UNIVERSITY OF KWAZULU-NATAL

AN ANALYSIS OF HERD BEHAVIOUR IN THE SOUTH AFRICAN STOCK EXCHANGE

By

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DECLARATION

I, Olivier Niyitegeka, declare that:

i. The research reported in this dissertation, except where otherwise indicated, is my original research.

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DEDICATION

This work is profoundly dedicated to the memory of my late brother Jean Pierre.

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ABSTRACT

The stock market is an important part of the economy of a country. It plays a crucial role in the growth of the industry and commerce of the country that eventually affects the economy of the country to a great extent. This is the reason that the government, industry and the country in general keep a close watch on the happenings of the stock market. It is in this frame of mind that the current study investigates the presence of herd behaviour in the South African stock market.

Herd behaviour occurs when investors disregard their individual information and base their trading decision on the actions of others. Herd behaviour was measured by testing whether or not there is a negative relationship between the dispersion of stock returns and the market return. The study also investigates whether herd behaviour is asymmetric in different market conditions, namely bull versus bear markets, highly volatile markets versus less volatile markets and high trading volumes versus low trading volumes. The results point towards a considerable presence of herd behaviour among investors at the Johannesburg Stock Exchange (JSE). An analysis of the asymmetric effect of herding on various market conditions reveals that herding is more pronounced during a bull market than a bear market, during low trading volume rather than high trading volume periods and is more prevalent during periods of low market volatility than in highly volatile markets.

This study also used the Autoregressive Distributed Lag (ARDL) approach to cointegration in order to examine short- and long- term dynamics of investors' herd behaviour at the JSE. The study noted that herd behaviour is not instantaneous; rather it takes place with a lapse in time. However, the unrestricted error correction results suggest that herd behaviour has a rather high speed of adjustment, implying that herding is a short-lived phenomenon.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 CONTEXT OF RESEARCH

The field of academic finance has come full circle from the time it was believed that "…no other proposition in economics …has more solid empirical evidence supporting it than the Efficient Market Hypothesis" (Jensen, 1978:1). For almost 30 years the Efficient Market Hypothesis (hereafter referred to as EMH) was the foundation for a great number of financial models, from its inception in the 1960s (Shleifer, 2000). With EMH it was generally believed that financial markets are efficient, with security prices reflecting all the information that is available pertaining to companies. This meant that there was no way investors could constantly 'beat the market'. In plain English, no one could earn excess profits, more than the overall market, by using his/her private information[1]. The EMH is consistent with the Random Walk Theory (Hall, 1978), which asserts that stock prices evolve according to a random walk; hence stock prices cannot be predicted[2].

At the beginning of the twenty first century both the theoretical foundations of the EMH and the empirical evidence backing it came under sharp criticism. The opponents of EMH challenged it on two basic assumptions: (1) the investors' rationality; and (2) the absence of arbitrage opportunities. With regard to investors' rationality, it has been established that individual investors are subject to cognitive biases that alter their expectations and preferences. As for the absence of arbitrage opportunities, it has been observed that in

[1] There are three versions of EMH: (1) the weak form asserts that prices incorporate only past information about the asset,(2) the semi-strong form states that stock prices reflect all publicly available information and (3) the strong form stresses that current prices incorporate all existing information (Laffont and Maskin, 1990).

[2] The random walk can be likened to a drunk trying to make his way down a narrow street. He is so inebriated that he is equally likely to take a step to the right (one way along the street) or the left (the opposite way).

financial markets there is a wide range of structural and institutional constraints that create arbitrage opportunities for informed investors.

Behaviour finance theories emerged as an alternative view of EMH. The core objective of behavioural finance was to investigate the psychological and sociological issues that impact the decision-making processes of individuals, groups and organisations (Ricciardi and Simon, 2000).

A considerable number of academic studies focused on one of the key concepts in behavioural finance, namely herd behaviour. Herd behaviour, according to Scharfstein and Stein (1991: 465), is a phenomenon that takes place when "managers simply mimic the investment decision of other managers, ignoring substantive private information". Hirshleifer and Teoh (2003) defined herding as the convergence of actions caused by mutual imitation. Saastamoinen (2008), cited by Ohlson (2010:6), preferred to define it according to the way it is measured "a decrease of dispersion of stock returns, or increase of dispersion at a less-than-proportional rate with the market return". Bikhchandani and Sharma (2001) stressed that herd behaviour occurs when an investor decides not to invest simply because others have decided the same, but would have made the investment if he/she had not known other investors' decisions. Conversely, he/she would change his/her decision about not investing after finding out what other investors did. These definitions are all similar, and refer to the common idea that investors disregard their individual information and base their trading decisions on the actions of others.

Conceptual models on herd behaviour were introduced in the early 1990s by Sharfeistein and Stein (1991), Banerjee (1992) and Bikchandani *et al*. (1992). In their papers they proved that when a large number of investors adopt a similar investment strategy, the subsequent investors are prone to adopt the same investment decision, disregarding their own private information (Cipriani and Guarino, 2007). Later on, econometric methods were used to explain the phenomenon of herd behaviour (Shleifer and Vishny, 1992; Christie and Huang, 1995; Wermers, 1999; Chang, Cheng and Khorana, 1999).

Other studies directed their attentions to the asymmetric effects of herd behaviour on various market conditions. These studies held that the direction of market returns affects investors' behaviour. The asymmetric effects can be associated with market returns, trading volume and return volatility (Caparrelli, D'Arcangelis, and Cassuto, 2004; Tan, Chiang, Mason, and Nelling, 2008; Al-Shboul, 2012).

More recently, a limited number of academic studies have associated herd behaviour with the presence of volatility clustering in stock market returns (Alfarano and Lux, 2007; MacQueen and Vorkink, 2004; Yamamoto, 2009). Volatility clustering is one of the stylised facts[3] of financial time series; it can be defined as a propensity for large changes in stock prices to follow large changes and small changes to follow small changes (Rama, 2005). Using agent-based models (computer simulation that represents individual actors in a dynamic social system), various studies have established that agents' herding behaviour causes volatility clustering. Indeed, these studies proved that when investors herd, their sensitivity to new information is time varying and is auto-correlated.

1.2 MOTIVATION

Herd behaviour has attracted the attention of academic researchers because of its perceived association with stock price movements and its subsequent implications for assets pricing models (Tan *et al*., 2008). The South African stock market is an appropriate place to investigate this market anomaly because of some of its unique characteristics. Indeed, the Johannesburg Securities Exchange (hereafter referred to as the JSE) has a rather high concentration of resources and mining-based stocks, which make up 45 percent of the South African stock market (Wesser, 2005). There are reasons to believe that this can stir up herd behaviour among investors, since they have a limited and homogeneous pool of information to rely on when it comes to making investment decisions. As Wermers explained, "managers may trade together simply because they receive correlated private information, perhaps from analyzing the same indicators" (1999: 582). Furthermore, resources and mining-based stocks

[3] In financial econometrics, a stylised fact is a structural observation that is believed to hold for a various collection of instruments, markets, and time periods.

are very volatile. It has been proved that herd behaviour is more prevalent under severe market conditions (Tan *et al*., 2008).

Another specific characteristic of the South African stock market is the fact that the majority of asset managers in South Africa use active investment strategies. According to Beere (2009), only five percent of institutional managers follow a passive buy and hold strategy (or index investment strategy); the rest follow an active investment strategy. Managers who adopt an active investment strategy seek to identify high-performing investments, with the aim of achieving above-average results. Consequently, their compensation and reputations are tied to how well they outperform the market. This situation can create moral hazards[4] among selfish money managers who would prefer to herd and 'share the blame' of picking a bad investment, instead of making individual investment decisions and running the risk of underperforming the market (Scharfstein and Stein, 1991). As Keynes (1965) explained, the risk of being the only one to be wrong surpasses the benefit of being the only one to be right. It is worth noting that active investment strategy is in contradiction to the EMH. Indeed, the EMH states that at any given time, securities' prices fully incorporate all existing information. Consequently there are no opportunities for achieving exceptional returns by following an active investment strategy; if such opportunity existed they would be quickly discovered and implemented by almost everyone (Stefan, 2009).

Besides these arguments, the fact that South Africa is an emerging economy reinforces the prospects of herd behaviour. It has been shown that herd behaviour is more significant in emerging countries:

- Investors in emerging markets are likely to encounter a certain number of problems such as asymmetric information and lack of transparency in reporting companies' activities. These problems force investors to base their investment decisions exclusively on collective market behaviour. In other words, investors rely on macro-economic information rather than firm-specific information when it comes to making investment decisions (Chang, Cheng and Khorana, 2000).

[4] Moral hazard is a tendency where one party, referred to as an agent, is more willing to take a risk, knowing that the potential costs or burdens of taking such a risk will be borne, in whole or in part, by others, referred to as principals.

- Financial markets in emerging countries are less liquid and market illiquidity affects the speed with which a market prices itself to available information (Kallinterakis and Kratunova, 2007). When this is the case, prices will deviate from their fundamentals, increasing volatility in the market, which, in turn, will give rise to herding.
- Foreign investors in emerging countries are blamed for creating inefficiencies in the market by entering and exiting in herds. This brings instability, especially during crises. A typical example is the 'Tequila effect' - the Mexican economic crisis that took place in 1994 (Calvi and Mendoza, 1996).

A survey of the literature by the present researcher revealed that the only study on herd behaviour in South Africa was conducted by Gilmour and Smit (2002). The study was inspired by the work of Wermers (1999) on the mutual fund industry in the United State of America. Gilmour and Smit (2002) found low levels of herding among South African institutional investors, a subgroup of investors in the JSE. The current study broadens the analysis to the stock market as a whole.

1.3 OBJECTIVES

The current study has four specific objectives:

1. Testing the presence of herd behaviour indirectly, by investigating whether or not stock returns in the JSE exhibit volatility clustering.
2. Testing the presence of herding directly, by demonstrating that the variation in market return is not only due to the arrival of new information.
3. Investigating whether or not herd behaviour in the context of the South African stock market varies with market conditions.
4. Examining whether herd behaviour occurs instantaneously, or with a lapse of time.

1.4 METHODS OF ESTIMATION AND DATA

Before the application of econometric methodology, normality and stationarity tests were conducted. For the normality test, the present study estimated the skewness and kurtosis. The purpose of testing for normality is to check the behaviour of the data to identify the size and the distribution of variables before applying any formal econometric methodology. For stationarity, two types of test were conducted, namely the Dickey-Fuller stationarity test and its extension, the Augmented Dickey-Fuller, and the Phillips–Perron unit root test. The main raison for testing stationarity is to help to minimise the possibility of spurious regressions (Chinzara, 2006).

To address the first objective, the present study uses three different types of Generalised Autoregressive Conditional Heteroscedasticity (hereafter referred to as GARCH) models. These are the (vanilla) GARCH, Exponential GARCH (EGARCH) and GRJ GARCH (or TARCH). To achieve the second and third objectives, the current study uses a model inspired by Chang, Cheng and Khorana (2000) (hereafter referred to as the CCK). This model tests the relationship between the absolute value of market return and equity return dispersion. Finally, to attain the fourth objective, the current study employs the Autoregressive Distributed Lag (hereafter referred as the ARDL) bound testing approach inspired by Pesaran and Shin (1995).

The dataset used in this analysis spans a period between 31 August 2006 and 30 September 2011. This period was chosen as during this time the world experienced a major financial crisis. It has been indicated that herding is more pronounced during financial crises (Philippas, Kastakis, Babalos and Economou, 2011). The data was obtained from McGregor BFA database. The following data were used: (1) the daily closing prices for the JSE's All Share Index (hereafter referred as ALSI), (2) the daily closing prices for the top 100 companies on the JSE by market capitalisation and (3) the daily trading volumes on the JSE. A schematic framework of the current study is displayed in Figure 1.1.

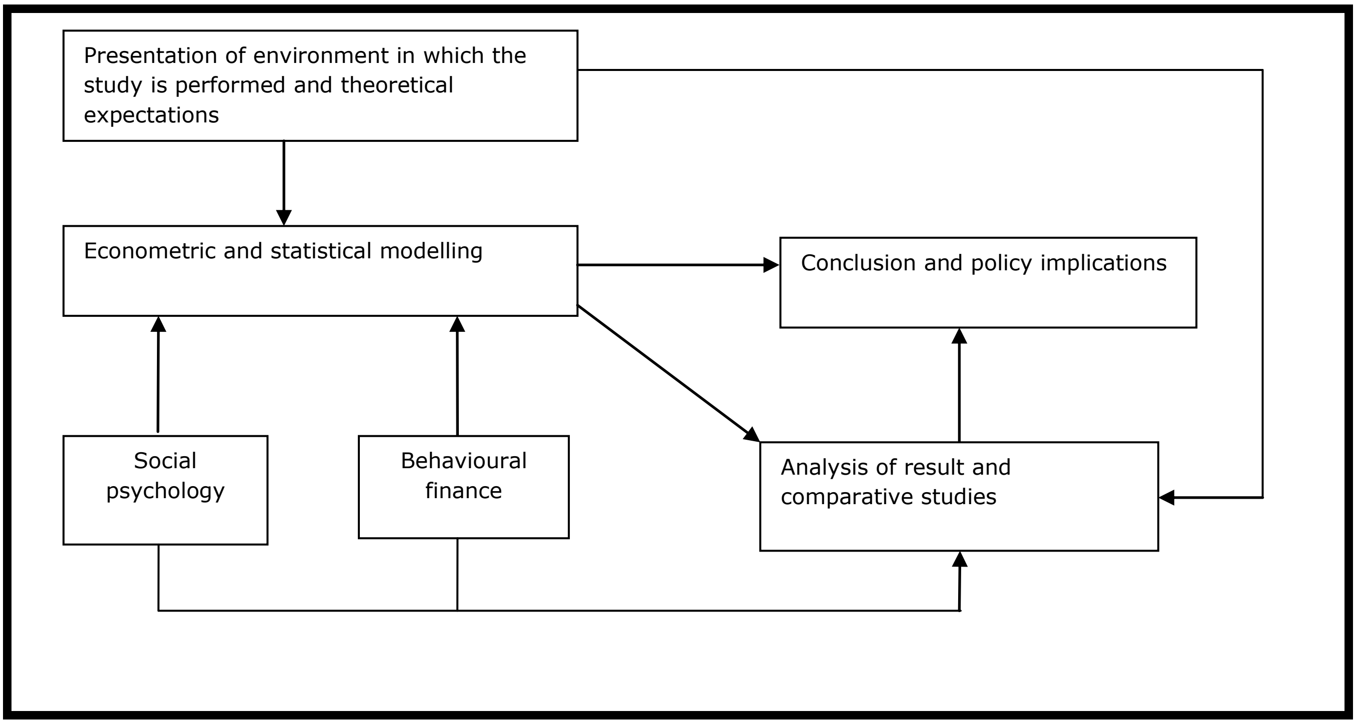

Figure 1.1: A Schematic Framework of the Study.

1.5. ORGANISATION OF THE STUDY

The present study is recorded in six chapters. Chapter 2 reviews the theoretical and empirical literature regarding herd behaviour. The theoretical part extensively discusses theoretical concepts of herd behaviour, as documented in the field of social psychology and behavioural finance. The empirical part covers econometric models that have been used to detect herd behaviour in financial markets. The review is by no means exhaustive, but it is a selection of results that represent a sample of the different findings. Chapter 3 provides an extensive overview of the JSE, with special emphasis on how trading and settlements are carried out at the JSE. Chapter 4 discusses the econometric models used in this study; these include the different GARCH-type models to test volatility clustering, the CCK model that uses the Cross-Sectional Absolute Deviation (CSAD) to detect herd behaviour and the ARDL model that tests the short-and long-term aspects of herding. In Chapter 5 the results are presented and discussed chronologically, as per the methodology discussed in the preceding chapter. Chapter 6 covers conclusions, policy and investment recommendations, as well as suggestions for further research.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews the literature on herding in financial stock markets. It is made up of five sections. The first section discusses the theoretical literature on herd behaviour, as documented in the field of social psychology. The second deals with the literature on herd behaviour, as documented in the field of behavioural finance. The third section reviews selected empirical studies on herding. Section four analyses herd behaviour in an emerging market and the fifth section focuses on herd behaviour in South Africa. The separation of theoretical and empirical literature was done intentionally, since there is no direct link between the theoretical arguments on herd behaviour and the empirical specifications used to test it (Bikhchandani and Sharma, 2001).

2.1 THEORETICAL LITERATURE ON HERD BEHAVIOUR IN THE FIELD OF SOCIAL PSYCHOLOGY

Various studies in social psychology attempted to provide plausible insights into what motivates individuals to imitate the actions of others. Early literature focused mainly on the way in which impulsive, irrational and primitive emotions of some individuals could lead to "a criminal collective consciousness" (Rook, 2006: 80). Asch (1952) noted that convergence in a group should be understood as a rational attempt by an individual to make sense out of social reality, by sharing their perceptions of social reality with a reference group. He challenged the idea that conformity with a reference group is an unconscious and irrational behaviour. In his ground-breaking experiment, Asch (1952) demonstrated that conformity with others is information-based, meaning that people rationally take into account information revealed by the actions of others, before making their own decisions. In this experiment he gave participants a simple and unambiguous perception task. The task consisted of judging which of three lines was similar to a target line. The majority deliberately and unanimously went for the wrong answer, despite the fact that they realised that their answer was incorrect. Deutsch and Gerard (1955) documented that there are two types of social influences, namely the normative and informational social influences. They defined normative social influence as a form of conformity that results from an internal motivation to conform to the perceived rules of others, whereas informational influence is centred on the acceptance of information from others, because individuals view others as a source of valid information. Kelman (1961) identified three distinct processes through which these two social influences operate, namely compliance, internalisation and identification.

