behaviour in the Chinese stock markets was present during the entire period (tranquil and turbulent periods). In general, on trading days when the Chinese stock market was considered turbulent, only countries in Asia, Africa, Eastern Europe and Europe were influenced by Chinese market conditions. Hence, countries in North America, Oceania and the Pacific were seen to be indifferent to the turbulent periods, and were not dependent on Chinese market returns. Interestingly, when Chinese markets were tranquil, countries categorised as high, medium and low trading countries revealed that China's market conditions generally influenced South Africa, Russia, Australia, New Zealand, Kenya, India and most other Asian countries. Moreover, Hong Kong, Indonesia, Malaysia, Taiwan, the UAE, Egypt, Croatia, Russia and South Africa herd around the Chinese stock market during this period (Bany-Ariffin, Chong, Matemilola, & McGowan, 2019). Hence, investors in these countries follow calm Chinese market movements.

Although China plays an essential role in the world economy and global finance, the study concluded that Chinese cross-sectional dispersions in turbulent periods were not stronger compared to the US cross-sectional dispersions during the global financial crisis. Other countries did not herd around the US stock market during the global financial crisis. This can be explained as follows: China's financial development is still rudimentary and China's stock market is vastly different from that of developed markets. Additionally, China's stock market is dominated by retail investors who treat stock markets as casinos (Chemi and Fahey, 2016).

In developed markets, the dominant force is institutional investors; therefore, developed markets are a global information processing centre. Asian markets tend to follow investment strategies and market news provided by institutional investors on Wall Street. If investors in

international markets believe that information from the US markets is reliable and valuable, they tend to ignore their own beliefs and herding behaviour becomes more dominant.

Furthermore, the standard trading times around the world differ, and many authors suggest that the difference in time zones reduce dependency amongst financial markets, since China and the US markets do not have overlapping trading hours. However, China is influential in the regions of Asia and Africa, regardless of opening and closing times (Bany-Ariffin, Chong, Matemilola, & McGowan, 2019). Hence, further herding behaviour studies can be done on these markets.

2.4 HERD BEHAVIOUR IN SOUTH AFRICA

Ababio and Mwamba (2017) adopted a quantile regression method to test for herding on the Johannesburg Stock Exchange from 4 January 2010 to 30 September 2015. Interestingly, the study emphasised that herding is not only present at a market level, but also evident at a sectoral level. The study only focused on the general financials sector (insurance firms, banks and real estate). The study found evidence of herding in the real estate and banking sector over the entire sample period.

Although only 10 insurance firms and 5 banks were included in the sample, the study found that herding in the banking sector and the real estate sector was more prevalent during periods of extreme market movements than in normal periods, i.e., herding was more prevalent in down markets (bear markets). These results are consistent with the findings of Chang et al. (2000), who found: the characteristics of emerging markets make herd behaviour more evident (dominance of relatively few institutional investors; exposure to highly volatile international capital flow; thin trading volumes; unsophisticated small stockholders). However, the general financials showed evidence of herding only in rising markets (bull markets). This suggests that investors in the JSE reduce their rational investment appetite and follow the herd (risk aversion increases). Also, herding in the general financial sector (insurance firms, banks and real estate) obscures the irrational investment behaviour exhibited by banking and real estate investors in bear markets (Ababio and Mwamba, 2017).

In contrast, Mekwa (2017) found no evidence of herd behaviour on the JSE when using a dispersion-based model. The study investigated herd behaviour at both a market level and a sectoral level (banking, resources, and the industrial and financial sectors) for the period 31 January 2003 to 31 May 2016. The study used the All-Share Index and not the Top 40 JSE index.

An alternative method that can be used to measure the relationship between cross-sectional dispersion of stock returns and market movement is the quantile regression model. The quantile

regression method is popular for studies measuring the change in a percentile of a response variable that was caused by a unit change in the endogenous variable (Ababio and Mwamba, 2017).

The residuals in the traditional non-linear equation method distorts the results when detecting for irrational behaviour (Chang et al., 2000), especially, when residuals are not normal (Ababio and Mwamba, 2017). Fundamentally, the model is very sensitive to outliers and focuses, in the main, on the extreme sides of the return distribution, rather than on the whole distribution. The quantile regression rectifies these flaws (Chang, Cheng and Khorona, 2000).

Ababio and Mwamba (2017) determined that using the conventional traditional method showed similar results compared to the results obtained when using the quantile regression method. Both methods used the same firms and sample size in South Africa. However, the traditional method only found evidence of herding in down markets for the banking sector, general financial sector and real estate sector (this was not evident in the entire sample period for each sector). Conversely, the quantile regression method only found evidence of herding in down markets for the banking sector and real estate sector.

2.4.1 Measuring herd behaviour in other markets

The cross-sectional standard deviation of stock returns (CSSD) was used by Christe and Huang (1995) to capture the herding effect (Dai Gong, Jun and Pu, 2017). They observed a correlation between high return dispersion and large market return movements, which is considered evidence of irrational investment behaviour or herd mentality amongst investors.

A linear CAPM model would suggest that the cross-sectional dispersion of stock returns would be proportional to the market returns. However: this linear relationship exists in an ideal market (no imperfections); the relationship between the cross-sectional dispersion of stock returns and stock returns tends to follow a non-linear relationship. This is more evident during turbulent periods (Economou, Kostakis and Philippas, 2011).

Therefore, Chang et al. (2000) suggested using the cross-sectional absolute deviation (CSAD) to measure return dispersion, and applying a non-linear model to detect herding behaviour. However, the model does impose asymmetric effects. Therefore, Chiang & Zheng (2010) suggested inserting an additional Rmt term at the right-hand side of the Chang et al. (2000) non-linear equation. This was done to reduce the error of misspecification in the model.

One study investigated herding behaviour amongst Vietnam investors over the period 2005 to 2016, i.e., before, during and after the financial crisis (Huang, Lin and Yang, 2014). The study

employed two measures: cross-sectional dispersion of stock returns; and cross-sectional absolute deviation (linear and non-linear models). Both models used in the study did not provide congruent conclusions (Huang, Lin and Yang, 2014). The non-linear relationship measured by CSAD supports the irrational behaviour linked to herding behaviour. However, the linear model suggested by Christe and Huang (1995) produced statically insignificant results (Vo and Phan, 2018).

In contrast, Khan, Shah and Shah (2017) used the CSSD method to examine the dispersion between the stock returns of individual firms and the market in Pakistan from January 2004 to December 2013. The results concluded that investors invest rationally in most individual firms. However, there was weak evidence in terms of firms herding towards the market when the market experiences a 5% negative return. Surprisingly, no evidence was found of herding during downward movements in the markets, but evidence suggests that investors tend to follow the market during a crisis period. Interestingly, investors in large firms follow the market more compared to investors in small firms. This could explain why many Pakistan herding studies have produced insignificant results. Mixing small firms with large firms while investigating herd behaviour can produce misleading results (khan, Shah and Shah, 2017).

Another study provides comprehensive evidence of testing for the existence of herding behaviour among four southern European countries (Portugal, Italy, Spain and Greece). The study used the daily stock market returns during the period January 1998 to December 2008. The analysis was performed using the CSAD model.

However, the calculation of CSAD requires the market return portfolio (Rmt) to be calculated. The market portfolio can be calculated using two methods: equal weighted and value weighted stock returns. Both methods were used simultaneously in the southern European study. However, the equal weighted average can be misleading, as it only represents a small cap stock, which consists of most of the listed stock of the four markets. The conclusion based on the results was that herding effects were present in mainly the Greek and Italian markets for both the equal weighted and the value weighted stock methods (Economou, Kostakis and Philippas, 2011).

This pattern was also evident in other European stock markets. Filip, Peca, Pochea (2017) investigated herd behaviour in 10 central and east European countries using both an OLS model and quantile regression model. Although, the study used the period from January 2003 to December 213. The results showed that OLS method only detected herd behaviour in Bulgaria, Estonia and Latvia. Meanwhile, the quantile regression model found evidence of herding all European countries except Poland and Romania.