Compliance takes place when a person conforms to other people's anticipations with an expectation of favourable responses from them. For example, an individual may strive to express only opinions that are regarded as correct by a particular group in order to be accepted into that group or to avoid rejection by the group (Kelman, 1961).

Internalisation occurs when an individual accepts social influence because it represents a behaviour that he/she perceives as instrumental in the achievement of his/her goal and which is in harmony with his/her value system. For him/her the content of the induced behaviour is fundamentally rewarding. For example, an individual might adopt the recommendations of an expert simply because he/she finds them relevant to his/her own predicament and because they are in accordance with his/her own values (Kelman, 1961).

Finally, identification takes place when an individual adopts behaviour derived from others' actions in an attempt to enhance his/her self-worth. Accepting influence through identification is therefore a way of creating and maintaining the desired relationship with others. Kelman (1961) gave an example of a communist party group member who would derive pride and a sense of identity from his/her self-definition as a revolutionary and an agent of historical destiny.

Burnkrant and Cousineau (1975) explained how each process identified by Kelman (1961) can be related to the two types of social influence identified by Deutsch and Gerard (1955). For instance, informational influence is accomplished through internationalisation. This is evident when informational influence enhances individuals' knowledge about their environment, as well as their capability to deal with specific characteristics of that environment. In other words, an individual would accept informational influence if he/she is convinced that it is instrumental in providing a solution to the problem he/she is facing or adds to what he/she already knows about his/her environment. By the same token, normative social influence can be achieved by means of identification or compliance processes. For identification, individuals embrace behaviours and opinions which they regard as representative of their positive reference groups, or adopt behaviours and opinions which they perceive as opposite to those held by their negative reference group. Equally, normative social influence can be achieved through compliance. This means that a person is prone to conform to the influence of a specific group because he/she anticipates a reward from that group, or needs to avoid sanctions from that specific group. Social influence, its process and the goal orientation relevant to each process are illustrated in Table 2.1, as inspired by the work of Burnkrant and Cousineau (1975).

Table 2.1: Social Influence and its Process

Influence	Process	Goal orientation
Informational	Internalisation	Knowledge
Normative	Identification	Self-maintenance or enrichment
	Compliance	External reward

Source: Burnkrant and Cousineau (1975)

2.1.1 LITERATURE ON INFORMATIONAL SOCIAL INFLUENCE

Bakhchandani *et al*. (1992) introduced the term ‘information cascade’ to refer to a situation where a rational individual unconditionally imitates others by observing information contained in their predecessor’s actions, without any regard to information from other sources. They illustrated that cascades most often develop spontaneously on the grounds of extremely little information. Banerjee (1992) analysed models where investors observe the decisions made by previous investors before making their own decisions. He concluded that in this context the behaviour of the individual decision-maker is rational, as different individuals might have important information that he/she does not have. Other literature refers to informational influence as 'observational learning'. This literature gives more emphasis to the fact that people learn by observing the decisions of others, before deciding to imitate what they do. Studies on observational learning were inspired by the work of Banerjee (1992) and Bakhchandani *et al*. (1992) on the information cascade. These include Çelen and Kariv (2004), who analysed observational learning among decision-makers and concluded that convergence of beliefs is unlikely to occur when decision-makers only observe the actions of their immediate predecessors. Callander and Hörner (2009) felt that it might be profitable to follow the actions that were adopted by the minority among previous decision-makers in instances where the decision-makers only monitor a fraction of others actions, instead of the whole series of actions.

2.1.2 LITERATURE ON NORMATIVE SOCIAL INFLUENCE

Normative social influence is very prevalent and widespread. A considerable number of academic studies have established that observing the actions of others has a strong impact on people's behaviour. It has been shown that normative social influence can induce people to make false statements (Asch, 1956; Deutsch and Gerard, 1955; and Milgram, Bickman and Berkowitz, 1969), to use illicit drugs (Maxwell, 2002), or to fail to react to an looming danger (Latané and Darley, 1970). More recent academic works has proved that direct observation of others is not required for normative social influence to have its effect. Instead, conveying a descriptive norm through written information can also induce conformity to the communicated behaviour (Parks, Sanna and Berel, 2001). Nolan, Schultz, Caldin, Goldstein and Griskevicius (2008) studied the persuasive effects normative social influence on a sample of consumers about energy conservation. They established that normative social influence produces the highest change in behaviour compared to information underlining a descriptive norm, even though individuals viewed the normative information as least motivating. Nolan *et al*. (2008) also found that descriptive normative beliefs were predictive of individual behaviour than any other relevant beliefs, even though individuals regarded such norms as least important in their conservation decisions. Brinberg and Plimpton (1986) studied the influence of product conspicuousness (or visibility) on reference groups. They noted that products viewed as conspicuous are susceptible to group influence. Schultz (1999) studied the impact that normative information had on households' recycling behaviour. He found that households that received normative information highlighting the amount recycled by an average neighbourhood family increased both the amount and frequency of their ensuing recycling behaviour.

2.2 THEORETICAL LITERATURE ON HERD BEHAVIOUR IN THE FIELD OF BEHAVIOURAL FINANCE[5]

Theoretical literature on herd behaviour can be traced as far back as the 1930s, when Keynes, the renowned economist, questioned the ability of long-term investors to make sound investment decisions. He pointed out that investors may be unwilling to trade using their private information out of fear that contrarian behaviour of others would spoil their reputations as credible decision-makers. He explained further that investors 'follow the herd' simply because they are worried that others will negatively assess their ability to make sound investment decisions (Sharfeistein and Stein, 1991). But it is during the 1990s that herd behaviour started to attract the attention of a considerable number of academic researchers in the field of behavioural finance. For instance, Sharfeistein and Stein (1991) developed a model with two kinds of managers, the 'smart ones', who receive good, useful information about the value of an investment, and the 'dumb ones', who receive merely noisy information. They came to the conclusion that herd behaviour can arise from various circumstances as a result of a rational attempt by managers to boost their reputations.

[5] This work relies heavily on that of Bikhchandani and Sharma (2000) and Gilmour and Smit (2002).

Banerjee (1992) proposed a model based on sequential decisions, where decision-makers observe the actions of their predecessors. He concluded that their behaviour is rational, as their predecessors might have important information that they do not have. Bikhchandani *et al*. (1992: 994) proposed a sequential model based on what they called "informational cascades". They used their model to explain not only conformity to the actions of others, but also to explain quick and short-lived phenomena such as trends, fashions and crashes.

Rama and Bouchaud (2000) criticised the idea of a sequential model proposed by Bakhchandani *et al*. (1992) as unrealistic, since traders submit their orders simultaneously. They noted that orders from various market participants enter the market at the same time and it is the interaction between different orders that determines the aggregate market variables. This prompted Rama and Bouchaud (2000) to consider a model that avoids a sequential decision process, by basing their model on a random communication process with groups of agents making independent decisions. They argued that these random interactions between agents give rise to a market structure which is heterogeneous. Bikhchandani and Sharma (2001: 4) stressed that one must differentiate between "intentional" and "spurious" herding; the latter occurs when a group of decision-makers faced with the same problems and information set arrive at the same conclusions about their investment decisions. An example of a spurious herding would be an increase in interest rates that induces investors to reduce their stock holdings *en masse*.

Interestingly enough, herd behaviour can also be construed as being either a rational or an irrational form of investor behaviour. On the one hand the irrational view focuses on investor psychology where investors disregard their prior beliefs and follow other investors blindly. On the other hand, the rational view focuses on the principal agent problem in which managers mimic the actions of others, completely ignoring their own private information to maintain their reputations and/or their compensation (Chang *et al.*, 2000). Even though herd behaviour might be rational at individual level, it is still irrational at the group level, since it leads to mispricing, and the resulting equilibrium is inefficient (Alemanni and Ornelas, 2006). Figure 2.1 shows the two types of herding, as documented in various academic literature. They are displayed together with their various causes. Figure 2.1 relies on Gilmour and Smit (2002) and Bikhchandani and Sharma (2001).

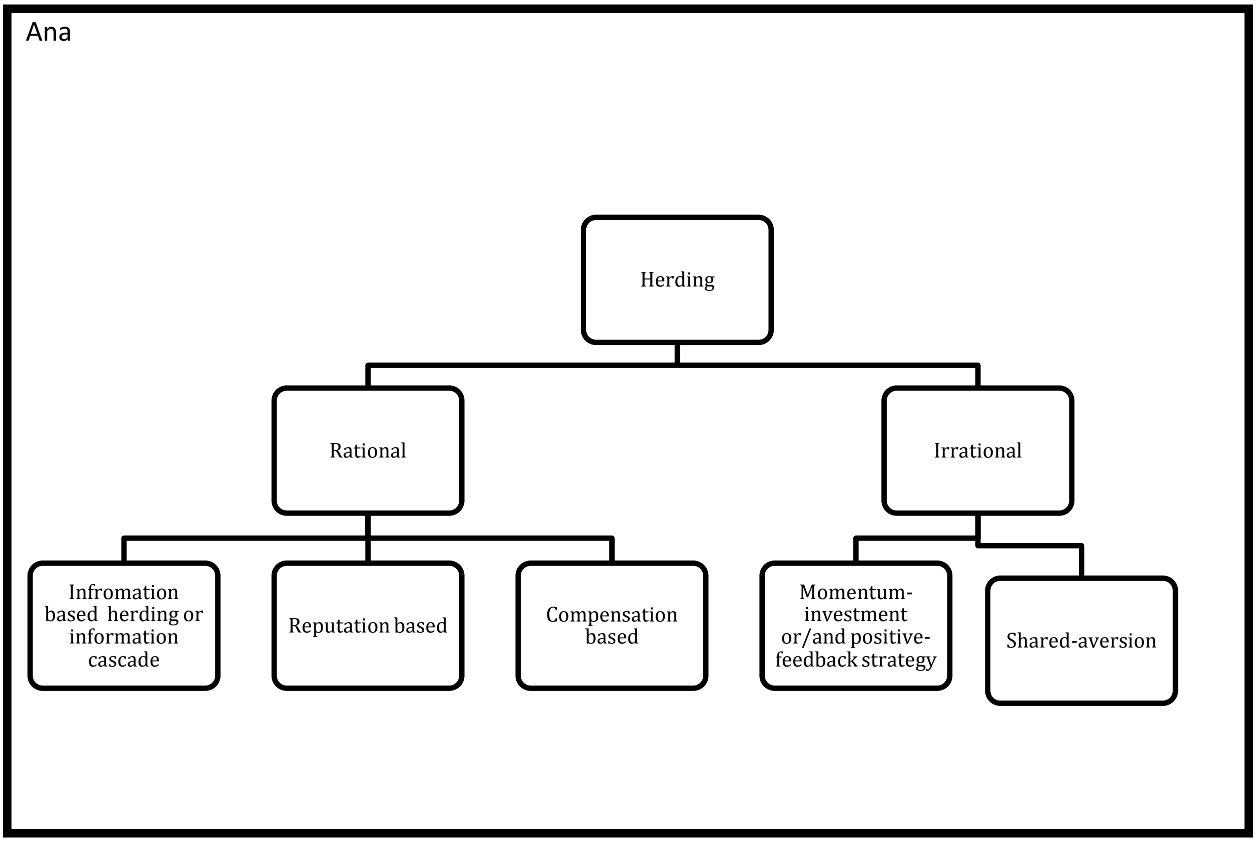

Figure 2-1: Taxonomy of Herding: the Two Types of Herding and their Causes

Source: Author’s construction from Gilmour and Smit (2002) and Bikhchandani and Sharma (2001).

2.2.1 IRRATIONAL HERDING

An irrational behaviour takes place when it is evident that investors are blindly following the actions of others. Irrational herding is therefore centred on investors’ psychology and holds that agents follow one another by foregoing rational analysis (Devenow and Welch 1996). Irrational herding is attributed to two factors, which are: (1) momentum-investment and/or positive-feedback strategy and (2) shared-aversion.

2.2.1.1 MOMENTUM-INVESTMENT AND/ OR POSITIVE-FEEDBACK STRATEGY

Momentum-investment consists of buying past winner and selling past loser stocks, whilst the positive-feedback strategy is an investment strategy that consists of purchasing shares when prices rise and selling them when they drop. These two strategies seem to be identical but as Girmour and Smit (2002) explained, momentum-investment strategy is long-term oriented, whilst positive-feedback strategy focuses on a short-term frame period. These two strategies can intensify price movements and lead to increased volatility. In their study on positive-feedback strategy, De Long, Shleifer, Summers and Waldmann (1989) refuted the idea advanced by the EMH that rational speculators counter the irrational movements in asset prices. They noted that the speculations of positive-feedback traders destabilise the market. De Long *et al*. (1989) argued that in the presence of positive-feedback investors it might be rational for speculators to jump on the bandwagon and not to resist the trend. As they explained further, rational speculators who expect some future buying by noise traders buy today in the hope of selling at a higher price tomorrow. Moreover, the purchases by rational speculators can make positive-feedback traders even more excited, thus pushing the current prices higher than fundamental news would warrant. Bikhchandani and Sharma (2001) pointed out that, although the momentum-investment and positive-feedback strategies seem to be irrational, they can also be regarded as rational. They explained that market participants take time to process new information. Consequently, the delay in market prices adjusting to new information will allow arbitrageurs to take advantage of mispriced assets to make profits.

2.2.1.2 SHARED-AVERSION

The shared-aversion source of herding occurs for reasons unrelated to other causes of herding. In other sources of herding, individual choices are based on what others are doing. For shared-aversion, investors search for securities that have certain characteristics and have the potential to give them a competitive advantage. As a security acquires these characteristics, investors in aggregate purchase them. Bhushan (1989) stated that analysts have a set of criteria on which they base their preferences when it comes to tracking a given share. These criteria are the ownership structure, the size of the firm, the variability of the return and the diversification of the company. These criteria dictate which stock they should choose when they are making investment decisions. Hirshleifer, Subrahmanyam and Titman. (1994) concurred and reasoned that investors are inclined to give preferential attention to a subset of shares because of their visibility or/and their potential profitability. Falkenstein (1996) analysed mutual fund managers in the United States between 1991 and 1992 and concluded that mutual funds had a preference for stocks with high visibility, higher share prices and a dislike for stocks with low idiosyncratic volatility. Brown and Mitchell (2008) studied price clustering on the Chinese stock exchange markets of Shanghai and Shenzhen. They found that investors in Chinese A-shares (the ones that are held by Chinese organisations or individuals) have a preference for share prices containing the number 8 and have an aversion on share prices containing the number 4. This is due to the fact that, for a significant number of Chinese, the digit 8 is appealing, as it is believed to be a lucky number, while 4 is regarded as an unlucky number and needs to be avoided.

2.2.2. RATIONAL HERDING

A behaviour is deemed rational when the investors would intentionally adopt a similar behaviour if put in an identical situation again (Caparrelli *et al.*, 2004). Rational views are centred on optimal decision-making being distorted by information difficulties or incentive issues (Devenow and Welch, 1996). Rational herding is therefore associated with: (1) information-based herding or information cascade; (2) reputation-based herding and (3) compensation-based herding.

2.2.2.1 INFORMATION-BASED HERDING OR INFORMATION CASCADE

Information cascade pertains to a situation where people with incomplete private information make decisions in sequence. The first few decision-makers reveal their information and subsequent decision-makers simply follow an established pattern, even when their private information suggests that they should deviate (Anderson and Holt, 2008). As a consequence of information cascades, trading is correlated and this is a major contributing factor to herding (Gilmour and Smit, 2002). Bikhchandani *et al*. (1992) proposed a model based on informational cascades, which assumed that individuals make their decisions sequentially, taking into account the decisions of the individuals preceding them. They came to the conclusion that localised conformity of behaviour and the vulnerability of mass behaviours can be explained by information cascades. Bikhchandani *et al*. (1992) argued that conformist behaviours can be fragile and idiosyncratic, since cascades start readily on the basis of even a small amount of information. Banerjee (1992) also used a sequential model. He stressed that investors who follow the herd can be viewed as rational when one bears in mind that previous investors might have important information which is revealed by their actions. However, Banerjee (1992: 798) noted that:

> information contained in the decisions made by others makes each person's decision less responsive to her own information and hence less informative to others. This will lead to inefficacies in the market consequently, the behaviour should be regarded as irrational and the society is better off by constraining individuals to use only their own information.

Bikhchandani and Sharma (2001: 7) observed that an investor is likely to be in an "invest cascade" ("reject cascade") if the total count of previous investors exceeds (or is less) by two or more than the number of preceding investors who do not invest. Using Bayes' Law, they demonstrate that the probability that a cascade will be initiated after only a few investors is very high. Bikhchandani and Sharma (2001) explained that, regardless of the fact that the signal is arbitrarily noisy, the probability of a cascade starting is greater than 0.93 after the first four individuals invest.

2.2.2.2 REPUTATION-BASED HERDING

Reputation-based herding is a result of the principal-agent problem. The reputation concerns that arise from uncertainty about the aptitude of a particular manager (agent) to make good investment decisions induce him/her to conform with other professional investors, instead of using his/her private information. Keynes (1936:141) stressed that "…it [is] better for reputation to fail conventionally than to succeed unconventionally". Sharfeistein and Stein (1991) observed that herd behaviour can arise from various situations as a result of rational attempts by agents to boost their reputations as decision-makers. They proposed a model to analyse reputation-based herding. The model consisted of a financial market with two types of institutional managers, ‘smart’ ones and ‘dumb’ ones. Given the fact that employers and customers (principals) are uncertain about the aptitude of a particular dumb manager, he will have a tendency to conceal this inability by imitating smart manager decisions and acting in conformity. In these instances, smart managers are also more likely to make investments decisions that do not conform to their own private information. For instance, if a smart manager acts alone and his act turns out to be a wrong investment, they stand to lose their reputation. Prendergast and Stole (1996) illustrated that in an attempt to appear to be a fast learner, managers will exaggerate the extent of their own information. But they eventually become conservative and unwilling to change their investments when new information becomes available. Rotheli (2001) documented reputation based herding in a bank where managers who are concerned about their reputation aggressively acquire new customers and expand the existing credit line. Scharfstein and Stein explained that reputation-based herding is mostly sparked by the “sharing-the-blame effect” (1990: 466), whereby investment managers (agents) adopt the same mistaken strategies, with the aim of collectively sharing the blame and making it difficult for the principals to identify managers with low ability.

2.2.2.3 COMPENSATION-BASED HERDING

Compensation-based herding is also a result of the principal-agent problem. A risk-averse investor (agent) prefers to skew his/her investment towards a benchmark if he/she realizes that his/her compensation is tied to a benchmark’s performance. Roll (1992) stressed that when the agent’s compensation is tied to his/her performance, as evaluated relative to the performance of the benchmark, it may cloud his/her investment decisions and may result in herd behaviour. Maug and Naik (1996) proposed a theoretical model, with a risk-averse manager whose compensation increases in line with his/her own performance and decreases in comparison with the performance of other agents. They assumed that all the agents have ‘imperfect private information’ and that the benchmark investors make their investment decisions first, then the agent chooses his/her portfolio after observing the benchmark’s action. They observed that linking compensation to the performance of the benchmarks is inefficient and in conflict with optimal risk sharing. Tying compensation to performance is therefore ineffective in overcoming moral hazards and adverse selection problems.

2.3. EMPIRICAL LITERATURE ON HERD BEHAVIOUR

As mentioned above, measuring herd behaviour empirically has proved to be a challenging task. This is due to the fact that it is not easy to differentiate empirically between rational and irrational behaviour. These two types of herding both represent correlated movements in the market. The following are some of the empirical models used to detect and measure herd behaviour. The first two (the Lakonishok Shleifer and Vishny Model and Portfolio-Change Measure of correlated trading) measure herding by analysing a particular subset of market participants, whilst the remaining three (Beta herding, Cross-Sectional Standard Deviation, and Cross-Sectional Absolute Deviation Models) use a market wide approach to detect herding.

2.3.1. LAKONISHOK SHLEIFER AND VISHNY (LSV) MEASURE OF HERDING

Earlier empirical studies on herding widely used the measure of herding based on Lakonishok, Shleifer and Vishny's (1992) Model (hereafter referred to as LSV). The model focuses on trades conducted by a specific subset of market participants over a period of time. The subset is a generally homogeneous group of fund managers whose behaviour is of interest (Bikhchandani and Sharma, 2001). LSV is built on the assumption that herd behaviour is a result of a disproportionate number of money managers who buy (or sell) a given stock. It is formulated as follows:

$$\overline{HM}_{i,t} = \left| p_{i,t} - E\left[p_{i,t} \right] \right| - AF\left(i \right) \quad \text{.. equation (2.1)}$$

with $p_{i,t}$ being the proportion of all buying activities relative to all trading activities (buys and sells). $E[p_{i,t}]$ is an expected fraction of buyers for fund trading stock i during quarter t. As a proxy of $E[p_{i,t}]$, LSV(1992) proposed the use a proportion of all-stocks trade by fund managers that are buyers during quarter t. $E[p_{i,t}]$ therefore remains constant across all stocks for a given quarter. AF(i) is the adjustment factor. It stands for the probability that buying is an outcome of a random process. AF(i) is therefore equal to $E|\ p_{i,t} - E[p_{it,}]|$, which is an expected value of $|\ p_{i,t} - E[p_{i,t}]|$ under the null hypothesis of no-herding. In the absence of herding, $\overline{HM}_{i,t}$ will be equal to zero. Conversely, in the presence of herding $\overline{HM}_{i,t}$ should have a non-zero value. The higher $\overline{HM}_{i,t}$ is, the more herding is prevalent on the given stock.

In some instances, herding is prevalent on one side of the market, especially in markets where an industry makes up a small portion of the overall stock holdings. In these instances, it might be possible that when an asset is bought (or sold) in a given industry, say pension funds, the other counterpart of the trade might come from parties outside that particular industry, such as mining; bearing this in mind, Wermers (1999) proposed the Conditional Count Herding measure. This herding measure consists of disaggregating the overall measure of herding into the buy side and sell side, denoted as $BMH_{i,t}$ and $SMH_{i,t}$ respectively; they are given by the following equations:

$$BMH_{i,t} = HM_{i,t} \left| p_{i,t} > E\left[p_{i,t} \right] \right| \qquad \text{...(2.2)}$$

and

$$SMH_{i,t} = HM_{i,t} \left| p_{i,t} < E\left[p_{i,t} \right] \right| \qquad \text{...(2.3).}$$

Therefore, by averaging $BMH_{i,t}$ we obtain $\overline{BMH}_{i,t}$ which is the average measure of herding on the buy side of the market for all shares i in all quarters t in a given time period. Equally, by averaging $SMH_{i,t}$, $\overline{SMH}_{i,t}$ is obtained, which represents the average measure of herding on the sell side of the market for all shares *i* in all quarters *t*. In principle, $\overline{BMH}_{i,t}$ is a recalculation of, $\overline{HM}_{i,t}$ for the shares that are on the buy side. Similarly, $\overline{SMH}_{i,t}$ is a recalculation of $\overline{HM}_{i,t}$ for the shares that are on the sell side.

It should be noted that the LSV model has a considerable number of shortcomings. First of all, the LSV measure is unable to identify herding at the market-wide level. Indeed, the LSV measure cannot detect herding, for the simple reason that for any stock that is bought there is a counterpart stock that is sold. Second, the LSV measure only takes into consideration the number of investors who traded, with no consideration to the volume of the stocks traded by investors. In cases where there are an equal number of buyers and sellers, where buyers as a group have a sizeable amount of stock, while the sellers' contribution in the market is comparatively small, herding will be present in the market, but it will not be detected by the LSV formula. Finally, the fact that the LSV measure follows a binomial distribution constitutes another shortcoming. Indeed, the LSV measure deals with either a buy or a sell transaction. In the case of short-selling, whereby one sells an asset that has been borrowed from a third party, the binomial distribution becomes inapplicable (Oehler and Chiao, 2000).

In order to give more context to the quantitative value of $\overline{HM}_{i,t}$, Monte Carlos simulation can be applied under the null hypothesis that herding is a result of random occurrence. This method was used by Gilmour and Smit (2002), who used simulated value of $\overline{HM}_{i,t}$ as follows:

$$HM_{i,t} = \left| p*_{i,t} - E\left[p*_{i,t}\right] \right| - E\left| p*_{i,t} - E\left[p*_{i,t}\right] \right| \qquad \text{.. (2.4).}$$

All the variables in the above equation are variables of the LSV equation simulated under the assumption that each trading decision is taken independently. The $p^*_{i,t}$ is taken from a binomial distribution ($n_{i,t}$, p_t), under the assumption of a random draw, then the draw is divided by $n_{i,t}$ which is the number of funds that trade stock *i* during quarter *t*, p_t is the fraction of funds that trade stock *i* in quarter *t*. As a proxy for p_t, $E[p^*_{i,t}]$ is used, which is the proportion of all stock *i* during quarter *t* that are purchases. As Gilmour and Smit (2002) explained, a simple LSV measure ($\overline{HM}_{i,t}$) only reflects herding in cases where the simulated value of herding is zero; nevertheless, when the simulated value is significantly different from zero the value of $\overline{HM}_{i,t}$ should be adjusted accordingly.

2.3.2 PORTFOLIO-CHANGE MEASURE (PCM) OF CORRELATED TRADING

One of the shortcomings of the LSV measure is the inability to take into consideration the volume of trade. To overcome this shortcoming, Wermers (1995) developed a measure of herding known as the Portfolio-Change Measure of correlated trading (hereafter referred to as the PCM). This measure was conceived to capture both the direction and the intensity of investors who are involved in trading. The rationale behind the PCM measure is to capture herding by measuring the extent to which the weight allocation of stocks in various portfolios by different money managers moves in the same direction. The intensity of beliefs is detected by the percentage change of the fraction accounted for by a stock in a fund portfolio (Bikhchandani and Sharma, 2001). The cross-correlation PCM of lag τ between portfolio I and J is defined as follows:

$$\hat{\rho}^{I,J}_{t,\tau} = \frac{\left(\frac{1}{N_t}\right)\sum_{n=1}^{N}\left(\Delta\tilde{\omega}^{I}_{n,t}\right)\left(\Delta\tilde{\omega}^{J}_{n,t-\tau}\right)}{\sigma^{I,J}(\tau)} \quad \text{....................................... (2.5)}$$

where $\Delta\omega^{I}_{n,t}$ is the change in portfolio I's weight of stock n during the quarter [t- 1,t], $\Delta\omega^{J}_{n,t-\tau}$ is the change in portfolio J's weight of stock *n* during quarter [*t* - τ - l, *t*- τ], N_t is the number of stocks in the intersection of the set of tradable securities in portfolio I during quarter

[t - l, t] and the set of tradable securities in portfolio J during quarter [t- τ - l, t-τ]. As for $\sigma^{I,J}(\tau)$ is the time series average of the product of the cross-sectional standard deviations computed as follows:

$$\hat{\sigma}^{I,J}(\tau) = \frac{1}{T}\Sigma_t \left\{ \frac{1}{N}\left[\Sigma_n \left(\Delta\tilde{\omega}^{I}_{n,t} \right)^2 \Sigma_n \left(\Delta\tilde{\omega}^{J}_{n,t-\tau} \right)^2 \right]^{\frac{1}{2}} \right\} \quad \text{.......................................} \ (2.6).$$

Despite the advantages that the PCM has over the LSV, the measure has its own limitations. As Bikhchandani and Sharma (2001) explained, given the fact that the amount of stock traded determines the weight of the buy or sell decision, this can create a bias toward managers of larger funds, because of the possibility of them being allocated a higher weight. Furthermore, the statistic used by Wermer (1995) to look at the fractional change in stock weight of a portfolio may yield spurious herding. Indeed, the weight of stocks that increase (decrease) in price tends to rise, regardless of whether the purchase (sell) has occurred. Finally, the justification for using net asset values as weight in computing PCM is ambiguous.

2.3.3 THE CONCEPT OF BETA HERDING TO MEASURE HERD BEHAVIOUR

In their attempt to solve the inability of some of the models to differentiate between a rational and an irrational behaviour, Hwang and Salmon (2001) proposed a nonparametric model based on the concept of beta. They reasoned that, in the presence of herding, individual asset returns follow the direction of the market, meaning that investors' views on risk and return relationship are distorted. Subsequently, individual assets' Capital Asset Pricing Model (hereafter referred as CAPM) betas deviate from their equilibrium. Put differently, the betas of stocks do not remain constant over time, but rather change with the fluctuations of investors' sentiments. Hence the conclusion that the cross-sectional dispersion of the stocks' betas would be expected to be smaller and will converge towards unity (1), which represents the value of the market beta.

Hwang and Salmon (2001) stressed that their measure is free from irrational behaviour tendencies, since idiosyncratic news has a minor effect on cross-sectional statistics of individual betas. Furthermore, because market-wide news is common for all assets, it is expected that individual betas move together relative to the market, and the upward or downward movement depend solely on the arrival of good or bad news.

Hwang and Salmon (2001) formulated a model based on CAPM equilibrium as follows:

$$E_t^b\left(r_{i,t}\right) = \beta_{imt} E_t\left(r_{m,t}\right) \qquad \text{.......................................} (2.7)$$

where $E_t^b\left(r_{i,t}\right)$ is the expected excess returns of asset i at time t , $E\left(r_{m,t}\right)$ is the expected excess returns of the market at time *t*, and β_{imt} the beta that prevail at time *t*.

When herding is present in the market the above relation no longer holds and both beta and asset return will be biased. The assumption here is that $E\left(r_{m,t}\right)$ is set by a general market-wide view. Therefore, instead of the above equation, the following relationship holds:

$$\frac{E_t^b\left(r_{i,t}\right)}{E_t\left(r_{m,t}\right)} = \beta_{imt}^b = \beta_{imt} - h_{mt}\left(\beta_{imt} - 1\right) \qquad \text{..} (2.8)$$

with β_{imt}^b expressing the market beta, β_{imt} is the beta that prevails in the presence of herd behaviour, $E_t^b\left(r_{i,t}\right)$ is the behaviourally biased conditional expectation of excess returns of asset *i* at time *t*, $E_t\left(r_{m,t}\right)$ is the conditional expectation of excess returns of the market at time t, and $h_{m,t}$ is a time-variant herding parameter which is always less or equal to 1, ($h_{mt} \leq 1$).

When $h_{m,t}$ is equal to 0, it will mean that β^{b}_{imt} is equal to β_{imt}, and that there is no herding. When $h_{m,t}$ is equal to 1, it will mean that β_{imt} is equal to 1 suggesting that there is perfect herding towards the market portfolio. It can therefore be deduced that every time $h_{m,t}$ is between 0 and 1(0 < $h_{m,t}$ < 1), some degree of herding exists in the market and the closer $h_{m,t}$ is to 1 the greater the magnitude of herding.

This measure of herding was criticised for two main reasons: Firstly, the problem of double hypothesis. Hwang and Salmon (2001) model principles are based on an efficient market, whilst the presence of herding assumes conditions of a market that is inefficient (Hachicha, 2010). Second, the assumption that systemic risk is equal to unity is not true. From the empirical point of view there are many other factors besides herding that result in deviation of systemic risk form unity. These are factors such as the market microstructure and the investor's psychology (Hachicha, 2010).

2.3.4 MEASURING HERDING USING CROSS-SECTIONAL STANDARD DEVIATION (CSSD)

Christie and Huang (1995) formulated a model to detect herding behaviour using stock return data. The model used a measure of dispersion between the average individual returns to the realized market returns, which they regressed on a constant and two dummy variables designed to depict extreme positive and negative returns. The measure of dispersion is called Cross-Sectional Standard Deviation (hereafter referred to as CSSD) and is formulated as follows:

$$CSSD = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t} - R_{m,t}\right)^2}{N - 1}} \qquad \text{...(2.9)}$$

where $R_{i,t}$ is the stock return of *i* at time *t*; and $R_{m,t}$ is the cross-sectional average of the *N* returns in the aggregate market portfolio at time *t*.

The idea behind the CSSD measure is that when herding is present in the market, investors have a tendency to converge to the market consensus, i.e. individual returns would not drift far away from the market return. On the basis of the aforementioned, an intuitive measure of herding would therefore be the dispersion between individual return and market return. The dispersion would be zero should individual return move in unison with market return and the dispersion would increase in absolute value as individual returns diverge from the market return.

As Christie and Huang (1995) elaborated, during normal periods, CAPM predicts that CSSD will increase in absolute value, since individual investors diverge in their understanding of the market return as investors are trading using their individual information. However, during intense market movements, individuals have a tendency to disregard their private information and start to imitate one another. Under these circumstances, individual stock returns will have a propensity to converge around the overall market return, leading to a decrease in CSSD.

Christie and Huang (1995) proposed an equation to empirically test this occurrence, expressed as follows:

$$S_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \qquad \text{.......................................(2.10)}$$

where S_t is CSSD at time *t*, D_t^L is a dummy variable at time *t* that captures extreme low market conditions. If D_t^L takes the value of unity, it will mean that the market return on day *t* is situated in the extreme lower tail of the distribution, and should be zero in other instances. Equally, D_t^U is a dummy variable at time *t* that captures extreme upwards market conditions. D_t^U takes the value of unity if the market return on day *t* is situated in the extreme upper tail of the distribution and equals zero in other instances. The purpose of the dummy variables is to capture dissimilarity in investors' behaviour in extreme up or down against comparatively normal markets. The statistically significant negative value of β^L and β^U coefficients indicate the presence of herd behaviour.

One of the setbacks of the Christie and Huang (1995) model is that it can lead to ambiguous results, because it arbitrarily chooses the cut-off points to classify the upper and lower tails of the return distribution. In their studies, Christie and Huang (1995) used 1 and 5 percent of the observation as cut-off points, but money managers may disagree as to what represents extreme market return. The fact that the model does not contain any parameter to control for the movements in fundamentals represents another shortcoming. It is impossible to conclude objectively whether the movements observed in the market are truly due to herding or whether they are efficient adjustment to fundamentals that are taking place (Wang, 2008). Another drawback is the fact that the CSSD of individual stock returns might be correlated with time series volatility. Indeed, as Goyal and Santa-Clara (2002) explained, it has been proved that the uncertainty of returns moves jointly with the CSSD of individual returns. They argued that there is significantly positive correlation between cross-sectional volatility and time-series volatility. Therefore, a negative relationship between CSSD of individual returns might be a result of a change in volatility, not herding. Finally, one should point out that, under these assumptions, individuals engage in herding only during extreme market movements; consequently the CH measure will not be able to detect herding under normal market conditions.