Interestingly, the study also investigated impact of market conditions (i.e., bear or bull markets, high or low volatility and high or low trading volume) on herd behaviour. Under down markets, herding was more evident in most European countries. This could be explained because Eastern European investors were easily influenced by fear or panic. They neglect their only analysis and quick to engage in overselling of transactions. This was also slightly evident under low and high price movement periods.

Surprisingly, when the Eastern European markets were up investors became optimistic, neglecting their own analysis and following each other in buying transactions. On the other hand, the study also suggested that investors in smaller firms tend follow other investors. This is known as institutional level herding. This implies that investors react simultaneous to fundamental values. Hence, a faster price adjustment and therefore a more efficient market.

In contrast, Lee (2017) found no evidence of herding activity amongst American investors under positive price movements. The study re-examined herd behaviour in the American market by employing a new measure of herding strategy. The proposed method is defined as the difference between the fraction of stocks whose prices rise and the expected value of that fraction under assumed traditional asset pricing models. This is known as the cross-sectional excess co-movement of returns (CSC).

As expected, the CSC model found evidence of herding during periods of large negative price movements, which was almost congruent to previous findings who adopted the cross-sectional dispersion of returns approach. Strangely, the study also found no evidence or weak evidence of herding during the global financial crisis. Therefore, herd behaviour is not always present during extreme market movement periods.

2.4.2 Idiosyncratic volatility and herd behaviour

One study investigated the impact of idiosyncratic volatility and herd behaviour in Vietnam's equity market (Phan and Vo, 2018). Evidence was found that herding was present before, during and after the global financial crisis periods. In particular, irrational investment behaviour was more intense during high volatility periods, and it was noticed that herd behaviour was stronger in a security or stock portfolio with the lowest level of idiosyncratic volatility (Phan and Vo, 2018).

Another study investigated the impact of idiosyncratic volatility on investment behaviour in terms of the Taiwan stock market (Huang, Lin and Yang, 2014). The methodology was congruent with that of the Vietnam study. The results showed that herd behaviour during turbulent events was different for portfolios with larger levels of idiosyncratic volatility. Hence,

both studies implied that the herd behaviour of market participants is different for stocks with different levels of idiosyncratic volatility and idiosyncratic volatility affects each country differently. The method used to measure how idiosyncratic volatility affects herd behaviour in both studies was using the single factor model to divide the stocks in the markets into three groups, according to the level of volatility of each stock (Phan and Vo, 2018). In addition, both studies identified cross-sectional dispersion in the different industries. For purposes of examining herding across industries, the stocks were assigned to three categories: financial sector; banking sector; technology sector. As the sub-prime mortgage crisis was a major cause of the global financial crisis in 2008, both studies focused on the banking and financial sector.

The Vietnam study suggested that, during the global financial crises, herding coefficients were significant and negative in all industries (Phan and Vo, 2018). However, there was weak evidence to support the theory of herd mentality before and after the global financial crisis. In addition, evidence suggested that herd behaviour was more pronounced during a period of declining markets within each industry (Phan and Vo, 2018).

In contrast, the Taiwanese study found no evidence of herd mentality in the financial sector, technology sector and banking sector during and after the financial crisis periods (Huang, Lin and Yang, 2014). However, evidence confirms that the herd mentality was present in various idiosyncratic volatile stocks during this period. This implies that investors in the Taiwanese market, who hold various levels of idiosyncratic volatility stock portfolios, practice different investment habits compared to investors in the industry sector portfolios.

2.5 BRICS AND INTERCONNECTIVITY

Since China joined the world trade organisation and the BRICS bloc, China has played an increasingly important role in the growth of the world's economy. China's fast-growing economy also facilitated economic growth in South Africa. This sub-section will briefly focus on how the formation of the BRICS bloc could increase herding behaviour in the South African markets.

Russia, India, China and South Africa belong to a bloc of countries called BRICS. The BRIC bloc was established in June 2009, and South Africa joined in 2010 - hence, the name BRICS (Jabalameli and Rasoulinezhadr,2018). Previous studies suggest that financial integration of the BRICS stock markets has strengthened following the formation of BRICS, in comparison to the period prior to the BRICS bloc being established (Al-Mohamad, Bakry, Jreisat Rashi and Vo, 2020).

The more interconnected a stock market becomes; the greater are the consequences of herding in financial markets, and the more vulnerable markets are to global shocks (Economou, Kostakis and Philippas, 2011). This could stimulate herding behaviour. Therefore, Al-Mohamad, Rashi, Bakry, Jreisat and Vo (2020) used the Variance Decomposition and Impulse Response Analyses to investigate how BRICS markets have responded to shocks emanating from BRICS countries or elsewhere in the world (before and after the formation of BRICS). The results revealed that Brazil, Russia, India and South Africa were more influenced by shocks in the Chinese economy than shocks emanating from the other BRICS countries. This could be because China has a strong international trade linkage.

The decomposition of forecast error variance in the Al-Mohamad, Rashi, Bakry, Jreisat and Vo (2020) study revealed that turbulent periods in the Chinese market during 2016 and 2018 heavily influenced the South African market and other BRICS markets. Furthermore, the Johansen-Juselius cointegration and exclusion test implied that China has a stronger long-term equilibrium relationship with South Africa during the post BRICS formation period than during the pre-BRICS formation period.

A study done by Al-Mohamad, Rashi, Bakry, Jreisat and Vo (2020) suggests that shocks in the Chinese stock market had more influence on the South African stock market in the post BRICS formation era, since herd behaviour is known to be more intense during unsteady events. It is possible that the formation of BRICS amplifies herd behaviour in the South African markets during unsteady events. Further studies should be done to examine the relationship between the Chinese markets and the South African markets in the post-BRICS formation era.

2.6 SUMMARY

Information-driven herding, psychology-related herding, and principal-agent relationship herding are theories that explain irrational investment behaviour in financial markets. If this phenomenon lasts a long time and markets fail to adjust to rational values, asset prices can be distorted and cause market instability. Therefore, herd mentality is being studied extensively in terms of both emerging and developed markets. The traditional cross-sectional method suggested by Chang et al. (2000) is used most frequently to test herding. However, studies suggest it is not a rhombus method to measure herd behaviour and that there are deficiencies. Many studies have found evidence of herd behaviour in other international markets using a dispersion-based model.

Ababio and Mwamba (2017) also emphasised that, under specific market conditions, herding can occur at sectoral level, but not at the market or sector level on the JSE. This could explain

why studies that investigated herd behaviour in terms of the All-Share Index produced insignificant results. Similarly, the study done in Taiwan (Huang, Lin and Yang, 2014) found no evidence of herd behaviour in different industry sector portfolios, but found evidence of herd behaviour in stocks that were categorised into different idiosyncratic volatility groups.

The Vietnam study (the second herd behaviour and idiosyncratic volatility study) found evidence of herd behaviour in both the different industry sectors and the idiosyncratic volatility portfolios (Phan and Vo, 2018). Therefore, South African investors cannot use these two studies to enrich their analysis, as idiosyncratic volatility affects each market differently (Fazil and Ipek, 2012). Investors in the industry sectors will not necessarily practise the same investment behaviour as investors in various idiosyncratic portfolios all the time.

The South African stock market was observed to be influenced by cross-sectional dispersion emanating from the Chinese stock market during the period 2016 to 2018 (Bany-Ariffin, Chong, Matemilola, & McGowan, 2019). However, the study only examined herd mentality at the market level. It may be that herd behaviour in stock portfolios (various idiosyncratic volatility stocks and different industry stocks) are less influenced by Chinese market conditions.

This study will help investors to revise their policies, and so make better investment decisions and develop improved hedging strategies. This could reduce herding behaviour, as evidence suggests that herding can be minimised through policy adjustment (i.e., China in 2006).

3 METHODOLOGY

3.1 INTRODUCTION

This chapter explains the measuring techniques used to investigate whether or not market movements and herding activity in the Chinese market influence investors' decisions regarding the JSE. The chapter consists of two components: section 3.2 discusses how the data was collected and sorted; section 3.3 explains the logical and coherent way that herd behaviour was measured in the study.