2.3.5 TESTING THE PRESENCE OF HERDING USING CROSS-SECTIONAL ABSOLUTE DEVIATION (CSAD)

Chang *et al*. (2000) proposed an alternative model to CSSD known as The Cross-Sectional Absolute Deviation (hereafter referred as CSAD). This measure of herding was also conceived in the framework of the conditional version of CAPM. Chang *et al*. (2000) defined the absolute value of the deviation (AVD) of security expected return in the period *t* from the portfolio expected return by the following specification:

$$AVD = \left|\beta_i - \beta_m\right| E_t\left(R_m - \gamma_0\right) \qquad \text{.......................................(2.11)}$$

where R_m is the return on the market portfolio, E_t (.) denotes the expectation in period t , γ_0 is the risk-free rate with the zero-beta portfolio, β_i is the time-invariant systematic risk measure of the security, i = 1, . . . ,N and β_m the systematic risk of an equally-weighted market portfolio. From AVD the Expected Cross-Sectional Absolute Deviation of stock returns (ECSAD) at time *t* can be defined as:

$$ECSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|\beta_i - \beta_m\right| E_t\left(R_m - \gamma_0\right) \qquad \text{.......................................(2.12)}$$

According to Chang *et al*. (2000), in the absence of herding, market participants estimate prices according to the conditional CAPM. Then the relationship between ECSAD and the expected returns will be positive and linear. Conversely, when herding is present in the market the relationship becomes negative and non-linear. By replacing the expected quantities $E_t\left(R_{m,t}\right)$ with realized market return $R_{m,t}$ and the ECSAD by Cross-Sectional Absolute Deviation of returns CSAD$_t$ the following equation is obtained:

$$CSAD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \varepsilon_t \qquad \text{......................................(2.13)}$$

where $CSAD_t$ and $R_{m,t}$ are proxies for $ECSAD_t$ and $E_t\left(R_{m,t}\right)$ respectively, $R^2{}_{m,t}$ is the square of $R_{m,t}$, γ_1 is the coefficient of $R_{m,t}$, γ_2 is the coefficient of $R^2{}_{m,t}$, and ε_t is the error term. During a period of large market movements investors will react in a similar fashion and the value of CSAD will decline (or increase at a decreasing rate) with the market return $R_{m,t}$, and a significantly negative γ_2 coefficient will be observed, indicating the presence of herd behaviour.

2.4 HERD BEHAVIOUR IN EMERGING MARKETS

As pointed out in Chapter 1, herd behaviour is more prevalent in emerging markets, for various reasons. These include the facts that investors in emerging markets are likely to encounter a certain number of problems, such as asymmetric information and lack of transparency in reporting companies' activities. These problems force investors to base their investment decisions exclusively on collective market behaviour (Chang *et al*., 2000). Foreign investors in emerging countries are blamed for creating inefficiencies in the market by entering and exiting in herds, bringing instability, especially during crises (Mendoza and Clavo, 1997).

A considerable number of studies have examined herd behaviour in emerging countries. Chang *et al*. (2000) examined several international stock markets and found evidence of herding in the emerging markets of South Korea and Taiwan. They observed that herding over weekly and monthly time intervals is less pronounced, suggesting that herding is a short-lived phenomenon. Tan *et al*. (2008) examined herding on dual-listed Chinese A- and B-shares[6], using daily data. Their results pointed towards the presence of herd behaviour in both the A- and the B-shares on both the Shanghai and Shenzhen stock exchange markets. Tan *et al*. (2008) also tested for potential asymmetries in herd behaviour that are related to market

[6] A-shares are the ones that are dominated by domestic individual investors, while B-shares are dominated by foreign institutional investors.

returns, trading volume and volatility. They noted that, for Shanghai, A-share herding behaviour is significantly stronger when markets are rising, when they are experiencing higher trading volume and when the volatility is high. However, no such asymmetries could be detected for B-share investors. Tan *et al*. (2008) emphasised that the apparent difference in investors' behaviour was due to the different characteristics of A and B markets. Lao and Singh (2011) examined herding behaviour in Chinese and Indian stock markets. Their findings suggested that herding is more significant during extreme market conditions in both markets. Herding was more pronounced in the Chinese market than in the Indian stock market. Patro and Kanagaraj (2012) published a study on herding in Indian mutual fund industries, using LSV[7] herding measure. They found strong evidence of herding in the overall sample.

Choe, Kho and Stulz (1999) stressed that, before the Asian crisis, domestic institutional investors in Korea tended to negative-feedback trade by buying recent losers and selling recent winners; in contrast, foreign institutional investors tended to positive-feedback trading. Kim and Wei (1999) disagreed and showed that both foreign and domestic institutional investors in Korea were positive-feedback traders and herding was more prevalent among foreign institutional investors.

Zaharyeva (2011) documented the presence of herding and its dynamic in the Ukrainian stock market. Using Huang and Salmon's (2004) measure of the herding[8], Zaharyeva (2011) found evidence of herding in the Ukrainian market. Zaharyeva (2011) contended that the main challenge that arises while analysing herding in emerging markets is the presence of thin trading, which creates a bias of estimators. The bias in herding measures that is generated by thin trading in emerging markets was also discussed by Kallinterakis and Kratunova (2007), who examined the herding behaviour in the Bulgarian stock market and documented on the

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[7] Refer to section 2.3.1 for more details on LSV model.

[8] Refer to section 2.3.3 for more details on Huang and Salmon's (2004) measure of the herding.

bias of estimators caused by thin trading. They concluded that the thin trading problem leads to an underestimation of the actual level of herding. Andronikidi and Kallinterakis (2010) studied the thin trading problem in the Israeli stock market and came to the conclusion that thin trading problem engenders bias in the estimation of herding measure. To account for thin trading, Andronikidi and Kallinteraki (2010) used adjusted returns of individual securities. Antoniou, Ergul and Holmes (1997) criticised the above Andronikidi and Kallinteraki's (2010) technique of adjustment for thin trading. They reasoned that when it comes to the analysis of herding in emerging markets, adjustment for thin trading must not be constant over time. Brooks, Dark, Faf and Fry (2006) agreed and pointed out that the technique of adjusting to thin trading enables some correction to be made in beta estimation for thin trades, but does not eliminate the problem entirely. They proposed the use of a selectivity corrected beta estimator. They also used the most liquid securities, that do not suffer from thin trading.

2.5 HERD BEHAVIOUR IN SOUTH AFRICA

Gilmour and Smit (2002) studied herd behaviour among South African institutional managers during the period March 1992 to September 1999, using Wermers' (1999) methodology, which was inspired by the LSV model. Their results indicate the presence of herd behaviour among institutional investors. They found that the average value of herding was 0.024, suggesting that among 100 funds two or more managers are likely to be on the same side of the market as they would have been should they have made independent investment decisions. Additionally, with a conditional count herding $\overline{BMH}$ [9] of 0.002, they reached the conclusion that herding takes place more on 'the buy side' than on 'the sell side' of the market.

A comparison of the herding level according to the risk profile of funds led to the conclusion that herding increases with an increase in the risk profile (volatility) of a fund. In this regard,

[9] Refer to section 2.3.1 for more explanations on $\overline{BMH}$.

Gilmour and Smit (2002) established that herding is more prevalent in aggressive growth funds with a herding measure of 0.077, followed by growth funds at a measure of 0.073 and finally income growth funds with a herding measure of 0.067. Concerning the above-mentioned relationship between herding and volatility, Gilmour and Smit (2002) found a positive relationship between the two with a limit of a 9 percent level, meaning that herding by institutional investors in South Africa increases with volatility up to a cut-off level of 9 percent in volatility.

2.6 SUMMARY

The field of social psychology identified two types of social influences, namely normative and informational social influences. Normative social influence results from an internal motivation to conform to the perceived rules of others, while informational influence is centred on the acceptance of information from others, because individuals view others as a source of valid information.

Theoretical studies on herding in the field of behavioural finance have differentiated two types of herding: irrational and rational herding. An irrational herd behaviour takes place when it is evident that investors are blindly following the actions of others, while a behaviour is deemed rational when the investors would intentionally adopt a similar behaviour if put in an identical situation again.

There are various empirical models that have been devised to test herd behaviour in financial markets. To test herding in a particular sub-group, two models were discussed: (1) the LSV and (2) PCM measures. In order to detect herding in the market as a whole three models have been discussed: (1) the measure of beta herding, (2) CSSD and (3) CSAD. The CSAD measure of herding is the most popular, because it incorporates a non-linear regression specification and does not require extreme market conditions in order to detect herding.

It has been established that herd behaviour is more prevalent in emerging markets for various reasons; these include the presence of asymmetric information and lack of transparency in reporting companies' activities. A study by Gilmour and Smit (2002) during March 1992 to September 1999 reveals that herd behaviour exists in South African institutional investor managers and that herding takes place more on 'the buy side' than on 'the sell side' of the market.

CHAPTER 3

THE JOHANNESBURG STOCK MARKET

Chapter 3 provides an overview of the trends of the South African stock market. The major thrust of the chapter is to present the economical environment of the stock exchange in which this study is conducted. The chapter is divided into three sections. The first section outlines the major features of the JSE and the section explains how trading and settlement are conducted. Special emphasis is given to changes that are believed to have contributed in a significant way in improving efficiency of trading and in decreased the cost of trading. The third section discusses how information is disseminated among market players at the JSE.

3.1 CHARACTERISTICS OF THE JSE

The JSE is the largest bourse in Africa and one of the major stock exchange markets in the world. It has the second highest equity market capitalisation to GDP ratio (Marais, 2008). The JSE is licenced as a stock exchange under the South African Securities Services Act of 2004. Although there is statutory provision in the Securities Services Act of 2004 to allow the operation of more than one stock exchange, the JSE remains the only stock exchange currently in operation in South Africa (Mabhunu, 2004). The JSE constitutes an important pillar in the South African economy. This is due to the fact that listed equities play a relatively dominant role in the South African economy in terms of capital allocation (Marais, 2008).

One of the distinctive characteristics of the JSE is that it is largely resource based. This is because the biggest listed companies in the South African stock market are mining conglomerates. As a result, movements of the main index follow movement in resource prices, especially of gold and platinum (Murayiwa, 2011).

The JSE possesses some of the attributes that characterise an emerging stock market. These attributes include low correlation to the world market, high non-normally distributed returns and volatility, weak market efficiency and higher costs of capital (Marais, 2008).

The JSE has undergone significant changes over the past decade in terms of foreign participation, legislation reform and modernisation of trading environment. The changes led to a rapid growth of the JSE, as reflected in the increase in the number of listed companies, the increase in market capitalisation and the rise in the value of the broad stock index. These indicators are discussed below.

3.1.1 NUMBER OF REGISTERED COMPANIES

Figure 3.1 shows the total number of listed companies and Figure 3.2 the number of foreign listings. It can be seen that there is a decline in the total number of listed companies from 427 companies in 2003 to 385 companies in 2013. The decline in the total number of listed companies can be attributed to various reasons. These include (1) an increase in mergers and acquisitions among South African companies as a result of stringent laws that encouraged South African companies to take over other firms and, at the same time, discouraged exporting capital (Yartey, 2008; Muzindutsi, 2011), (2) the development of private equity funds in South Africa (Yartey, 2008) and (3) the introduction of new listing requirements that forced a number of smaller firms to de-list, as they failed to meet the new listing requirements (Mbendi, 2008). It should be drawn to the attention of the reader that, even though the numbers of listed companies have declined slightly, it can be seen from Figure 3.2 that the number of foreign listed companies has significantly increased over the same period. Indeed, the number of foreign listings increased from 22 to 49; this increase is an indication of the confidence in South African markets among foreign investors.

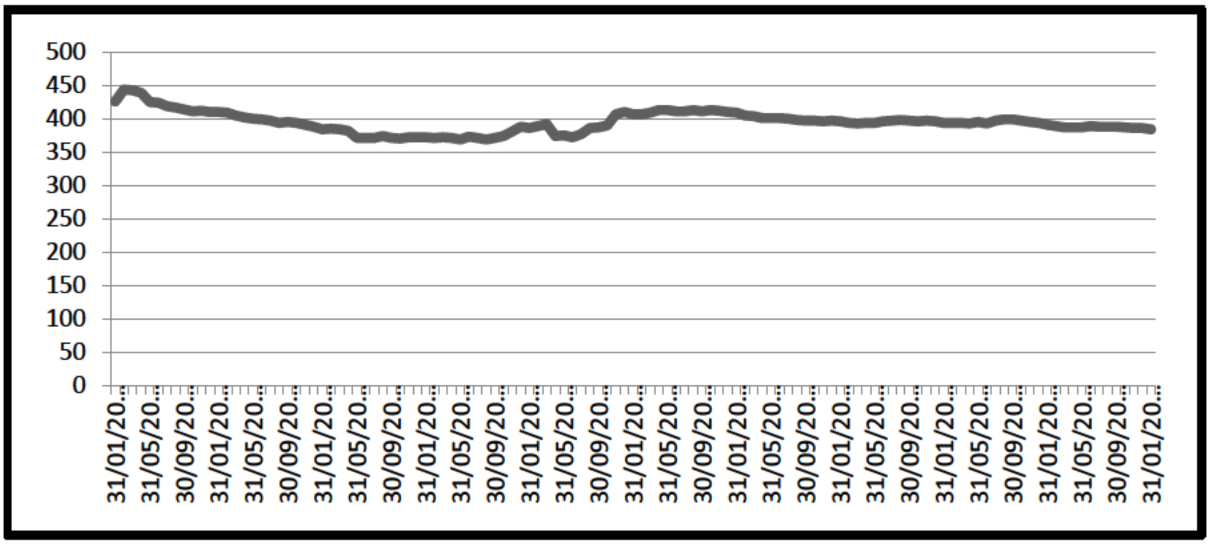

Figure 3.1: Number of Listed Companies on the JSE

Source :World Federation of Exchanges (2013)

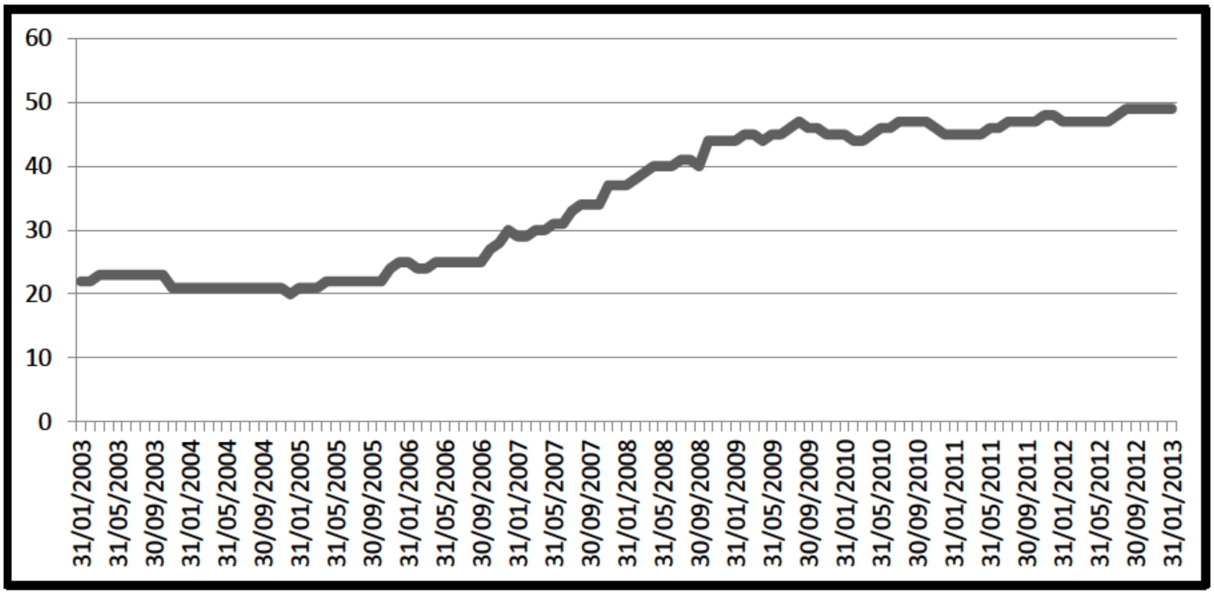

Figure 3.2: Number of Listed Foreing Companies on the JSE

Source :World Federation of Exchanges (2013)

3.1.2 DOMESTIC MARKET CAPITALISATON AND THE BROAD STOCK VALUE INDEX

Figure 3.3 presents domestic market capitalisation at the JSE. The domestic market capitalisation of a stock exchange is the total number of issued shares of domestic companies, including their several classes, multiplied by their respective prices at a given time. This figure reveals a comprehensive value of the market at a given time (World Federation of Exchanges, 2013). Figure 3.3 reveals that the domestic market capitalisation has been on an upward trend for the past 10 years, with the exception of a sharp decline between November 2007 and February 2009[10]. The increase in the market capitalisation can be associated with the high level of GDP growth experienced by South Africa in the period under consideration (Muzinutsi, 2011). The highest domestic market capitalisation of R8 000 billion was achieved in January 2013, while the lowest domestic market capitalisation for this period was in April 2003, with R1 266 billion.