3.2 DATA COLLECTION AND SORTING

3.2.1 CSI 300 and JSE 40

The previous chapters showed evidence that Herd behaviour was easily detected and measured using high-frequency data in various countries, i.e. China, Southern European countries, Vietnam, Taiwan, Pakistan and South Africa. The daily data from both the South African and Chinese stock markets were used in this study. The CSI 300 Index represents the top 300 firms from both the Shanghai stock exchange and the Shenzhen stock exchange.

The South African data only includes firms in the top 40 list. The top 40 listed companies provide a fair reflection of what happens in the South African stock market, even though it only constitutes 10% of the listed companies on the JSE (40/400). However, it represents approximately 80% of the total market cap of all JSE listed companies. Firms that were not actively listed in the top 40 for the entire selected analysis period were removed.

In order to be consistent with previous herd behaviour studies, the raw stock prices for the CSI 300 and JSE 40 index were obtained from a Bloomberg terminal. The returns were computed as follows:

$$R_t = 100*\ln (P_t/P_{t-1}) \quad (1)$$

Where: R_t is market return on day t; P_t is the price on day t; P_{t-1} is the price on day t-1.

3.2.2 Data source

The global financial crisis of 2007 is not dealt with in this study, as many studies have addressed this period, including the global crisis; therefore, including it in the current study will not provide new insight into herd behaviour. The aim of the study was to test and analyse herd behaviour in terms of the JSE 40 over the period January 2010 to June 2019.

The Chinese stock market turbulence and the tariffs imposed in July 2018 on Chinese shipments entering the US caused the Chinese markets to become very volatile during the periods 12 June

2015 to 12 February 2016 and 6 July 2018 to 14 June 2019 (Bany-Ariffin, Chong, Matemilola, & McGowan, 2019). Thus, the study performed a sub-period analysis by looking at periods when the Chinese stock markets were considered either tranquil or turbulent. The sub-periods are as follows:

- 4 January 2010 to 31 May 2015 (tranquil 1)
- 1 June 2015 to 15 February 2016 (Chinese stock market turbulence)
- 16 February 2016 to 31 May 2018 (tranquil 2)
- 1 July 2018 to 14 June 2019 (US-China trade war)

When data was not available for certain days (national holidays) in the Chinese or South African markets, those days were removed from the data set. Also, high-frequency data can cause a high level of serial correlation in the model; serial correlation occurs in a time series when the errors related for a given time carry over into the next time periods. Hence, if the model slightly overestimates / underestimates the results. This effect will be magnified using high frequency data. Therefore, the Newey and West (1987) "heteroscedasticity and autocorrelation consistent standard" errors were used to calculate the estimated coefficients.

3.2.3 Idiosyncratic volatility groups

In order to obtain a deep understanding of how idiosyncratic volatility plays a role in herd mentality amongst South African investors, the firms listed on the Johannesburg Stock Exchange were separated into three categories: low, medium, and high idiosyncratic volatility groups. The idiosyncratic volatility of each stock was measured on a rolling window basis for each sub-period.

The variance of the stock i returns gives the total volatility of each firm. Therefore, the French Fama single factor model was used to estimate the idiosyncratic volatility of each firm (Bali and Cakici, 2008). The standard deviation of the residuals from equation 2 were used to categorise each firm.:

$$ER_{i,t} = \alpha + \beta_1 ER_{m,t} + \varepsilon_t \quad (2)$$

$$Idiovolati_{j,t} = \sqrt{var(\varepsilon_t)} \quad (3)$$

Where: $ER_{m,t}$ and $ER_{i,t}$ are excess returns of individual stock i and market (R_m or R_i less the 10-year government bond yield); *Idiovolati* denotes the standard deviation of the residuals of stock i.

3.2.4 Herd behaviour in different industry sectors

The second stream of the study examined herd behaviour in different industry sectors. The JSE is divided into 10 industries, 19 supergroups, 41 sectors and 114 sub-sectors. Due to the enormous size of the JSE listings, the study focused on just the major sectors.

Interestingly, Khan, Shah and Shah (2017) identified that investors in large firms tend to herd more compared to investors in small firms. Therefore, investors see more value in studies that represent a large portion of wealth and have a greater effect on investment wealth. Therefore, the studied examined three major industry sectors, which constitute 61.38% of the JSE total market capitalisation: Resources, Industrial and Banking. The Resource sector represents all the listed metal and mining firms in South Africa. The Industrial sector includes all the technology firms. The banking sector includes all the major financial intermediators in South Africa.

3.3 RESEARCH DESIGN

3.3.1 CSAD model

Chang, Cheng and Khorona (2000) suggest that a dispersion-based model will be sensitive to outliers and possible lead to misleading conclusions. However, the objective of the study is update and deepen the knowledge of previous studies. Since majority of studies have used a dispersion base model. A comparative analysis would be easier if the studies execute the same methods. Therefore, the study deployed a dispersion-based model.

Empirical studies suggest that if cross-sectional dispersion continues to increase at a decreasing rate, it is considered evidence of herd behaviour. To test the relationship between cross-sectional dispersion and market returns, the test equation should hold a square term to capture the non-linearity. Therefore, the relationship between cross-sectional dispersion of stock returns and squared market returns should be negative, in order to indicate the presence of herd behaviour (Chang et al., 2000).

Two dispersion-based models are used to detect herd behaviour in financial markets: the cross-sectional standard deviation model (CSSD); and the cross sectional absolute standard deviation model (CSAD). The CSSD method used to test for herd behaviour is more useful during extreme price movements and picks up very little evidence of herding during normal trading days.

However, the definition of large price movements is cryptic or arbitrary. It was quite tricky to identity large price movements and not all subperiods in this study showed clear evidence of large price movements. The CSAD equation was also believed to be the model that best

explains the data compared to the CSSD model (Phan and Vo, 2018). Therefore, this study focused only on the CSAD equation. The CSAD equation was also believed to be the model that best explains the Data. The following equation was used:

$$\mathrm{CSAD_t} = \frac{\sum_{i=1}^{N} |Rit - Rmt|}{N} \quad (4)$$

Where: $R_{m,t}$ and $R_{i,t}$ is the observed index and stock returns of firm i on day t; N is the number of stocks in the market portfolio; CSAD is the cross-sectional absolute return on day t.

The benchmark equation suggested by Chang et al. (2000):

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

Where: $R_{m,t}$ is the observed index t; $CSAD_t$ is the cross-sectional absolute return on day t.

Because equation 5 approach is dated and imposes asymmetric effects, Chiang and Zeng (2010) modified the equation by adding the $R_{m,t}$ term into the Chang et al. (2000) equation:

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

Equation 6 is similar to equation 5: a statistically significant negative coefficient for γ_3 indicates the presence of herding within financial markets, while removing the asymmetric problem. Hence, the LHS (dependent variables) of equation 4 will be substituted on the LHS of equation 6.

If herding is tested in a portfolio or sector, the cross-sectional dispersion is compared to the weighted average returns of a sector or portfolio.

3.3.2 Role of China's stock market in terms of the JSE Index

In order to measure if China's cross-sectional dispersion of stock returns and market returns influence herd mentality among South African investors, the CZ (2010) equation was adjusted by adding two additional terms:

$$CSAD_t = \gamma_0 + \gamma_1 (R_{m,t}) + \gamma_2 |R_{m,t}| + \gamma_3 (R_{m,t})^2 + \gamma_4 CSAD_{CHN,t-1} + \gamma_5 (R_{CHN,t-1})^2 + \varepsilon_t \quad (7)$$

CHN represents the CSI 300 index, whereas $CSAD_{CHN,t-1}$ and $R_{CHN,t-1}$ are the cross-sectional dispersion of stock returns and the market returns of the CSI 300 index. Similarly, $\mathrm{CSAD_t}$ and Rm,t are the cross-sectional absolute returns of stock returns and market returns on the JSE. It is important to note that the Chinese markets open before the South African markets; therefore, CSI returns and CSAD lag by one day.