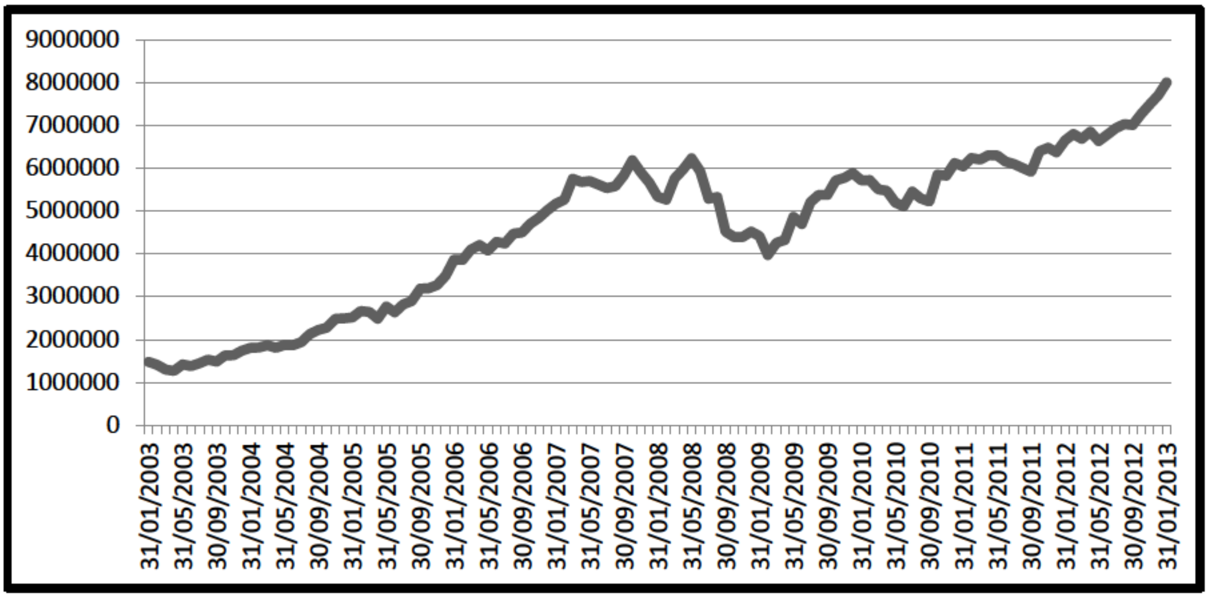

Figure 3.3:Domestic Market Capitalisation at the JSE

Source :World Federation of Exchanges (2013)

[10] This decrease can be associated with the financial crisis that occurred in 2007 and 2008.

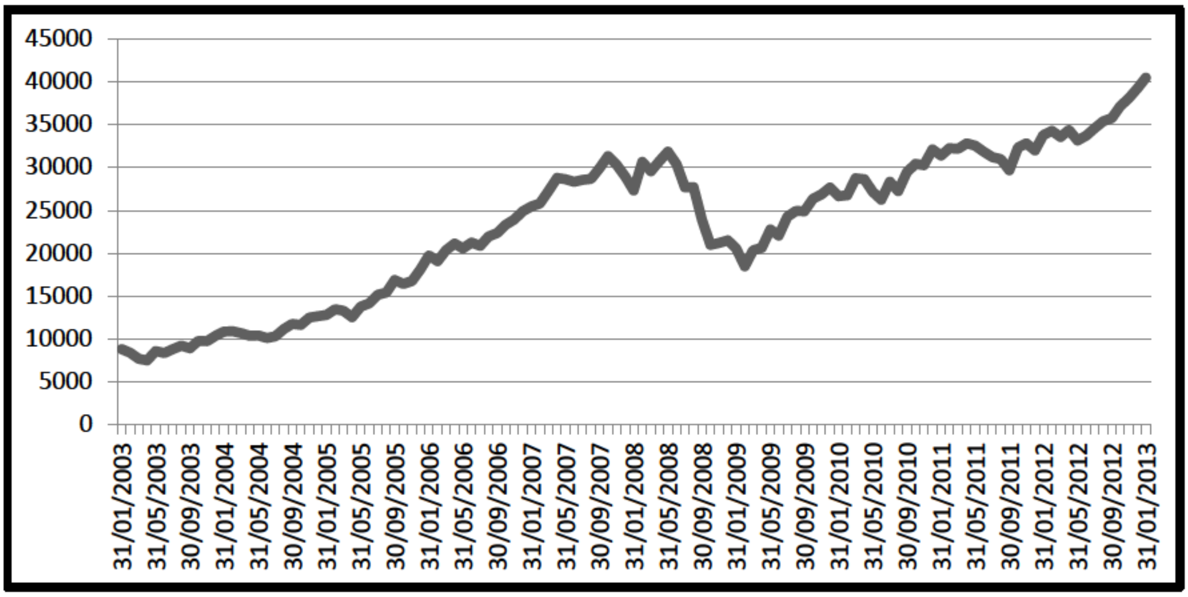

Figure 3.4: Broad Value Index

Source :World Federation of Exchanges (2013)

The good performance of the JSE is also illustrated by an upward trend in the broad stock index. The value of the broad index serves as a benchmark for measuring the performance of the stocks or portfolios such as mutual fund investments; the index is generally market capitalisation-weighted. It includes a large sample of listed domestic companies, as the all-share or composite indices (World Federation of Exchanges, 2013). Figure 3.4 shows that the broad stock index increased by 460.12 percent, as it moved from 8 798.35 in 2003 to 40 482.92 in 2013.

3.2 TRADING AND SETTLEMENT AT THE JSE

Trading and settlement at the JSE is done using the latest technologies, to keep in line with global developments. For instance, in June 1996 a centralised and automated trading system, known as the Johannesburg Equities Trading (JET) system, was introduced. This marked the end of the open outcry-trading floor that had been in use. In May 2002 the JET system was replaced by the Stock Exchange Trading Systems (SETS), which are also used on the London

Stock Exchange (LSE). The SETS are state-of-the art, flexible and robust trading platforms that contributed significantly to improving liquidity and ensuring a more efficient functionality. SETS also enabled South African based companies to access offshore privileges without having to relocate offshore (Mlambo and Biekpe, 2007).

Clearing and settlement is done electronically through STRATE (Share TRAnsactions Totally Electronic), a system introduced in November 1999. STRATE Ltd is the licenced Central Securities Depository (CSD) for the electronic settlement of financial instruments in South Africa. It provides electronic settlement for securities, including equity, bond and derivative products, such as warrants, Exchange Traded Funds (ETFs), retail notes and tracker funds for the JSE (Mkhize and Mswell-Mbanga, 2006).

3.3 STOCK EXCHANGE NEWS SERVICE (SENS)[11]

In order to make informed decisions, investors use information on companies in particular, and on the economy, in general. This information is conveyed to the market through various channels, which include company announcements, as well as government's announcements on its fiscal and monetary policies (Mabhunu, 2004). It is important for companies to comply with the legal and regulatory requirements and, at the same time, maintain a positive relationship with the market by providing accurate information. Prior 1997, there were no clear guidelines as to when company should make their announcements and what exactly should be contain in these announcements (Samkenge, 2010). In this regard, the JSE issued *The Guidelines on the Dissemination of Price Sensitive Information* and subsequently introduced the Stock Exchange News Service (SENS) in August 1997.

The main purpose of the SENS guidelines is to improve the propagation of price-sensitive information; to help companies to manage price-sensitive information and to give all stakeholder more insight on the framework within which companies should propagate such

[11] This section realies heavily on Mabhunu's (2004) work.

information (Mabhunu, 2004). In terms of the SENS framework, price sensitive information is any “unpublished information, which, if it were to be published, would reasonably affect a company’s share price” (Mabhunu, 2004: 17). However, as long as the information remains confidential, possession of price-sensitive information does not necessarily compel the company to disclose it. If it is realistically believed that confidentiality cannot be maintained, or that the information been divulged to the public, a company has the obligation to make cautionary announcements as soon as possible (Mabhunu, 2004).

The JSE, also through SENS, provides comprehensive guidelines to ensure that shareholders receive equal treatment when it comes to information dissemination. For instance, companies should avoid consulting on price-sensitive issues with material shareholders before other shareholders. In fact, the listing requirements at the JSE stipulate that:

> companies may not release price sensitive information to any third party during JSE trading hours until the information has been published through SENS; and outside JSE trading hours, unless arrangements have been made for such information to be published through SENS, prior to the next opening of [the] JSE (JSE, 2011).

Even after a cautionary announcement has been made public, more cautionary announcements must be issued every six weeks, until a full announcement is made public, or a declaration retracting the previous cautionary announcement, has been realised to the public (Mabhunu, 2004). The guideline stipulates that, regardless of the analysts’ constructive role in assisting the market in their understanding and evaluation of companies, companies should decline to answer analysts’ questions where the answers, on their own or when combined with others, might reveal, or at least expose, price-sensitive information. Therefore draft reports from analysts sent with an intention to comment on discrepancies in figures or assumptions should not even be rectified, unless the contents of the report cannot be regarded as price-sensitive. In the same vein, companies should not feel compelled to make a formal announcement rectifying forecasts by analysts unless it is beyond doubt that the market is being materially misled (Mabhunu, 2004). Should there be suspicions of being misinterpreted, or wrongly accused of publishing price-sensitive information, companies should initiate internal procedures to reduce that risk. Bearing in mind the contributions of the media to a well-informed market, companies are required to exercise extreme caution when dealing with the media, especially when price-sensitive, or prospective price-sensitive, information is involved. When journalists are pressing for unpublished price-sensitive information, companies should be ready to give a 'no comment' response.

In instances where there is the likelihood that sufficient price-sensitive information has been gathered for a story to be 'broadly' accurate, a company is under the obligation to insure that the information is made public through SENS and in the press to guarantee that the correct information is widely available. If it appears that the publication of the full information is premature, a cautionary announcement, through SENS and the press, should be made.

According to Sinkenge (2011), five minutes before the release of any announcements through SENS, a neutral warning of an impending announcement is sent through the JSE SETS system. This gives traders an occasion to retract their orders from the system, if they so wish. Announcements received by SENS that have been authenticated and approved are broadcasted electronically to the major wire services, where customers to these services will then have access to the full announcements. The onus is on companies to establish clear communication policies. Furthermore companies are under the obligation to publish announcements in the press once the announcements have been issued through SENS.

In May 2002 the JSE introduced another live information dissemination system known as InfoWiz (Mabhunu, 2004). InfoWiz is a new innovation in information dissemination. It is internationally acclaimed for its live public data delivery system. InfoWiz broadcasts live data to subscribed information vendors, JSE members and financial institutions. Data broadcast by InfoWiz include, among others, best bid and offer; mid price; number and volume at best price; uncrossing price and volume; official closing price; trade report volume and price; start of day reference data; as well as full market depth and indices values. SENS publications are also broadcast through InfoWiz.

3.4 SUMMARY

The JSE is the largest bourse in Africa and is one of the major stock exchange markets in the world. The JSE is characteristically an emerging market as it possesses some attributes of an emerging equity market. These include low correlation to the world market, high non-normally distributed returns and volatility, weak market efficiency and higher costs of capital.

Trading and settlement on the JSE is done using SETS, which is a world-class flexible and robust trading platform that helps to improve liquidity and ensure more efficient functionality at the JSE. Clearing and settlement is done electronically through STRATE; its core objective is to reduce risk, bring efficiencies to South Africa's financial markets and improve its profile as an investment destination.

The information dissemination is done through the SENS, which is a system responsible for ensuring that listings' obligations and regulations are met. SENS provides the ability to publish price-sensitive information and announcements to the market, ensuring that this information is distributed fairly and timeously to all parties. Another system used by the JSE for information dissemination is InfoWiz. InfoWiz is one of the most highly ranked live public data delivery systems in the world. It transmits live data to subscribed information vendors, JSE members and financial institutions (Mabhunu, 2004). With SENS and InfoWiz up and running, the JSE can be said to have done much to increase shareholder value in terms of meeting shareholders' need for information.

CHAPTER 4

DATA AND METHODOLOGY

Chapter 4 describes the data used in the current study; it sets out the analytical framework that will provide answers to the objectives formulated in Chapter 1. The first section explains the selection of the data, variables and sample period covered. This section also presents the summary statistics of the variables used. In the second section, stationarity of the data is examined. The third section describes the analytical framework used to analyse volatility clustering and to test herding in the South African stock market.

4.1 DISCRIPTIVE ANALYSIS OF DATA

The present study used the data set for the daily closing prices of the top 100 stocks on the JSE by market capitalisation. High frequency data were used, since herding is a short-lived phenomenon. The data set used in this analysis spans a period between 31 of August 2006 and 30 of September 2011. This period was chosen, as during this time the world experienced the major financial crisis of 2007/08, the biggest financial crisis since the Great Depression of 1929. It has been established that herding is more pronounced during a financial crisis (Philippas *et al*., 2011). The data was obtained from McGregor BFA database. Three categories of data were used: to test volatility clustering, (1) daily closing prices for the JSE's All Share Index were obtained, to test herd behaviour, (2) daily closing prices for the top 100 companies in the JSE by market capitalisation were obtained, as well as (3) the daily trading volumes of the JSE. By using only the most liquid securities (i.e. the top 100 stocks by market capitalisation), the current study sought to circumvent bias in estimations that might be caused by thin trading (Brooks *et al*., 2006). As Zaharyeva (2009) posited, the typical problem that arises in analysing the emerging markets is the presence of thin trading that creates a bias of estimators.

Form the above daily stock and index prices, daily continuous compounded returns were calculated as follows:

$$R_t = \ln(P_t) - \ln(P_{t-1}) \qquad \text{.. (4.1)}$$

where R_t is the one day return from the period t-1 to t, P_t is the daily closing price recorded at t, and P_{t-1} is the daily closing price recorded on the previous day t-1.

The summary statistics of the variable used in the present study, namely the Cross-Sectional Absolute Deviation (CSAD), the absolute value of weighted market return ($|R_{m,t}|$) under various market conditions and the return of the All Share Index(R_{ALSI}) are listed in the Table 4.1. These summary statistics are the sample mean, maximum, minimum, median, standard deviation, skewness and Jarque-Bera tests (with their P-value).

Table 4.1: Descriptive Statistics of Variable Used in Econometric Analysis

	CSAD	|Rmt|	|Rmt| up	|Rmt| down	|Rmt| Volume up	|Rmt| Volume down	|Rmt| Vol up	|Rmt| Vol down	R(ALSI)
Number of observation	1250	1250	682	568	656	594	599	621	1250
Mean	1.2620	0.30204	0.28364	0.32414	0.340471	0.259608	0.43733	0.17548	0.011994
Median	1.2174	0.23150	0.22716	0.23486	0.259564	0.201823	0.36862	0.11945	0.046483
Minimum	0.61759	0.00021654	0.00043028	0.00021654	0.000216543	0.000430281	0.0025253	0.0002165	-3.2922
Maximum	3.1237	2.8725	0.00043028	2.8725	2.87248	1.62549	2.8725	1.1024	2.9680
Standard Deviation	0.32022	0.28690	1.9879	0.32134	0.323027	0.233837	0.32111	0.17159	0.65080
Skewness	1.2727	2.2031	1.9879	2.2057	2.22367	1.60510	2.0249	1.9330	-0.12141
Kutosis	6.592496	11.77158	9.695379	11.60286	8.46009	3.49648	10.59777	7.775735	140.6393
Jarque-Bera	1009.65	5018.53	1723.06	2212.12	2496.95	557.635	1850.1	976.863	403.997
P- vaule	5.73e-220	0.00	0.00	0.00	0.00	8.15e-122	0.00	7.53e-213	1.889e-088

Source: Author’s construction

From Table 4.1 it can be seen that all these statistics are non-normal and have leptokurtic distribution, features that are common with most financial data (Chinzara, 2006). All the variables except the return for All Share Index are positively skewed, this means that the majority of actual series are below the mean. Furthermore, for all the variables the kurtosis is more than three, meaning that the distributions are slim and long tailed (leptokurtic). The leptokurtic distribution is confirmed by the Jarque–Bera test of normality that shows a significantly low P-value in all the variables under consideration. Therefore the null hypothesis for normal distribution should be rejected.

4.2 STATIONARITY

Empirical analysis of time series data like the one used in this study require that the underlying series are stationary, in other words, the series must be integrated of order I[0] (Gujarati 2003: 792). A stationary stochastic process is the one that contains constant mean (E (Y_t) = μ) and variance (E (Y_t - μ)^2 = $\sigma^2 < \infty$) over time and a covariance that is not serially correlated (γ_k = E [(Y_t - μ) (Y_{t+k} - μ)) (Gujarati 2003: 797). Stationarity of series is important for two reasons. Firstly, if series are stationary then it is possible to make forecasts. Secondly, stationarity minimises the possibility of spurious regressions (Chinzara, 2006).

The condition of stationarity is achieved through testing for the presence of a unit root in a time series. Unit root is tested either by checking the significance of autocorrelation function coefficients or by examining the correlogram plots to determine whether the correlogram is decaying or not (Brooks, 2002). However, Brooks (2002) warns that by analysing the decay of a correlogram, one can sometimes reach the wrong conclusion about the existence of stationarity within a time series. Thus only formal stationarity hypothesis testing is presented.

Two concepts of stationarity are discussed. They are the conventional Dickey-Fuller stationarity test (hereafter referred to as DF) and its extension, the Augmented Dickey-Fuller (hereafter referred to as ADF), as well as the Phillips–Perron unit root test (hereafter referred to as PP). The PP test will be used for purposes of robustness and completeness, as it tackles the problem of uncorrelated error term differently, as compared to ADF (Hussain and Malik, 2011).

4.2.1 DICKEY-FULLER (DF) AND AUGMENTED DICKEY-FULLER (ADF) UNIT ROOT TESTS

Given the following three random walk processes, with no drift (4.2), with drift (4.3) or with both deterministic and stochastic trend (4.4):

$$\Delta Y_t = \delta Y_{t-1} + \mu_t , \delta < 1 \qquad \text{...(4.2)}$$

$$\Delta Y_t = \delta Y_{t-1} + \beta_1 + \mu_t , \delta < 1 \qquad \text{...(4.3)}$$

$$\Delta Y_t = \delta Y_{t-1} + \beta_1 + \beta_2 + \mu_t , \delta < 1 \qquad \text{...(4.4)}$$

where $\Delta Y_t = Y_t - Y_{t-1}$, with Y_t the value of a time series Y for any given period of study, and Y_{t-1} the value of a time series is the value of Y seen in the previous time period t-1 and μ_t is with noise error term. The DF test consists of testing the null hypothesis of $\delta = 0$, i.e. the time series is stationary, against the alternative hypothesis of $\delta < 1$, i.e. the time series is not stationary (Gujarati, 2003: 815). The critical values of the DF test are different for each of the above-mentioned specifications; using the wrong estimate for a given specification will result in a specification error. Unfortunately, there is no clear-cut way of identifying the correct specification other than trial and error and data mining notwithstanding (Gujarati, 2003: 816).