A negative coefficient of γ_3 would indicate the existence of herding in the South African markets, whereas a positive and significant coefficient of γ_4 would indicate that cross-sectional dispersion in the South African markets is influenced by herding behaviour in the Chinese markets. Interestingly, a negative coefficient for γ_4 would suggest that South African investors tend to herd in the opposite market conditions than Chinese investors. Lastly, a significant negative coefficient of γ_5 indicates that herding behaviour in South African markets is being influenced by Chinese market returns. If the coefficient is positive, herd behaviour among investors is not dependent on Chinese market movements.

3.3.3 Role of China's stock market in terms of each stock portfolio

After analysing herd behaviour and the dependency on Chinese market conditions at the JSE at a market level, the first step was to examine herding patterns in various idiosyncratic volatile stock portfolios. Simultaneously, herding behaviour in the major sectors of the JSE must also be looked at.

Equation 7 was modified; the cross-sectional dispersion was compared to the weighted average returns of a sector or portfolio and not the weighted average returns of the JSE market. The following equations were used to detect herd behaviour in each portfolio (low, medium and high idiosyncratic volatile stock portfolios; Resources, Industrials and Banking sectors):

$$CSAD_t^{LowVol} = \gamma_0 + \gamma_1\left(R^{LowVOL}{}_{m,t}\right) + \gamma_2\left|R^{LowVOL}{}_{m,t}\right| + \gamma_3\left(R^{LowVOL}{}_{m,t}\right)^2 + \gamma_4 CSAD_{CHN,t-1} + \gamma_5\left(R_{CHN,t-1}\right)^2 + \varepsilon_t \quad (8)$$

$$CSAD_t^{MedVol} = \gamma_0 + \gamma_1\left(R^{MedVOL}{}_{m,t}\right) + \gamma_2\left|R^{MedVOL}{}_{m,t}\right| + \gamma_3\left(R^{MedVOL}{}_{m,t}\right)^2 + \gamma_4 CSAD_{CHN,t-1} + \gamma_5\left(R_{CHN,t-1}\right)^2 + \varepsilon_t \quad (9)$$

$$CSAD_t^{HighVol} = \gamma_0 + \gamma_1\left(R^{HighVOL}{}_{m,t}\right) + \gamma_2\left|R^{HighVOL}{}_{m,t}\right| + \gamma_3\left(R^{HighVOL}{}_{m,t}\right)^2 + \gamma_4 CSAD_{CHN,t-1} + \gamma_5\left(R_{CHN,t-1}\right)^2 + \varepsilon_t \quad (10)$$

$$CSAD_t^{resource} = \gamma_0 + \gamma_1\left(R^{resource}{}_{m,t}\right) + \gamma_2\left|R^{resource}{}_{m,t}\right| + \gamma_3\left(R^{resource}{}_{m,t}\right)^2 + \gamma_4 CSAD_{CHN,t-1} + \gamma_5\left(R_{CHN,t-1}\right)^2 + \varepsilon_t \quad (11)$$

$$CSAD_t^{industrial} = \gamma_0 + \gamma_1\left(R^{industrial}{}_{m,t}\right) + \gamma_2\left|R^{industrial}{}_{m,t}\right| + \gamma_3\left(R^{industrail}{}_{m,t}\right)^2 + \gamma_4 CSAD_{CHN,t-1} + \gamma_5\left(R_{CHN,t-1}\right)^2 + \varepsilon_t \quad (12)$$

$$CSAD_t^{Banking} = \gamma_0 + \gamma_1\left(R^{banking}{}_{m,t}\right) + \gamma_2\left|R^{Banking}{}_{m,t}\right| + \gamma_3\left(R^{Banking}{}_{m,t}\right)^2 + \gamma_4 CSAD_{CHN,t-1} + \gamma_5\left(R_{CHN,t-1}\right)^2 + \varepsilon_t \quad (13)$$

The equations presented above allowed the study to test if herd behaviour exists in each stock portfolio and if this was dependent on Chinese market conditions. This was done to determine

if herding patterns are different at the market level, sector level, and idiosyncratic volatility level.

3.4 ETHICS

The study applied for ethical clearance from the University of the Witwatersrand Human Research Ethics Committee. The data used in the study was secondary data; therefore, there were no human participants and therefore no ethical consideration relating to informed consent were applicable to this study. Once ethical clearance was provided by the committee, the required data was collected. The data was extracted from the Bloomberg Terminal and saved on a computer that requires a password to operate it. The documents could only be accessed by the researcher and the data was deleted on completion of the research.

4 RESULTS AND DISCUSSION

4.1 INTRODUCTION

This chapter provides the data gathered from Bloomberg that was used to run 63 regressions. Section 4.2 explains the descriptive statistics of the data. Section 4.3 shows the findings from the regression analyses, and section 4.4 provides a summary of the chapter.

4.2 DESCRIPTIVE STATISTICS

Table 4.1 and Table 4.2 illustrate the summary statistics of six stock portfolios. Low, medium and high represent each idiosyncratic volatility group. Interestingly, when moving backwards from 2019 to the Chinese stock market's turbulent sub-period in 2016, the mean values decrease in both the Resources and medium idiosyncratic volatility portfolios. This indicates that herd behaviour was most likely to be evident in the Medium and Resources portfolio during the Chinese stock market's turbulence subperiod. Furthermore, the various CSAD standard deviation figures suggest that each stock portfolio reflects a different investing pattern, which confirms the importance of testing herd behaviour in each stock portfolio.

Table 4.1: Descriptive statistics for idiosyncratic volatility

CSAD	Tranquil 1	Chinese stock market turbulence	Tranquil 2	US-China trade war
Low Mean	0.8551	1.0112	1.0243	1.1224
Low Median	0.8245	0.9559	0.9174	1.0029
Low Maximum	2.2496	6.5034	3.9061	4.5314
Low Minimum	0.1955	0.5013	0.3284	0.3015
Low Std. Dev.	0.2971	0.6570	0.4807	0.5185
Medium mean	1.2431	0.9299	1.0822	1.1647
Medium median	1.1206	0.8826	0.9771	1.0626
Medium Maximum	2.9045	7.0857	4.6403	4.5216
Medium Minimum	0.1941	0.3783	0.2806	0.4301
Medium Std. Dev.	0.3372	0.6662	0.4985	0.5108
High Mean	1.2156	2.4249	1.7997	1.6402
High Median	1.0979	2.1724	1.5948	1.5079
High Maximum	4.8896	5.7029	18.7227	5.9819
High Minimum	0.1901	0.7663	0.4819	0.5634
High Std. Dev.	0.5350	1.1716	1.0493	0.7092

Table 4.2: Descriptive statistics for industry sectors

CSAD	Tranquil 1	Chinese stock market turbulence	Tranquil 2	US-China trade war
Banking mean	0.728	0.822	0.697	0.720
Banking median	0.6745	0.7787	0.6549	0.6418
Banking Maximum	3.7789	2.3851	4.0956	1.6816
Banking Minimum	0.0805	0.0977	0.0942	0.1488
Banking Std. Dev.	0.3422	0.3874	0.3845	0.3025
Resources mean	2.3706	1.2105	1.5308	1.7709
Resources median	2.1381	1.1054	1.4110	1.5718
Resources Maximum	4.7159	6.4889	6.7110	4.0249
Resources Minimum	0.3198	0.8192	0.5097	0.4400
Resources Std. Dev.	0.5056	1.0786	0.7914	0.5818
Industrials mean	0.9980	1.1768	1.1098	1.4849
Industrials median	0.9206	1.0269	0.9995	1.3344
Industrials Maximum	3.9722	3.8941	3.5172	5.9004
Industrials Minimum	0.1790	0.1579	0.1978	0.4867
Industrials Std. Dev.	0.4621	0.6073	0.5443	0.7946

The ban on shadow lenders in the Chinese stock market made the Chinese markets extremely volatile between 2015 and 2016. Figure 4.1 shows that the South African markets were highly volatile during this period. However, there was not enough information here to suggest that the South African markets depend on the Chinese markets. However, it is possible that both the Chinese and South African markets respond to a common factor, but without one market influencing the other.

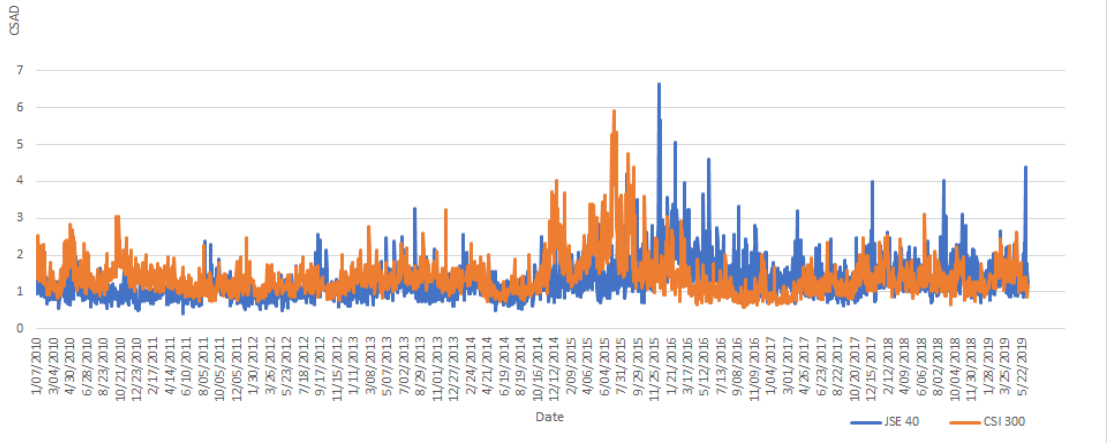

Figure 4.1: CSI 300 and JSE 40 CSAD

Figure 4.2 to Figure 4.7 show the cross-sectional dispersion of each stock portfolio and CSI 300 on the same axis. Figure 4.2 suggests that the Industrial sector seems to commove, but this cannot be used as the basis to conclude that there was dependency between the Industrial stock portfolio and the CSI 300 Index. Generally, the Industrial sector consistently followed the CSI 300 dispersion activity over the entire sample period.

It was observed that all the stock portfolios displayed extremely high dispersion activity during the turbulent sub-period of the Chinese stock market. Hence, it could be expected that herd behaviour would be found during the turbulent sub-period of the Chinese stock market, which would lead to the conclusion that herd behaviour is more prevalent during unsteady periods.