The critical values for DF tests are given in Fuller (1976: 373), Brooks (2002: 675) and Gujarati (2003: 975) and can be obtained by simulation.

The DF test assumes that the error term in Equations 4.2, 4.3 and 4.4 are independent and identically distributed. In other words, the error terms are uncorrelated. In cases where the error terms are correlated, Dickey and Fuller (1979) developed a test commonly known as Augmented Dickey-Fuller (ADF). The ADF test consists of augmenting the initial DF regressions by the lagged dependent variables (ΔY_{t-1}). In this way the autocorrelation is removed. To be specific, given Equations 4.2, 4.3 and 4.4, the ADF test consists of estimating the following regression:

$$\Delta Y_t = \delta Y_{t-1} + \sum_{i=1}^{m} \alpha \Delta y_{t-1} + \varepsilon_t \quad \text{.........(4.5)}$$

$$\Delta Y_t = \beta_1 + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha \Delta y_{t-1} + \varepsilon_t \quad \text{.........(4.6)}$$

$$\Delta Y_t = \beta_1 + \beta_2 t + \sum_{i=1}^{m} \alpha \Delta y_{t-1} + \varepsilon_t \quad \text{.........(4.7)}$$

where ε_t is pure white noise error term and $\Delta Y_{t-1} = Y_{t-1} - Y_{t-2}$ and $\Delta Y_{t-2} = Y_{t-2} - Y_{t-3}$, etc. The number of lagged difference terms to include must be determined empirically by including enough terms so that the error term in the above equations is serially uncorrelated (Gujarati 2003: 817). As in the DF test, the ADF tests the null hypothesis of $\delta = 0$, and it follows the same asymptotic distribution as the DF test.

4.2.2 PHILLIPS–PERRON (PP) UNIT ROOT TEST

The DF test assumes that error terms are uncorrelated. To solve the problem of possible serial autocorrelation in the error terms, ADF includes the lagged difference term of the dependent variable. The PP test tackles this problem differently; it uses a non-parametric statistical method to deal with serial correlation in the error term, without adding a lagged difference term (Gujarati, 2003).The test regression for the PP tests is therefore specified as follows:

$$\Delta Y_t = \delta\, Y_{t-1} + u_t \quad \text{..(4.8)}$$

where $\Delta Y_t = Y_t - Y_{t-1}$, with Y_t the value of a time series Y for any given period of study, and Y_{t-1} the value of a time series is the value of Y seen in the previous time period $t-1$ and μ_t is with noise error term. The error term u_t is I(0) and may be heteroskedastic. The PP test corrects for any serial correlation and heteroskedasticity in the errors u_t, by directly modifying DF test statistics. The PP's Z_t and Z_π statistics are calculated as follows:

$$z_t = \left(\frac{\hat{\sigma}^2}{\hat{\lambda}^2}\right)^{1/2} \times t_{\pi=0} - \frac{1}{2}\left(\frac{\hat{\lambda}^2 - \hat{\sigma}^2}{\hat{\lambda}^2}\right) \cdot \left(\frac{T \times SE\left(\hat{\pi}\right)}{\hat{\sigma}^2}\right) \quad \text{..(4.9),}$$

$$Z_\pi = T_\pi - \frac{1}{2}\frac{T^2 \cdot SE\left(\hat{\pi}\right)}{\hat{\sigma}^2}\left(\hat{\lambda}^2 - \hat{\sigma}^2\right) \quad \text{..(4.10).}$$

The terms σ^2 and λ^2 are consistent estimates of the variance parameters

$$\sigma^2 = \lim_{T \to \infty} T^{-1} \sum_{t=1}^{T} E\left[u_t^2\right] \qquad \text{...(4.11)}$$

and

$$\lambda^2 = \sum_{t=1}^{T} E\left[T^{-1} S_T^2\right] \qquad \text{...(4.12)}$$

respectively, where $S_T = \sum_{t=1}^{T} = \mu_t$ is the sample variance of the least squares residual, μ_t is a consistent estimate of σ^2 and the Newey-West long-run variance estimate of μ_t using μ_t as a consistent estimate of λ^2. Under the null hypothesis that δ = 0, the PP Z_t and Z_π statistics have the same asymptotic distributions as the ADF t-statistic and normalised bias statistics. As mentioned above, one advantage of the PP test over the ADF test is that it is robust to general forms of heteroskedasticity in the error term μ_t. Another advantage is that the user does not have to specify a lag length for the test regression (Zivot and Wang, 2006).

4.3 METHODOLOGY

To accomplish the first objective, the current study hypothesises that volatility clustering is associated with agents' aptitude to observe and mimic the strategy details of others. Therefore the present study proposes to identify volatility clustering in the South African stock market as an indirect way to detect herding; to this end the current study suggests the use of GARCH-type models. GARCH-type models were chosen because of their ability to model non-linear dynamics. As for the second and third objectives, the current study proposes the detection of herd behaviour directly by using the model of Chang *et al*. (2000). The model analyses the relationship between the absolute value of market return and equity return dispersion. This model is chosen because it uses a market-wide approach to test herding. In the model of Chang *et al*. (2000), the equity return dispersion is referred to as a Cross-Sectional Absolute Deviation (CSAD). To achieve the fourth objective, the present study uses the Auto Regressive Distributed Lag (ARDL) bound test approach to cointegration, to determine whether herd behaviour occurs instantaneously, or with lapses of time.

Table 4.2 illustrates the four specific objectives, together with the methods used to achieve those objectives, as well as the data that is going to be used.

Table 4.2: A Schematic Outline of the Study Objectives and Estimation Methodology

Objectives	Method	Data
1. Testing the presence of herd behaviour indirectly by investigating whether volatility clustering is present in South African stock market	GARCH and EGARCH	Daily data JSE All Share Index
2. Testing the presence of herding directly by demonstrating that the variation in market return is not only due to the arrival of new information	CCK model	Daily data for the closing prices for top 100 stocks on the JSE based on market capitalisation
3. Investigate whether herd behaviour in the context of South African stock market varies with market conditions	Modified CCK model	Daily data for: • Closing prices for top 100 stocks on the JSE based on market capitalisation • Daily trading volume at the JSE
4. Examine whether herd behaviour occurs instantaneously or with lapses of time	ARDL bound test approach to cointegration	Daily data for: • Closing prices for top 100 stocks on the JSE based on market capitalisation

Source: Author's construction

4.3.1 TESTING THE PRESENCE OF VOLATILITY CLUSTERING

It has been established that many financial time series data, such as stock returns that are used in this study, are nearly unpredictable (Chinzara and Azakpioko, 2009). Neither Autoregressive Moving Average (ARMA) models nor non-linear time series models allow reliable predictions. The series deviate in two aspects from usual white noise generated from a Gaussian stochastic process. Firstly, the unconditional distribution is severely leptokurtic. In other words, it is more peaked in the centre and displays fat tails, with more unusually large and small observations than would be implied from the Gaussian law. Secondly, they exhibit volatility clustering, where calm and volatile episodes are observed, such that at least the variance appears to be predictable (Chinzara and Azakpioko, 2009). Figure 4.1 represents the daily return of the JSE's All Share Index for a period of five years. This raw time series data suggests that there are periods of volatility clustering where days of large movement are followed by days with the same features.

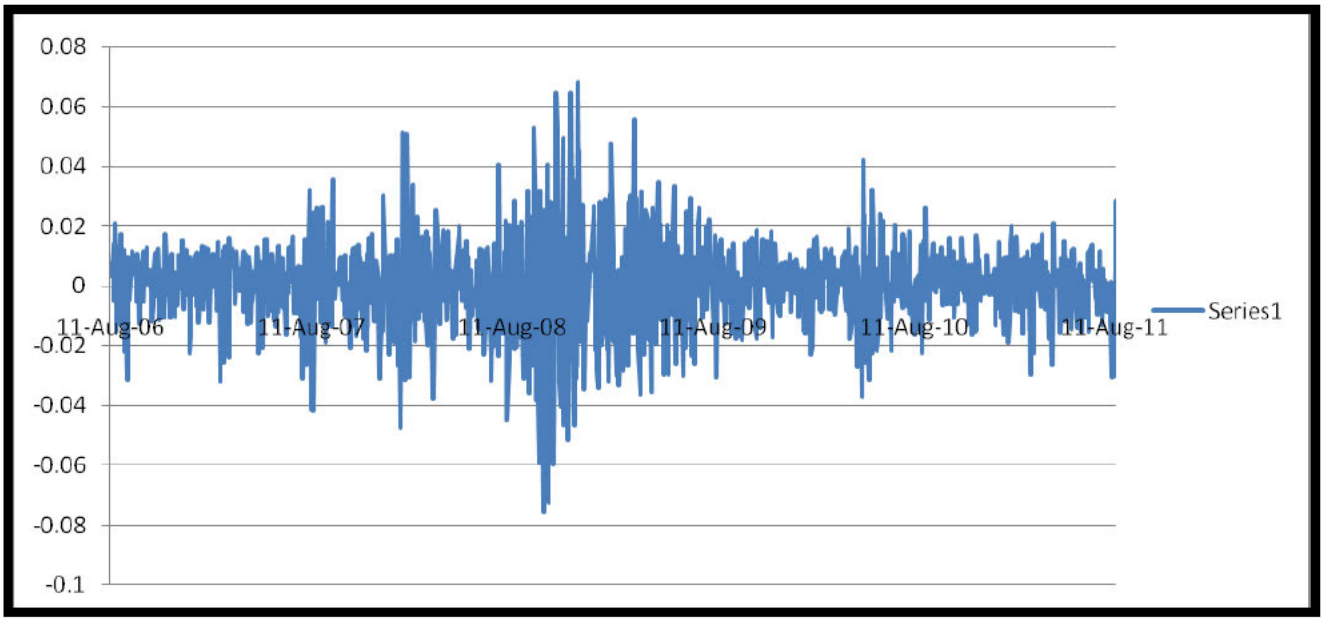

Figure.4.1: Daily Returns for the JSE's All Share Index during for the Period between 10 August 2006 to 10 August 2011

Source: Author's construction from McGregor BFA

Volatility clustering has attracted significant attention from academics for the past five decades. For instance, Xue and Gençay (2012), Engle (1982, 2000) and Bollerslev (1986) proposed use of (G)ARCH-family models to test this market anomaly. GARCH-family models have proved to be capable of effectively capturing conditional volatility. The GARCH models employ the maximum likelihood procedure and allow the conditional variance to be dependent upon previous own lags, hence the conditional variance equation is expressed as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{J=1}^{P} \beta\sigma_{t-1}^2 + \sum_{i=1}^{q} \alpha_1\varepsilon_{t-1}^2 \qquad \text{...(4.13)}$$

where α_0 is a constant term, σ_t^2 is the volatility at time *t*, ε_{t-1}^2 is the previous period's squared error term and σ_{t-1}^2 is the previous period's volatility. For any GARCH (p, q), the order is normally chosen through the Schwarz Bayesian Information Criteria (SBIC) and is based on the following formula:

$$SBIC = 1 + \ln(2\pi) + \ln(\frac{ESS}{T}) + \frac{k}{T}(\ln T) \qquad \text{...(4.14)}$$

where *T* is the sample size, *k* is the number of estimated parameters and *ESS* is the sum of the squared residuals in the regression. The SBIC is usually chosen over the Akaike Information Criterion (AIC) because it penalises more heavily for degrees of freedom and therefore it tends to select more parsimonious models. The model with the smallest criterion value for each GARCH specification is used (Chinzara and Azakpioko, 2009).

Interestingly enough, first-order GARCH models, i.e. GARCH (1,1) models, are so often empirically adequate to test volatility clustering that they have achieved something of a canonical status (Diebold, 2012). In this study three variants of the GARCH model are used. They are: (1) the (Vanilla) GARCH, (2) the GARCH specification of Glosten, Jagannathan and Runkle (1993) (hereafter referred to as GJR GARCH) and (3) the Exponential GARCH specification of Nelson (1991) (hereafter referred to as EGARCH).

It has been established that return volatility may be generated by trades related to the arrival of new information in markets (Park, 2008). By using agent-based models (computer simulation that represents individual actors in a dynamic social system), academics have established that agents' herding behaviour causes volatility clustering in stock markets (Yamamoto, 2009). Alfarano and Lux (2007) noted that the existence of herd behaviour among market participants modifies the distribution of market returns and is characterized by the presence of fat tails and volatility clustering in these financial data. MacQueen and Vorkink (2004) explained why the presence of volatility clustering in financial data might be caused by herd behaviour. They stressed that when investors herd, their sensitivity to new information is time varying and is autocorrelated, hence the presence of volatility clustering. Yamamoto (2009) used an agent-based model to run simulations on an artificial stock market. The simulations consisted of two economies; one with and the other without herding. He established that a herding economy can engender volatility clustering, but volatility could not be found when agents do not herd. Capriani and Guirion (2005) warned that the presence of clustering may or may not be due to herding; it can also be caused by spurious herding. Therefore the detection of volatility clustering does not necessarily attest to the presence of herding. The three types of GARCH models used in the current study are discussed below.

4.3.1.1 GENERALISED AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTICITY (GARCH)

Working under the assumption that volatility depends on the last period's conditional volatility the GARCH (1,1) model is expressed as:

$$Y = \mu_t + \varepsilon \qquad \text{...(4.15)}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad \text{...(4.16)}$$

where Equation 4.15 is the mean equation and Equation 4.16 is the conditional variance equation, α_0 is a constant term, σ_t^2 is the volatility at time *t*, ε_{t-1}^2 is previous period's squared the error term and σ_{t-1}^2 is the previous period's volatility. Statistically significant positive parameter estimates α_1 and β (with the constraint $\alpha_1 + \beta < 1$) would indicate the presence of clustering, with the rate of persistence expressed by how much closer $\alpha_1 + \beta$ is to unity, the bigger the persistence of conditional volatility (that is volatility clustering). The constraint $\alpha_1 + \beta < 1$ allows the process to remain stationary, with the upper limit of $\alpha_1 + \beta = 1$, which represents an integrated process.

A key feature for an appropriate mean equation (Equation 4.15) is that it should be 'white noisy', meaning that its error terms should be serially uncorrelated. In this regard the mean equation must be tested for autocorrelation using the Durbin Watson (DW) test and the LM autocorrelation test. Should there be evidence of autocorrelation, lagged values of the dependent variable should be added to the right hand side of Equation 4.16 until serial correlation is eliminated. The appropriate mean equation must also be tested for ARCH effect[12], to ensure that it is necessary to proceed to estimating GARCH models (Chinzara and Azakpioko, 2009).

Volatility seems to be affected asymmetrically by positive and negative news. This fact was first identified by Black (1976). One of the drawbacks of the GARCH is that it cannot capture the above-mentioned asymmetric effects. Indeed, the GARCH model assumes that good and

[12] The ARCH (AutoRegressive Conditional Heteroskedasticity) effect takes place when the variance of the current error term is related to the size of the previous period's error term.

bad news have a symmetrical effect on volatility and this is not always the case in various financial time-series. To remedy this problem, the study estimated GJR GARCH and EGARCH models.

4.3.1.2 GLOSTEN, JAGANNATHAN AND RUNKLE GARCH (GJR GARCH)

The GJR GARCH (1,1,1) model is a simple extension of GARCH(1,1) with an additional term added to account for possible asymmetries. The conditional variance is given by:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} \qquad \text{...(4.17)}$$

where I_{t-1} equal to 1 if $\varepsilon_{t-1}^2 < 0$ and I_{t-1} equal to 0 otherwise. *I* is the asymmetry component and γ is the asymmetry coefficient. The presence of asymmetric effects is indicated by a significantly positive γ. The idea behind this is that good news ($\varepsilon_t > 0$) and bad news ($\varepsilon_t < 0$) will have different impacts on conditional variance. Good news will have an impact of α_1, bad news will have an impact of $\alpha_1 + \gamma$. As a result, if γ is significantly different from zero, the impact of good news is different from the impact of bad news on current volatility (Arguile, 2012). The condition for non-negativity will be $\alpha_0 \geq 0$, $\alpha_1 \geq 0$, $\beta \geq 0$, and $\alpha_1 + \beta$.

4.3.1.3 EXPONENTIAL GARCH (EGARCH)

Another GARCH model that accounts for asymmetric affects is Exponential GARCH (1,1,1). It is expressed as follows:

$$\ln\left(\sigma_t^2\right) = \alpha_0 + \alpha_1\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \mathrm{E}\left[\frac{|\varepsilon_{t-1}|}{\sigma_t}\right]\right) + \beta\ln\left(\sigma_{t-1}^2\right) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad \text{.. (4.18)}$$

where α_1 and β are still interpreted as they are in the GARCH (1, 1) model, i.e. the coefficient of lagged residuals and the coefficient of the lagged conditional variance, respectively, and γ is the asymmetry coefficient. For $\varepsilon_t \sim N\left(0, \sigma_t^2\right)$ the standardised variable $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ follows a standard normal distribution, hence $\mathrm{E}\left[\frac{\left|\varepsilon_{t-1}\right|}{\sigma_t}\right] = \sqrt{\frac{2}{\pi}}$ (Schmitt, 1996). The inclusion of standardized residual $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ allows the EGARCH model to be asymmetric for $\gamma \neq 0$.The asymmetry is captured by the ARCH effect, represented by $\left(\alpha_1 + \gamma\right) \cdot \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ for positive residuals $\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} > 0\right)$ or good news and by $\left(\alpha_1 - \gamma\right) \cdot \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ for negative residual $\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} < 0\right)$ or bad news. If γ = 0, $\ln\left(\sigma_t^2\right)$ responds symmetrically to $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ (Schmitt, 1996). Besides accounting for asymmetric effects, another advantage of EGARCH (1,1,1) is the fact that when $\ln(\sigma_{t-1}^2)$ is modelled, σ_t^2 will remain positive even in instances where the parameters are negative. There is thus no need to artificially impose no-negativity constraints on the model parameter (Brooks, 2002).