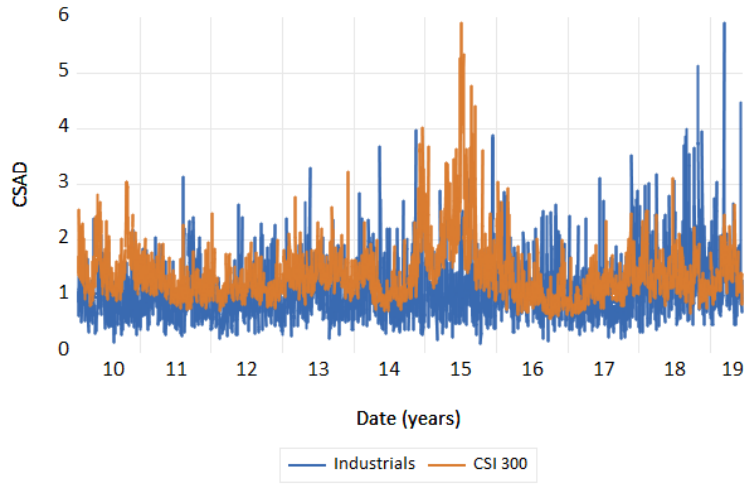

Figure 4.2: Industrials CSAD

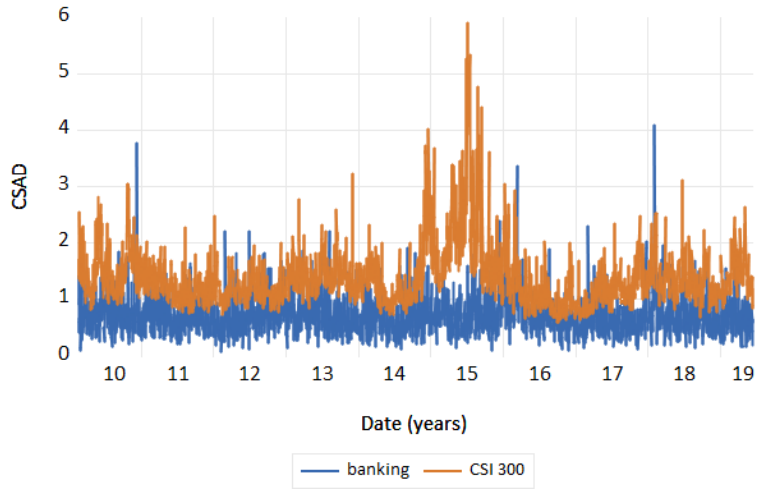

Figure 3.3: Banking CSAD

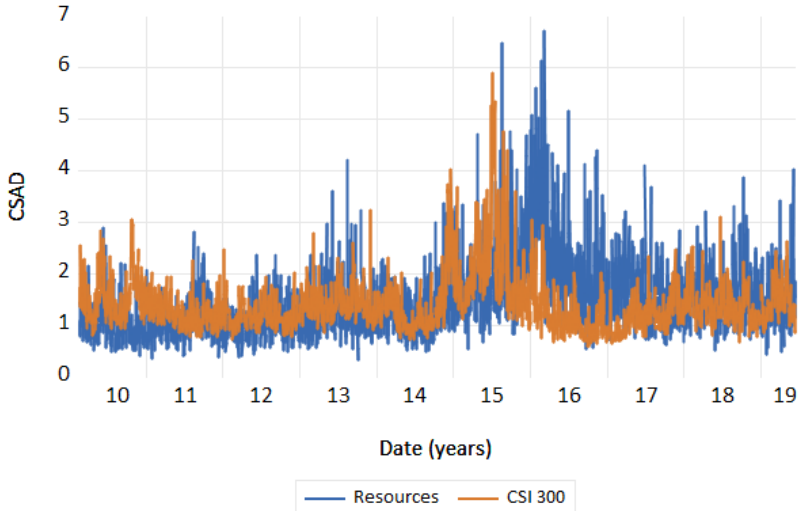

Figure 4.4: Resource CSAD

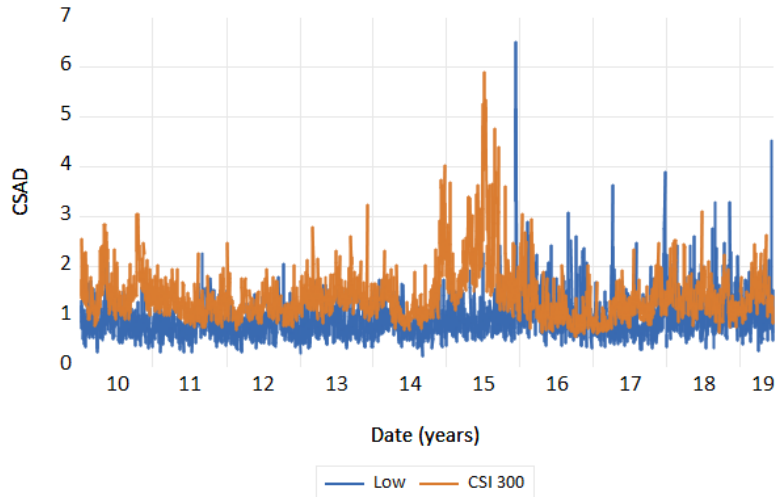

Figure 4.5: Low CSAD

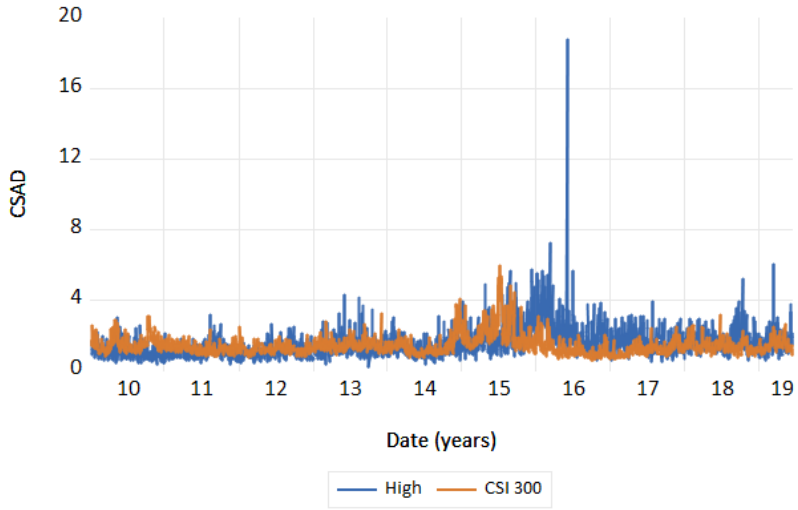

Figure 4.6: Resource CSAD

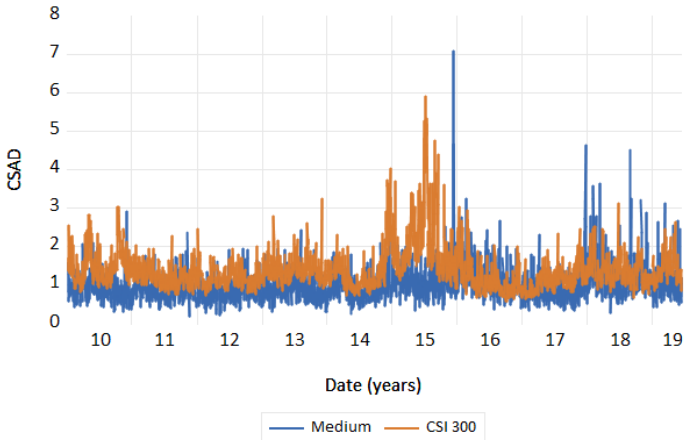

Figure 4.7: High CSAD

Although, there has been one published study using equation 7 (Bany-Ariffin, Chong, Matemilola, & McGowan,2019). It was important investigate potential multicollinearity (i.e., constructing a correlation matrix of the independent variables from equation 7). As expected, table 4.3 shows that there was no evidence of multicollinearity for all the variables except for $|R_{m,t}|$ and $(R_{m,t})^2$.

Table 4.3: Correlation matrix

	$R_{m,t}$	$\|R_{m,t}\|$	$(R_{m,t})^2$	$CSAD_{CHN,t-1}$	$(R_{CHN,t-1})^2$
$R_{m,t}$	1				
$\|R_{m,t}\|$	0.0182	1			
$(R_{m,t})^2$	0.0149	0.9182	1		
$CSAD_{CHN,t-1}$	0.0094	0.1076	0.1073	1	
$(R_{CHN,t-1})^2$	0.0136	0.0689	0.0632	0.4492	1

4.3 ESTIMATED RESULTS

4.3.1 Herd behaviour in the CSI 300

In order to do a deep analysis of how extreme events in the Chinese stock market influence the South African equity markets, it was important to confirm that herding activity in the Chinese stock market was evident across all sub-periods. Table 4.4 illustrates that all the γ_3 coefficients were negative and significant across all periods, which provides evidence of herd behaviour.

Table 4.4: Herd behaviour on the Chinese stock market

Chinese stock market turbulence		*Trade war*	
γ_1	-0.0665 (-2.31) ***	γ_1	-0.0328 (-2.52) ***
γ_2	0.6795 (4.89) ***	γ_2	0.323 (3.69) ***
γ_3	**-0.0661 (-4.03) *** **	γ_3	**-0.0230 (-1.95) ** **
Adjusted R-squared	0.3005	Adjusted R-squared	0.2634
Tranquil 1		Tranquil 2	
γ_1	-0.0358 (-3.43) ***	γ_1	-0.0624 (-3.78) ***
γ_2	0.3653 (7.51) ***	γ_2	0.4881 (7.10) ***
γ_3	**-0.0241 (-2.10) *** **	γ_3	**-0.0491 (-2.64) *** **
Adjusted R-squared	0.2821	Adjusted R-squared	0.2821

*Note, ***, ** and * represents 1 %, 5% and 10 % significant levels. The test equation used in table 3 was* $CSAD_t = \gamma_1 + \gamma_2|R_{m,t}| + \gamma_3(R_{m,t})^2 + \varepsilon_t$*, where a negative and significant coefficient of* $(R_{m,t})^2$ *indicates the presence of herd behaviour.*

4.3.2 Herd behaviour on the JSE 40

The first step was to examine if herd behaviour was present on the JSE 40. This was done to determine if the results were consistent with the findings of Ababio and Mwamba (2017), who suggested that herd behaviour patterns are different at a sector level or portfolio level compared to a market level.

Table 4.5 shows that when the Chinese markets were highly volatile, the γ_3 coefficients in the JSE market were either positive or insignificant. This indicates that there was no evidence of herd behaviour during both the turbulent sub-period on the Chinese stock market and the US-China trade war sub-period.

However, herd behaviour on the JSE was present when the Chinese stock markets were tranquil: the γ_3 coefficients were negative and significant. Similarly, Ababio and Mwamba (2017) found evidence of herd behaviour on the JSE between 2010 and 2015, i.e., the tranquil 1 sub-period. Since herd behaviour has not been tested on the JSE for 2016 or later, it is possible that herding activities on the Chinese stock market reduce herding activities on the JSE 40.

Hence, the γ_4 coefficients were positive and significant across all periods. However, the γ_4 coefficients were greater in the turbulent periods. This could explain why herd behaviour was present when the Chinese stock markets were tranquil but not when the Chinese markets were turbulent.

On calm trading days in the Chinese stock market, South African investors who mimic the JSE 40 Index herd around the Chinese stock market: the γ_5 coefficients were negative and significant. This coincides with the findings of Bany-Ariffin, Chong, Matemilola, & McGowan (2019). Therefore, institutional investors who mimic the JSE 40 believe that following the Chinese stock market on calm trading days provides a haven.

Table 4.5: Herd behaviour in terms of the JSE 40

Chinese		***Trade war***	
γ_1	0.0101 (0.206)	γ_1	0.0123 (0.403)
γ_2	0.4703 (1.92) *	γ_2	0.0643 (0.645)
γ_3	-0.0513 (-0.628)	γ_3	0.0860 (2.79) ***
γ_4	**0.1620** **(1.91) ** **	γ_4	**0.1517** **(2.701) *** **
γ_5	0.0022 (0.554)	γ_5	-0.0003 (-0.0398)
Adjusted R-squared	0.1119	Adjusted R-squared	0.1785
Tranquil 1		**Tranquil 2**	
γ_1	0.0222 (2.35) **	γ_1	-0.0425 (-1.51)
γ_2	0.3116 (7.13) ***	γ_2	0.7485 (4.99) ***
γ_3	**-0.0307** **(-2.11) *** **	γ_3	**-0.1883** **(-2.64) *** **
γ_4	**0.0783** **(3.19) *** **	γ_4	**0.0586** **(1.96) ** **
γ_5	**-0.0670** **(-1.78) ** **	γ_5	**-0.0250** **(-2.79) *** **
Adjusted R-squared	0.2795	Adjusted R-squared	0.1608

*Note, ***, ** and * represents 1 %, 5% and 10 % significant levels. The test equation used in table 4 was* $CSAD_t = \gamma_0 + \gamma_1(R_{m,t}) + \gamma_2|R_{m,t}| + \gamma_3(R_{m,t})^2 + \gamma_4 CSAD_{CHN,t-1} + \gamma_5(R_{CHN,t-1})^2 + \varepsilon_t$ *where* $CSAD_t$ *is the cross-sectional dispersions in the JSE,* $(R_{m,t})$ *is the JSE 40 returns,* $|R_{m,t}|$ *is the absolute JSE 40 returns,* $(R_{m,t})^2$ *is the squared JSE 40 returns ,*$CSAD_{CHN,t-1}$ *is cross-sectional dispersions in the CSI 300 and* $(R_{CHN,t-1})^2$ *is the CSI 300 returns.*

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4.3.3 Idiosyncratic volatility results

Each stock on the JSE was categorised into three idiosyncratic volatility groups, Table 4.6 illustrates that all coefficients of quadratic terms were either insignificant or positive in the low and high idiosyncratic volatility groups (i.e. no evidence of herd behaviour). Surprisingly, the results showed homogenous trading behaviour in the medium idiosyncratic portfolio. This was only evident during the Chinese stock market turbulence subperiod. In addition, investors in all the different idiosyncratic volatility groups do not herd around the Chinese stock market: all the γ_5 coefficients were either positive or insignificant.