4.3.2 TESTING THE PRESENCE OF HERDING USING CROSS-SECTIONAL ABSOLUTE DEVIATION (CSAD)

In order to achieve the second and third objectives, the current study uses the CCK model, which is centred on the relationship between equity return dispersions and market returns. The model assumes that herding occurs when investors attempt to exploit the information contained in the cross-sectional stock price movement. When this is the case, the cross-sectional standard deviation of stock returns will more likely decrease or increase at a decreasing rate (Al-shboul, 2012). This means that the presence of herding is accompanied by a reduction of cross-sectional standard deviation of returns. Compared to the CH[13] model, the CCK model is more powerful, since it incorporates a non-linear regression specification. Another advantage of the CCK model over the CH model is that, unlike the CH model, the CCK measure does not require extreme market conditions to detect herding, but can identify herding during normal market conditions. The CCK model is based on the following principles.

First, from the CAPM model, under conditions of market equilibrium (Black, 1972), the following equation is formulated:

$$E_t\left(R_i\right) = \gamma_0 + \beta_i E_t\left(R_m - \gamma_0\right) \qquad \text{...(4.19)}$$

where R_i is the return on a given asset *i*, R_m is the return on the market portfolio, E_t (.) denotes the expectation in period *t* , γ_0 is the risk free rate with the zero-beta portfolio and β_i is the time-invariant systematic risk measure of the security. Second, β_m, the systematic risk of an equally-weighted market portfolio, is computed :

$$\beta_m = \frac{1}{N}\sum_{i=1}^{N}\beta_i \qquad \text{...(4.20)}$$

using Equations 4.19 and 4.20 the absolute value of the deviation (AVD) of stock *i*'s expected return in period *t* from the *t*-th period portfolio expected return can be expressed as:

$$AVD = \left|\beta_i - \beta_m\right| E_t\left(R_m - \gamma_0\right) \qquad \text{...(4.21).}$$

[13] CH model is discussed in Chapter 2.

From the above equation the Expected Cross-Sectional Absolute Deviation of stock returns (ECSAD) in period *t* can be deduced:

$$ECSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|\beta_i - \beta_m\right| E_t\left(R_m - \gamma_0\right) \quad \text{..(4.22).}$$

By calculating the first and the second derivative (which are positive and equal to zero respectively) it can be seen that the function is linear and positive, i.e.

$$\frac{\partial ECSAD_t}{\partial\left(R_m\right)} = \frac{1}{N}\sum_{i=1}^{N}\left|\beta_i - \beta_m\right| > 0 \quad \text{..(4.23)}$$

and

$$\frac{\partial^2 ECSAD_t}{\partial\left(R_m\right)^2} = 0 \quad \text{..(4.24).}$$

CCK argued that in the presence of herd behaviour the linearly positive relationship between the dispersion and market return (demonstrated above) gives way to a non-linearly increasing or even decreasing relationship. Thus, CCK suggested a measure of herding which involves a further parameter to cater for the possibility of a non-linear relationship, with the following specification:

$$CSAD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R^2_{m,t} + \varepsilon_t \quad \text{..(4.25)}$$

where $CSAD_t$ and $R_{m,t}$ are proxies for $ECSAD_t$ and $E_t\left(R_{m,t}\right)$,respectively, the values of which are unobservable. $R^2{}_{m,t}$ is the square of $R_{m,t}$, γ_1 is the coefficient of $R_{m,t}$, γ_2 is the coefficient of $R^2{}_{m,t}$ and ε_t is the error term.

CSAD stands for Cross-Sectional Absolute Deviation of returns and is calculated as follows:

$$CSAD = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \qquad \text{..(4.26)}$$

where $R_{m,t}$ is the average return of equally weighted market portfolio at time *t*, and $R_{i,t}$ is the individual stock return of firm i at time *t*, and *N* is the number of firms. From Equation 4.25, it can be seen that during a normal period, the absolute value of $R_{m,t}$ increases, so should be the value of CSAD, and consequently γ_1 is positive and γ_2 equals zero. However, during a period of large market movements, investors will react in a similar fashion and the value of CSAD will decline (or increase at a decreasing rate) with the market return $R_{m,t}$, hence a significantly negative γ_2 coefficient will be observed indicating the presence of herd behaviour. It is worth mentioning that a positive and greater than unity γ_2 (γ_2 > 1) would be indicative of the presence of anti-herding behaviour or exaggeration of differences, meaning that market movements cause more dispersion in stock returns than expected under rational pricing (Tessaromatis and Thomas, 2009).

The CCK model does have some drawbacks. For instance, the measure relies on CAPM's single market factor that has come under criticism. For instance, Fama and French (1993) contended that some of the variables, such as book-to-market ratio and the firm size, are not included in CAPM theory. However, these variables display reliable power to explain crosssection average returns. Another shortcoming is the fact that the CCK model assumes that risk is constant over time, as Tan *et al*. (2008: 64) explained, “the characterisation of time-varying risk requires the specification of an appropriate time window over which to measure risk. In practice, the time window is arbitrary.”

In order to take care of the asymmetric investor behaviour under different market conditions, the present study specifies a modified CCK model, by adding $R_{m,t}$ term to the right hand side of the original CCK’s equation (Equation 4.25). This specification allows taking care of the asymmetric investor behaviour under different market conditions. The modified equation is specified as follows:

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \varepsilon_t \qquad \text{.......................................(4.27)}$$

with the above specification it can be shown that $\gamma_1+\gamma_2$ captures the relation between return dispersion and market return when $R_{m,t} > 0$, while γ_1-γ_2 shows the relation when $R_{m,t} \leq 0$. The ratio of $\frac{(\gamma_2+\gamma_1)}{(\gamma_2-\gamma_1)}$ can be regarded as the relative amount of asymmetry between stock return dispersion and the market’s return (Ching and Zeng, 2010).

The present study also investigates whether or not the reduction in the dispersion of cross-sectional returns is more pronounced during financial crises. Put in plain English, the present study also examined whether herding is more pronounced during a financial crisis. Economou, Kostakis, and Philippas (2010) emphasised that herd behaviour is more pronounced during periods of market distress. In this regard the current study tests whether herd behaviour intensified at the JSE during the recent world financial turmoil that covers the period of August 2007 to December 2008, a period identified by Phillipas *et al*. (2011) as the broad definition the crisis period. To achieve this, Equation 4.25 was extended by incorporating a dummy variable for the square market return during this period. Hence the following equation was obtained:

$$CSAD_t = \alpha + \gamma_1 \left|R_{m,t}\right| + \gamma_2 R^2_{m,t} + \gamma_3 D^{CRISIS} R^2_{m,t} + \varepsilon_t \quad \text{...(4.28)}$$

where D^{CRISIS} takes the value of 1 on trading days during crisis and 0 otherwise.

4.3.3 TESTING THE PRESENCE OF HERDING IN VARIOUS MARKET CONDITIONS

To achieve the third objective a modified CCK models were used to analyse possible asymmetries in herding, in response to different conditions of market returns, volume traded and volatility of returns.

4.3.3.1 HERD BEHAVIOUR DURING INCREASING AND DECREASING MARKET RETURNS

In order to find out whether or not the direction of market return may have an impact on investors' behaviour, the current study examines potential asymmetries in herding in response to a rising or a falling market. To capture these asymmetries the herding regressions were estimated in two separate equations for positive and negative market returns as follows:

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP} \left|R_{m,t}^{UP}\right| + \gamma_2^{UP} \left(R_{m,t}^{UP}\right)^2 + \varepsilon_t \qquad \text{if } R_{m,t} > 0 \quad \text{........................(4.29)}$$

$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN} \left|R_{m,t}^{DOWN}\right| + \gamma_2^{DOWN} \left(R_{m,t}^{DOWN}\right)^2 + \varepsilon_t \qquad \text{if } R_{m,t} < 0 \quad \text{........................(4.30)}$$

Equations 4.29 and 4.30 represent positive and negative market returns, respectively. $R_{m,t}^{UP}$ is the equally-weighted portfolio return at time t when the market rises and $CSAD_t^{UP}$, is $CSAD$ at a time corresponding to $R_{m,t}^{UP}$. Likewise, the variables with superscript word 'down' imply the situation in which the market declines.

4.3.3.2 HERD BEHAVIOUR DURING HIGH AND LOW TRADING VOLUME

Concerning the asymmetric effect of trading volume, the present study examines the asymmetric effects of high and low trading volume on herding. As in Lao and Singh's (2011) model, the trading volume V_t is described as high on day t if it is greater than the previous 30 days' moving average. Conversely, it is described as low if it is smaller than the preceding 30 days' moving average. The potential asymmetries are therefore detected using the specifications below:

$$CSAD_t^{V-HIGH} = \alpha + \gamma_1^{V-HIGH} \left|R_{m,t}^{V-HIGH}\right| + \gamma_2^{V-HIGH} \left(R_{m,t}^{V-HIGH}\right)^2 + \varepsilon_t \quad \text{.................................(4.31)}$$

$$CSAD_t^{V-LOW} = \alpha + \gamma_1^{V-LOW} \left|R_{m,t}^{V-LOW}\right| + \gamma_2^{V-LOW} \left(R_{m,t}^{V-LOW}\right)^2 + \varepsilon_t \quad \text{.................................(4.32)}$$

where *V-HIGH* and *V-LOW* refer to high and low trading volume, respectively.

4.3.3.3 HERD BEHAVIOUR DURING HIGH AND LOW MARKET VOLATILITY

Finally, the effects of volatility on investors herding behaviour were studied, using a similar analysis as the one applied for trading volume. Volatility is defined as the realised standard deviation of the daily closing prices of the 30 days' return interval. The following formula is used to compute the standard deviations:

$$S = \sqrt{\frac{\Sigma \left(R_{i,t} - \bar{R} \right)}{n - 1}} \qquad \text{.................................(4.33)}$$

where $R_{i,t}$ is individual return at time t, $\bar{R}$ is the average return and n is the number of the observation.

As in the model of Tan *et al*. (2008), the volatility is described as high on day *t* if it is greater than the previous 30 days' moving average. Conversely it is regarded as low if it is less than the previous 30 days' moving average. The potential asymmetry is therefore detected using the equations:

$$CSAD_t^{\sigma^2 HIGH} = \alpha + \gamma_1^{\sigma^2 HIGH} \left| R_{m,t}^{\sigma^2 HIGH} \right| + \gamma_2^{\sigma^2 HIGH} \left(R_{m,t}^{\sigma^2 HIGH} \right)^2 + \varepsilon_t \qquad \text{.................................(4.34)}$$

$$CSAD_t^{\sigma^2 LOW} = \alpha + \gamma_1^{\sigma^2 LOW} \left| R_{m,t}^{\sigma^2 LOW} \right| + \gamma_2^{\sigma^2 LOW} \left(R_{m,t}^{\sigma^2 LOW} \right)^2 + \varepsilon_t \qquad \text{.................................(4.35)}$$

with superscript $\sigma^2 HIGH$ and $\sigma^2 LOW$ denoting high return volatility and low return volatility, respectively.

4.3.4 TESTING FOR LAGS IN HERDING[14]

In order to achieve the fourth objective the present study employs the bounds testing procedure within an AutoRegressive Distributed Lag framework (hereafter referred to as ARDL) pioneered by Pesaran and Shin (1995). ARDL model incorporates current and lagged values of independent variables as explanatory variables, in addition to lagged value of dependent variable (Gujarati, 2003). As pointed out by Narayan and Narayan (2005), this

[14] This section relies heavily on the work of Narayan and Narayan, (2005).

procedure has several advantages over alternatives such as Engle and Granger's (1987) the two-step residual-based procedure for testing the null hypothesis of no cointegration or the system-based reduced rank regression approach by Johansen (1988). The first and most important advantage is that the bounds test approach is applicable irrespective of whether the underlying regressors are purely stationary, purely nonstationary or mutually cointegrated. Consequently, the bounds test does not depend on pre-testing the order of integration. This eliminates the uncertainty associated with pre-testing the order of integration. Another advantage is that the Unrestricted Error Correction Model (UECM) is likely to have better statistical properties than the two-step Engle-Granger method because unlike the Engle-Granger method, the UECM does not push the short-run dynamics into the residual terms (Narayan and Narayan, 2005).

The ARDL (p, q_1, q_2,. . .,q_k) model is formulated as follows:

$$\Omega\left(L, p\right) y_t = \alpha_0 + \sum_{i=1}^{k} \beta_i \left(L, q_i\right) x_{it} + \delta' w_t + \mu_t \qquad \text{.................................(4.36)}$$

where

$$\Omega\left(L, p\right) y_t = 1 - \Omega_1 \delta_1 L^1 - \Omega_2 \delta_2 L^2 - \ldots - \Omega_P L^P, \qquad \text{.................................(4.37)}$$

$$\beta_1 \left(L, q_i\right) = \beta_{i0} + \beta_{i1} L + \beta_{i2} L^2 + \ldots + \beta_{iqi} L^{qi}, \; i = 1, 2, \ldots, k, \qquad \text{.................................(4.38)}$$

y_t is the regressor; α_0 is a constant; L is a lagged term such that $Ly_t = y_{t-1;}$ and w_t is an $S \times 1$ vector of deterministic variables such as seasonal dummies, exogenous variables, or time trends with fixed lags. The x_{it} in Equation 4.36 is the *i* regressand where *i*=1,2,. . .,k. As for the long-run, we get $y_t = y_{t-1} .... = y_{t-p}; x_{i,t-1} = ... = x_{i,t-q}$ where $x_{i,t-q}$ denotes the q^{th} lag of the i^{th} variable. Hence the long-run equation with respect to the constant term can be written as follows:

$$y = \alpha + \sum_{i-1}^{k} \beta_i x_i + \delta^{'} w_t + v_t \qquad \Omega = \frac{\alpha_0}{\Omega(1, p)} \quad \text{.................................(4.39)}$$

The long-run coefficients for a response of y_t to a unit change in x_{it} are calculated by:

$$\beta_i = \frac{\hat{\beta}_i\left(1, \hat{q}_i\right)}{\Omega\left(1, \hat{p}\right)} = \frac{\hat{\beta}_{i0} + \hat{\beta}_{i1} + \ldots + \hat{\beta}_{iq}}{1 - \Omega_1 - \Omega 2 - \ldots \hat{\Omega p}}, \quad i = 1, 2, \ldots, k \quad \text{.................................(4.40)}$$

with p and q_i, i=1,2,. . .,k, being the estimated values of p and qi, i=1,2,. . .k. The error correction representation of the ARDL $\left(p, q_1, q_2, \ldots, q_k\right)$ model can be obtained by expressing Equation 4.36 in terms of the lagged levels and the first differences of $y_t, x_{1t}, x_{2t}, \ldots, x_{kt}$ and w_t. Hence we have the following equation:

$$\Delta y_t = \Delta\alpha_0 - \sum_{j=1}^{p-1} \Omega^{*}_{j} \Delta y_{t-j} + \sum_{i=1}^{k} \beta_{i0} \Delta x_{it} - \sum_{i=1}^{k} \sum_{j=1}^{q_{t-1}} \beta^{*}_{ij} \Delta x_{i,t-j} + \delta^{'} \Delta w_t - \Omega\left(1, \hat{p}\right) ECM_{t-1} + \mu_t \quad \text{..........(4.41)}$$

where ECM_t is the correction term, expressed by

$$\mathrm{ECM}_t = y_t - \hat{\alpha} - \sum_{i=1}^{k} \hat{\beta}_i x_{it} - \delta^{'} w_t \quad \text{.................................(4.42);}$$

The symbol Δ is the first difference operator; Ω^{*}_{j}, β^{*}_{ij} and $\delta^{'}$ are the coefficients relating to the short-run dynamics of the model's convergence to equilibrium, while Ω (1, p) measures the speed of adjustment. The ARDL's bounds testing procedure involves two stages. The first stage is to establish the existence of a long-run relationship. The second step procedure is used in estimating the long-run relationship.