However, it was seen that herding activity on the Chinese stock market influences the medium idiosyncratic portfolio positively. This was strongly evident during the turbulent sub-period of the Chinese stock market: γ_4 coefficients were positive and significant. Interestingly, during the tranquil 1 sub-period, cross-sectional dispersion in the Chinese stock market increased dispersion in all the different groups marginally.

One explanation for this is that China has a strong long-term cointegration relationship with South Africa (Al-Mohamad, Bakry, Jreisat, Rashi and Vo, 2020). Since tranquil sub-period 1 was by far the longest of the Four sub-periods, it is possible that China influences all idiosyncratic volatility groups over long periods, regardless of extreme volatility in the Chinese markets.

Table 4.6: Herd behaviour in various volatile group

Tranquil 1	*High*	*Medium*	*Low*
γ_1	0.0209	0.0044	0.01702
	(1.99) ***	(0.438)	(1.74) **
γ_2	0.2755	0.286	0.199
	(8.64) ***	(8.49) ***	(4.41) ***
γ_3	0.0027	-0.0238	-0.0062
	-0.354	(-1.94) *	(-0.309)
γ_4	**0.0842**	**0.0431**	**0.0322**
	(3.18) * **	**(2.36) *** **	**(1.79) ** **
γ_5	0.0026	-0.0001	0.0001
	-0.73	(-0.0767)	-0.0804
Adjusted R-squared	0.2102	0.4869	0.119
Chinese stock market turbulence			
γ_1	0.0339	0.0135	0.0274
	-0.948	-0.565	-0.765
γ_2	0.3624	0.267	0.2324
	(3.04) ***	(2.56) ***	-1.39
γ_3	-0.0074	**-0.1593**	0.1843
	(-0.469)	**(-6.34) *** **	(3.23) ***
γ_4	-0.1802	**0.1817**	-0.05112
	(-2.897)	**(2.488) *** **	(-1.17)
γ_5	0.0092	-0.0009	0.0001
	-1.47	(-0.337)	-0.0562
Adjusted R-squared	0.2385	0.5228	0.1676
Tranquil 2			
γ_1	0.0309	-0.0533	0.0173
	-0.944	(-2.10)	-0.557
γ_2	0.3895	0.2441	0.1039
	(3.85) ***	(3.25) ***	-0.885
γ_3	-0.0227	-0.008	0.1107
	(-1.04)	(-0.442)	-2.69
γ_4	0.0219	0.1264	0.0741
	-0.218	(1.70) *	-1.04
γ_5	0.0024	-0.0043	0.0015
	-0.222	(-0.539)	-0.197
Adjusted R-squared	0.1338	0.1216	0.2038
Trade war			
γ_1	0.0018	0.0053	-0.0042
	-0.0902	(0.205)	(-0.146)
γ_2	-0.0952	0.2747	0.3975
	(-1.65) *	(2.94) ***	(3.29) ***
γ_3	0.1091	-0.0199	-0.0790
	(0.109) ***	(-0.455)	(-1.38)
γ_4	0.0213	0.1017	0.0072
	-0.258	(1.56) *	-0.151
γ_5	0.0283	0.0122	0.0231
	(1.81) *	(1.62) *	(1.42)
Adjusted R-squared	0.4402	0.2139	0.0826

*Note, ***, ** and * represents 1 %, 5% and 10 % significant levels. The test equation used in table 5 was* $CSAD_t = \gamma_0 + \gamma_1(R_{m,t}) + \gamma_2|R_{m,t}| + \gamma_3(R_{m,t})^2 + \gamma_4 CSAD_{CHN,t-1} + \gamma_5(R_{CHN,t-1})^2 + \varepsilon_t$ *where* $CSAD_t$ *is the cross-sectional dispersions of each portfolio,* $(R_{m,t})$ *is the portfolio returns,* $|R_{m,t}|$ *is the absolute portfolio returns,* $(R_{m,t})^2$ *is the squared portfolio returns ,*$CSAD_{CHN,t-1}$ *is cross-sectional dispersions in the CSI 300 and* $(R_{CHN,t-1})^2$ *is the CSI 300 returns.*

4.3.4 Industry sector results

Lastly, the study examined whether herd behaviour was evident in the major sectors of the South African stock market. Table 4.7 suggests that there was no evidence of herd behaviour, as all the γ_3 coefficients in each sector and sub-period were either insignificant or positive. However, both the Resources and Industrials were influenced by cross-sectional dispersion in the Chinese stock market.

Firstly, the Resource sector was only positively affected by herding activity on the Chinese stock market during and before the Chinese stock market turbulence subperiod: the γ_4 coefficients were significant in two sub-periods. This was expected, because the turbulence on the Resource sector was attributed to the falling commodity price during the Chinese stock market turbulence subperiod. Hint, the commodity price was linked to the Chinese stock market, and over long periods the Resource sector is dependent on Chinese stock market conditions. This is evident in Figure 4.7.

Secondly, the γ_4 coefficients were all positive and significant in the Industrials column, which indicates that herding activity on the Chinese market influences industrials across all periods. This is because Industrials has a strong link with the Chinese stock market.

Table 4.7: Herd behaviour in different sectors

Tranquil 1	***Banking***	***Resources***	***Industrials***
γ_1	-0.0077 (-1.06)	0.0254 (1.95) *	-0.0016 (-0.09193)
γ_2	0.1143 (4.38) ***	0.02446 (0.0141)	0.2231 (3.23) ***
γ_3	0.0001910 (0.026)	0.04627 (2.67) ***	0.0769 (3.20) ***
γ_4	0.0147 (0.66)	**0.1883** **(3.66)** ***	**0.1363** **(2.254)** **
γ_5	0.0011 (0.49)	0.0006 (0.20)	0.0038 (0.566)
Adjusted R-squared	0.0712	0.1907	0.3686
Chinese stock market turbulence			
γ_1	0.0115 (0.602)	0.0504 (1.51)	0.0276 (1.07)
γ_2	0.0743 (1.83) *	0.3426 (2.64) ***	0.3081 (1.63) **
γ_3	0.0018 (0.612)	-0.0039 (-0.195)	0.0223 (0.724)
γ_4	-0.0256 (-0.904)	**0.2258** **(2.91)** ***	**0.1234** **(2.31)** ***
γ_5	0.0015 (0.627)	0.0078 (1.47)	-0.0026 (-0.962)
Adjusted R-squared	0.1316	0.2264	0.2510
Tranquil 2			
γ_1	0.0057 (0.61)	-0.0173 (-0.79)	0.0064 (0.529)
γ_2	0.0904 (2.47) ***	0.0012 (0.15)	0.2510 (6.89) ***
γ_3	0.0017 (0.23)	0.0772 (3.74) ***	0.0242 (1.89) ***
γ_4	0.14743 (1.89) *	0.0352 (0.24)	**0.0777** **(2.59)** ***
γ_5	0.0098 (1.51)	0.0259 (1.70)	-0.0043 (-1.25)
Adjusted R-squared	0.1048	0.1840	0.3283
Trade war			
γ_1	0.0055 (0.425)	-0.0429 (-1.46)	-0.0605 (-2.49) ***
γ_2	0.0100 (0.208)	0.0267 (0.225)	0.1395 (1.54)
γ_3	0.0155 (1.29)	0.0477 (0.391)	0.0550 (3.07) ***
γ_4	0.0673 (1.03)	-0.1889 (-0.991)	**0.2567** **(1.93)** **
γ_5	-0.0005 (-0.118)	0.0035 (0.391)	-0.0181 (-1.79) *
Adjusted R-squared	0.0616	0.0584	0.3726

*Note, ***, ** and * represents 1 %, 5% and 10 % significant levels. The test equation used in table 5 was* $CSAD_t = \gamma_0 + \gamma_1(R_{m,t}) + \gamma_2|R_{m,t}| + \gamma_3(R_{m,t})^2 + \gamma_4 CSAD_{CHN,t-1} + \gamma_5(R_{CHN,t-1})^2 + \varepsilon_t$ *where* $CSAD_t$ *is the cross-sectional dispersions of each portfolio,* $(R_{m,t})$ *is the portfolio returns,* $|R_{m,t}|$ *is the absolute portfolio returns,* $(R_{m,t})^2$ *is the squared portfolio returns ,*$CSAD_{CHN,t-1}$ *is cross-sectional dispersions in the CSI 300 and* $(R_{CHN,t-1})^2$ *is the CSI 300 returns.*

4.4 SUMMARY AND DISCUSSION

Although herd behaviour was tested in the entire market, while the study focussed on six portfolios, the results suggest that investment behaviour was different in all portfolios and indices. This was evident in the descriptive statistics. The conclusions drawn from the model coefficients were different for each stock portfolio.

Firstly, idiosyncratic volatility influences the South African markets differently compared to other international markets, which confirms the findings of Fazil and Ipek (2012). The studies done in both Taiwan and Vietnam found evidence of herd behaviour across all volatility groups. However, only the medium idiosyncratic volatility portfolio displayed evidence of herd behaviour on the JSE 40 during periods of extreme market movements. This could suggest that investors who partly diversify their portfolios evidence irrational decision making during unsteady periods. Undiversified or partly diversified investors were considered less educated than diversified investors (Phan and Vo, 2018). Perhaps during periods of unsteady events, partly diversified investors tend to mimic the behaviour of other institutional investors.

Surprisingly, there was no evidence of herd behaviour found in the three major sectors of the JSE across all sub-periods. Knowing that the Resource sector was extremely volatile during the Chinese stock market turbulence sub-period suggests that herd behaviour was not always evident in highly volatile periods.

A portfolio that mimics the JSE 40 index showed evidence of herd behaviour on days when the Chinese stock markets were calm. Although, Mekwa's (2017) findings align with this study's results in terms of the major industry sector portfolios, Mekwa found no evidence of herding in a portfolio that is pegged to the JSE All Share Index. Therefore, the findings were consistent with those of Khan, Shah and Shah (2017), who found that: herd behaviour is more prevalent in large firms; mixing large firms with smalls firms can distort the results.

The results were not consistent with the findings of Ababio and Mwamba (2017). When using the quantile regression model, evidence was found of herd behaviour in the Banking sector, but a dispersion-based model found no evidence of herd behaviour in the banking sector. This could

be because the dispersion-based model is sensitive to outliers, and because the South African markets displayed extreme returns, this could have distorted the results.

The second aspect of the study was to determine whether Chinese market conditions influence the JSE. Since China has strong trade links with South Africa, it was no surprise that cross-sectional dispersion in the Chinese stock market influenced the JSE 40 across all four sub-periods. Interestingly, it appears that intuitional investors who mimic the JSE 40 Index only herd around the Chinese markets when the Chinese markets were tranquil. This is in line with the findings of Bany-Ariffin, Chong, Matemilola and McGowan (2019).

It was concluded that Chinese market conditions influence each stock portfolio differently compared to the entire market, but none of the six portfolios herd around the Chinese market. The Industrial portfolio was the only stock portfolio that was positively influenced by herding activity in the Chinese stock market across all periods. This was to be expected, considering that Naspers represents a large portion of industrials and Naspers is linked to the Chinese stock market.

Both the medium idiosyncratic volatility portfolio and the Resource stock portfolio were strongly influenced by Chinese market conditions. This was evident during the Chinese stock market turbulence subperiod. Hence, these portfolios were influenced by extremely volatile periods on the Chinese stock market, because there was no evidence of this in the US-China volatility subperiod. Given that South Africa has a strong long-term cointegration relationship with China, it was no surprise that Chinese market conditions had a marginal influence on all the idiosyncratic volatility groups over long tranquil periods, and influenced the Resource sector strongly.

Interestingly, the findings also suggest that dispersion in the Chinese stock market moves individual stocks marginally further from the market consensus, which leads to an increase in dispersion. This contradicts the definition of herd behaviour which requires a decrease in dispersion. Therefore, Chinese stock market conditions reduce herding activity on the South African markets at both a portfolio level and a market level.

Although, the CSAD model fits the data better than the CSSD model (Phan and Vo, 2018), the adjusted R squared values were low. This indicates that the dispersion-based model does not fully explain movements in the South African market. One possibility is that perhaps other international markets had more influence on the South African markets. Or perhaps a quantile regression model should be used.

5 CONCLUSION

5.1 INTRODUCTION

Herd behaviour is a phenomenon that shows that individuals do not make their own decisions, but rather mimic the decision making of other individuals. Herding behaviour in financial markets often results in financial instability, but this behaviour could be eliminated through policy changes. Hence, the more up to date and the more diversified the studies on herd behaviour that are made available to the public, the better the policy decision making will be.

This chapter outlines the key findings of the study and explains how the key findings can benefit future investors. The chapter also provides recommendations for future research on herd behaviour.

5.2 SUMMARY OF KEY FINDINGS

The study used the dispersion-based model to examine herd behaviour in six stock portfolios: low idiosyncratic volatility; medium idiosyncratic volatility; high idiosyncratic volatility; Resources; Banking; Industrials. The model only revealed evidence of herd behaviour in the medium idiosyncratic volatility portfolio and a portfolio that mimics the JSE 40.

Surprisingly, the fallen commodity price did not cause herd behaviour to be more pronounced in the Resource sector. Therefore, herd behaviour cannot always be attributed to down markets or highly volatile markets. The findings also suggest that herd behaviour in the entire market does not guarantee that herd behaviour will be present in certain major stock portfolios. Therefore, it can be said that irrational investment behaviour cannot be properly understood by testing at a market level, which supports the argument offered by Ababio and Mwamba (2017).

Chinese market conditions influence the JSE 40 index differently compared to other stock portfolios. For example, the banking sector was not influenced by Chinese market conditions. However, when the Chinese markets were calm for a long period, the five other stock portfolios were influenced by Chinese cross-sectional dispersion. This was more evident in the Resource portfolio and the Industrial portfolio. On the other hand, when the Chinese markets were extremely volatile, the Resource portfolio, the Industrial portfolio and the medium idiosyncratic volatility portfolio were strongly influenced by Chinese dispersion activity. However, only the JSE 40 index and the Industrial portfolio were influenced by dispersion across all Chinese market conditions. Hence, the results suggest that herding activity in the Chinese market reduces herding in the South African markets marginally.

Interestingly, when the Chinese markets were tranquil, only investors who follow the JSE 40 index herded around the Chinese stock market, but this was not evident in the six stock portfolios. It is possible that institutional investors were more educated than undiversified investors, and considered following calm Chinese market movements as a haven.

5.3 RECOMMENDATIONS AND FUTURE RESEARCH DIRECTIONS

The study concluded that South African investors who hold partly diversified and fully diversified stock portfolios tend to practise herd behaviour. Therefore, future investors should use this study to realize that investors who hold low and high idiosyncratic volatility portfolios display plausible decision making. This finding is applicable to all three major sectors of the JSE.

The Banking sector was the only major sector that was not dependent on Chinese market conditions. Perhaps investors can use the Banking sector to hedge against unfavourable Chinese market conditions in the future.

Overall, the study is beneficial for investors, as it will help to enhance and implement hedging strategies in their stock portfolios. However, the study did contradict some of the findings by Ababio and Mwamba (2017). This could be explained because some of the major criticisms of a dispersion-based model is that its overly sensitive to outliers.

Acknowledging the consequences of herd behaviour. Perhaps, future studies could remove outliers from the data and re-estimate the dispersion-based model to see if the results will mimic those of Ababio and Mwamba (2017).

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