As stated in section 4.3, by using the ARDL approach to cointegration, the current study sought to detect simultaneously short- and long-run effects in order to find out whether herd behaviour is instantaneous or occurs with a lapse of time .i.e. whether the relationship between equity returns dispersions and market returns is instantaneous or not. To achieve this, the CCK Equation 4.25 was specified in an ARDL format as follows:

$$\Delta CSAD_t = a + \sum_{i=1}^{n} a_i \Delta CSAD_{t-1} + \sum_{i=1}^{p} b_i \Delta \left|R_{m,t-i}\right| + \sum_{i=1}^{q} c_i \Delta R_{m,t-i}^2 + \gamma_1 CSAD_{t-i} + \gamma_2 \left|R_{m,t-i}\right| + \gamma_3 R_{m,t-i}^2 + \mu_t \quad \text{.... (4.43)}$$

where *n, p* and *q* are number of lags, $\Delta CSAD, \Delta\left|R_{m,t-i}\right|$ and $\Delta R_{m,t-i}^2$ are the first deference of CSAD, $\left|R_{m,t-i}\right|$ and $R_{m,t-i}^2$, respectively; a_i, b_i and c_i are short-run coefficients; γ_1, γ_2 and γ_3 being long-run coefficients and μ_t is the stochastic error term. Pesaran, Shin and Smith (2001) suggested the following steps for the estimation of Equation 4.43. The first step consists of testing cointegration by carrying out an F-test, where the null hypothesis of non-existence of cointegration of $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$ is tested against its alternative of $H_1 : \gamma_1 \neq \gamma_2 \neq \gamma_3 \neq 0$ or cointegration. Pesaran *et al.* (2001) proposed two sets of suitable critical values to test cointegration. One set assumes that all variables are purely nonstationary or I(1) and another assumes that they are all purely stationary or I(0). If the calculated F-statistic lies above the upper level of the band, the null 'non-existence of cointegration' is rejected, indicating cointegration. Should cointegration be detected, the long-run herding or lagged herding is inferred by the sign and size of estimates of γ_3. In the second steps a maximum lag is selected. Then, on each of the first differenced variables in Equation 4.43, the Schwartz Bayesian Criteria (SBC) criterion is used to select the optimal model. Short-run herding or instantaneous herding will be indicated by the sign and size of c_i

.

In cases where the calculated F-statistic calculated in the first step falls below the lower level of the band, the null cannot be rejected, suggesting lack of cointegration. Another scenario is when the calculated F-statistic falls within the band; in this case the result is inconclusive and the error-correction term will be a used in establishing cointegration (Kremers *et al*., 1992).

4.4 SUMMARY

In this chapter, the data and the methodology used in this study were examined. First, the data review discussed two methods used to test stationarity, being DF and its extension, ADF, as well as the PP tests. Then the analytical framework utilised in this study was set out in order to address questions regarding the presence of herd behaviour in the JSE. Firstly the analytical framework for examining volatility clustering in the South African stock market was described; in this regard the univariate GARCH was discussed together with its asymmetric extensions GRJ-GARCH and EGARCH. Secondly, the CCK model was discussed; the model is based on the relationship between the Cross-Sectional Absolute Deviation (CSAD) of market return and equity return dispersion. This relationship can be used to detect the presence of herd behaviour in stock markets, as well as detecting asymmetric effects of herding in various market conditions. Finally, an ARDL model was used to investigate whether herd behaviour occurs simultaneously or not.

CHAPTER 5

ANALYSIS OF EMPIRICAL RESULTS

In Chapter 1 the following objectives were set:

1. Testing the presence of herd behaviour in the JSE indirectly, by investigating the presence of volatility clustering.
2. Testing the presence of herding directly, by demonstrating that the variation in market return is not only due to the arrival of new information.
3. Investigating whether or not herd behaviour in the JSE varies with market conditions.
4. Examining whether herd behaviour occurs instantaneously or with a lapse of time.

Having reviewed the existing theoretical and empirical literature and set out the analytical framework, this chapter applies the analytical framework to address these objectives. But before running the regressions put forward in Chapter 1, the present study tested the presence (or the absence) of stationarity in the data.

Chapter 5 is divided into four sections. The first presents the results of the stationarity test. The second illustrates the results of GARCH, EGARCH and GJR GARCH that were used to detect volatility clustering. The third section discusses the results obtained from the CCK model. The fourth explains the results obtained while using CCK model to analyse herding in various market conditions. The fifth section examines the results of the ARDL to test whether or not the relationship between equity returns dispersions and market return is instantaneous.

5.1 STATIONARITY TESTS

Table 5.3 shows the results from the ADF and PP unit root tests. In performing both tests, the number of lags of each variable were determined through considering the minimum values of Schwarz-Bayesian information criterion (SBIC) statistics and is 5. The SBIC was chosen because it penalises strongly any term added to the regressors with the intention of investigating the presence of unit roots within time series data (Brooks, 2002: 427).

Using Augmented Dickey Fuller (ADF) and Phillip Perron (PP) tests, the results indicate that all variables are stationary at level. The results are given in Table 5.1. It can be seen that the null hypothesis of unit root is rejected at 1 percent level of significance. Experiments with more lags in the augmented regression yielded the same conclusion. When the variables are differenced the results became more significant.

Table 5.1: Stationarity Tests/Unit Root Test for CSAD, $|Rm_t|$, Rm_t^2, R_{ALSI}

	ADF		PP	
	Level	1st Difference	Level	1st Difference
CSAD	-10.618 ***	-24.505***	-25.855 ***	-72.043***
|Rmt|	-7.644***	-25.432***	-29.736***	-72.043***
Rmt2	-7.372***	-26.350***	-30.343***	-101.941***
R_{ALSI}	-24.756***	-40.144***	-33.860***	-61.023***

***Significant at 1 percent, ** Significant at 5 percent, * Significant at 10 percent level

Source: Author's estimation from Stata 11 software

5.2 TESTING VOLATILITY CLUSTERING USING GARCH-TYPE MODELS

Before running GARCH-type models, the mean equation, as expressed in Equation 4.15 was estimated and tested for autocorrelation and ARCH effect. The results are reported in Table 5.2.

Table 5.2: Test for Autocorrelation and ARCH Effects

	DW stat test	Arch LM test
R_{ALSI}	1.92	45.230 [0.000]***

***Significant at 1 percent, ** Significant at 5 percent, * Significant at 10 percent level

Source: Author's estimation from Stata 11 software

The result of the Durbin-Watson[15] statistic test is 1.92, implying that there is evidence of autocorrelation in the mean equation. An ARCH LM test was also performed, which is a Lagrange multiplier (LM) test for autoregressive conditional heteroscedasticity in the residuals (Engle, 1982: 999). Since the test statistic (which follows a Chi-squared distribution) is significant, the null hypothesis was rejected, hence the conclusion that there is evidence of ARCH effects in the data. This indicates that the mean equation did not adequately capture volatility; hence the current study proceeded to estimate the GARCH model and its extensions in order to detect volatility clustering. GARCH(1,1), EGARCH(1,1,1) and GJR GARCH(1,1,1,1) were therefore estimated and the results are presented in Table 5.3.

Table 5.3: Testing for Volatility Clustering

	GARCH(1,1)	EGARCH(1,1,1)	GJR GARCH(1,1,1)
α_0	0.0064***	- 0.104 ***	0.0063***
α_1	0.108 ***	0.105 ***	0.031
β	0.876***	0.982 ***	0.906***
$\alpha_1 + \beta$	0.984	1.807	0.937
γ	n/a	-0.114 ***	1.199
AIC	2067.009	2027.480	2033.276
BIC	2092.664	2035.196	2053.801

***Significant at 1 percent, ** Significant at 5 percent, * Significant at 10 percent level

Source: Author's estimation from Stata 11 software

The sum of the α_1 and β coefficients is high in all models, indicating the presence of volatility clustering. Indeed, for GARCH (1,1) the sum of $\alpha_1 + \beta$ is 0.984, indicating the presence of volatility clustering. In the EGARCH model, however, the stationarity condition ($\alpha + \beta < 1$) is violated, since the sum of α and β is more than unity. For this reason, the EGARCH model should not be used to test the asymmetric effect. As for the GJR GARCH model, although the asymmetry coefficient is positive, it is not significant at 10 percent level

[15] The critical DW is 2. If the test statistic is below 2 there is evidence of positive autocorrelation and when it is above 2 there is evidence of negative autocorrelation (Chinzara, 2008).

of significance. Given the fact that EGARCH and GJR GARCH could not reach conclusive results, the current study concluded that asymmetric effects of news on conditional volatility are not prevalent in the JSE. These results for EGARCH are in line with Chinzara's (2008) findings, who used the EGARCH model to examine the nature of volatility in South African and other world stock markets. Chinzara (2008) found that, in all stock markets, the sum of coefficients α and β was greater than unity (i.e $\alpha + \beta > 1$) for the EGARCH model, hence the conclusion that EGARCH was inadequate in capturing volatility clustering. However the current study's GJR GARCH results differ from the Chinzara's (2008) findings. Indeed, Chinzara (2008) established that the coefficients α , β and γ were significant and concluded that the asymmetry in volatility were present in all the stock markets.

5.3 TESTING THE PRESENCE OF HERDING USING CROSS-SECTIONAL ABSOLUTE DEVIATION (CSAD)

The CCK model was estimated and the results are shown in Table 5.4. The results indicated that the herding coefficient γ_2 is positive but less than unity. This means that the relationship between CSAD and market return is non-linear and that an increase in Cross-Sectional Dispersion (CSAD) is companied by an increase in market return Rm_t, at less than proportional rate. However γ_2 is not statistically significant and hence inclusive. A significantly low R^2 and the adjusted R^2 also indicate poor goodness of fit.

Table 5.4: Results of CCK Regression Equation (Equation 4.25)

	Coefficient	Standard Error	t-statistics	P-value
α	1.158319	0.0602485	77.37	0.000
γ_1	0.3049705	0.0424513	5.06	0.000
γ_2	0.0663896	0.0149708	1.56	0.118
R^2	0.1220			
Adjusted R^2	0.1206			

Source: Author's estimation from Stata 11 software

The current study reran Equation 4.25 by suppressing the constant and by adding a time trend to the CCK regression equation. The results of Equation 4.25 without a constant, but with a trend, are displayed in Table 5.5. A statistically significant negative herding coefficient γ_2 of -0.875 was obtained. This suggests that herd behaviour exists in the JSE. Note that R^2 and adjusted R^2 also improve significantly when the constant is removed and the time trend is added to the CCK regression model.

Table 5.5: Results of CCK Regression Equation (Equation 4.25) without Constant and with Trend

	Coefficient	Standard error	t-statistics	p-value
trend	0.0008843	0.0000308	28.70	0.000
γ_1	2.226965	.0923577	24.11	0.000
γ_2	-0.8751498	0.0728049	-12.02	0.000
R^2	0.8146			
Adjusted R^2	0.8142			

Source: Author's estimation from Stata 11 software

The present study used the modified CCK model that takes care of the asymmetric investor behaviour under different market conditions, as specified in Equation 4.27.see Table 5.6.

Table 5.6: Results of Modified CCK Equation (Equation 4.27)

	Coefficient	Standard Error	t-statistics	p-value
α	1.154	0.007	154.03	0.00
γ_1	0.179	0.030	5.92	0.00
γ_2	0.640	0.010	61.07	0.00
γ_3	0.281	0.022	13.06	0.00
R^2	0.7801			
Adjusted R^2	0.779			

Source: Author's estimation from Stata 11 software

Table 5.6 shows that the value of γ_3 is positive and statistically significant at 1 percent level of significance. The fact that the coefficient γ_3 is positive but less than unity suggests that the relationship between the dispersion and market return is non-linearly increasing at a decreasing rate, suggesting a moderate presence of herd behaviour. The current study reran Equation 4.27 by suppressing the constants and adding a time trend. The results are shown in Table 5.7.

Table 5.7: Results of Modified CCK Regression Equation (Equation 4.27) without Constant but with Trend

	Coefficient	Standard error	t-statistics	p-value
γ_1	2.08	0.082	25.5	0.00
γ_2	0.658	0.034	19.14	0.00
γ_3	-0.645	0.065	61.-9.91	0.00
trend	0.0008	0.000	32.72	0.00
R^2	0.857			
Adjusted R^2	0.856			

Source: Author's estimation from Stata 11 software

Table 5.7 shows that the values of γ_3 becomes statistically significant negative at 1 percent level of significance. The fact that the coefficient γ_3 is negative suggests the presence of herd behaviour when the asymmetric investor behaviour under different market conditions has been taken into consideration. The findings are in line with Ching and Zeng (2010), who used the modified CCK equation, similar to Equation 4.27, and found evidence of herd behaviour in the emerging Asian markets of China, Indonesia, Malaysia, Singapore, South Korea, Taiwan and Thailand.

The current study also tested the behaviour of investors during the financial crisis of 2007/2008. The results of Equation 4.28 are displayed in Table5.8.

Table 5.8: Results of Modified CCK Regression Equation (Equation 4.28)

	Coefficient	Standard Error	t-statistics	p-value
α	0.151	0.15	75.54	0.000
γ_1	0.384	0.066	5.68	0.203
γ_2	-0.098	0.078	-1.27	0.011
$\gamma_3^{D^{CRISIS}}$	0.1385	0.541	2.56	0.000
R^2	0.1266			
Adjusted R^2	0.300			

Source: Author’s estimation from Stata 11 software

The coefficient $\gamma_3^{D^{CRISIS}}$ is positive (0.1385) and significant but less than unity. This suggests low level of herd behaviour[16] during the 2007/2008 financial crisis. However, the coefficient γ_1 is not significant. Additionally the results display a very low R^2.

The current study reran Equation 4.28 by suppressing the constant and by adding a trend. The results are presented in Table 5.9.

Table 5.9: Results of CCK Regression Equation (Equation 4.28) without Constant but with Trend

	Coefficient	Standard error	t-statistics	p-value
Trend	0.0009	0.098	26.19	0.00
γ_1	2.575	0.128	-14.14	0.00
γ_2	-1.802	0.097	8.66	0.00
$\gamma_3^{D^{CRISIS}}$	0.836	0.00003	29.20	0.00
R^2	0.8251			
Adjusted R^2	0.8246			

Source: Author’s estimation from Stata 11 software

[16] An increase, at a less than proportional rate, of dispersion of cross-sectional stock returns in relationship to the market return is also construed as herding.

The coefficient $\gamma_3^{D^{CRISIS}}$ remains significantly positive (0.836), but less than unity. This indicates a low level of herding during a financial crisis. The results contradict Tan *et al*. (2008) and Economou (2011), who asserted that herding effects are more pronounced during a crisis period. The results agree with those of Phillipas *et al*. (2011), who analysed herd behaviour in the Real Estate Investment Trust (REIT) market in the US and concluded that the subprime financial crisis did not intensify herding.

5.4 ASYMMETRIC EFFECT ON HERDING

To achieve the third objective, the present study used a modified CCK model to analyse possible asymmetries in herding in response to different conditions of market returns, volume traded and volatility of returns.

5.4.1 HERD BEHAVIOUR DURING INCREASING AND DECREASING MARKET RETURNS

In order to test asymmetric effect on herding during bear and bull markets in the JSE the current study used a modified CCK model as expressed by Equation 4.29 and Equation 4.30. The results are given in Table 5.10 and Table 5.11.

Table 5.10 Results for CCK Regression Equation for Bull Market (Equation 4.29)

	Coefficient	Standard Error	t-statistics	p-value
α	1.022972	0.0077497	148.97	0.000
γ_1^{UP}	0.010942	0.0354536	28.85	0.000
γ_2^{UP}	0.010942	0.0294328	0.37	0.710
R^2	0.8146			
Adjusted R^2	0.8142			

Source: Author’s estimation from Stata 11 software

Table 5.11: Results for CCK Regression Equation for Bear Market (Equation 4.30)

	Coefficient	Standard error	t-statistics	p-value
α	1.125713	0.012744	88.33	0.000
γ_1^{DOWN}	-0.4921972	0.0472718	-10.41	0.000
γ_2^{DOWN}	0.3579151	0.0303166	11.81	0.000
R^2	0.1980			
Adjusted R^2	0.1951			

Source: Author's estimation from Stata 11 software

A very low R^2 was obtained for both the bull and bear markets, implying a poor goodness of fit for Equations 4.29 and 4.30. Additionally, the value of parameter γ_2 is not statistically significant for a bull market. To remedy this, the present study suppressed the constants and added time trends in both equations. See Tables 5.12 and 5.13

Table 5.12: Results for CCK Regression for Bull Market (Equation 4.29) without Constant but with Trend

	Coefficient	Standard Error	t-statistics	p-value
trend	0.0015356	0.1194963	24.05	0.000
γ_1^{UP}	3.374378	0.1123142	28.24	0.000
γ_2^{UP}	-1.409306	0.0000638	-12.55	0.000
R^2	0.9038			
Adjusted R^2	0.9034			

Source: Author's estimation from Stata 11 software

Table 5.13: Results for CCK Regression for Bear Market (Equation 4.30) without Constant but with Trend

	Coefficient	Standard Error	t-statistics	p-value
trend	0.0019523	0.0000901	21.66	0.000
γ_1^{DOWN}	1.127045	0.113096	9.97	0.000
γ_2^{DOWN}	-0.351595	0.0801837	-4.38	0.000
R^2	0.7718			
Adjusted R^2	0.7706			

Source: Author's estimation from Stata 11 software

With the inclusion of the time trend, the coefficient γ_2 becomes significantly negative, with a value of -1.409 for a bull market in the JSE and -0.356 for a bear market. These results show that herding is more prevalent during an increasing market than during a decreasing market. The explanation would be that herding is aggravated by excess of confidence among investors during high market returns. Over-confidence can result from excessive confidence in the quality of one's information and an exaggerated view of one's ability to interpret that information. This can lead to herding due to a widespread disregard of market information and an unwarranted degree of certainty about the accuracy of one's forecasts (Redhead, 2008).

As a robust test, the current study analysed the equality of herding coefficients obtained from Equations 4.29 and 4.30. In this regard the current study used the Joint Wald test where the null hypothesis of $H_0: \gamma_2^{UP} = \gamma_2^{DOWN}$ was tested against the alternative hypothesis of $H_1: \gamma_2^{UP} \neq \gamma_2^{DOWN}$. The results are presented in Table 5.14.

Table 5.14: Wald Test for the Null Hypothesis of $H_0: \gamma_2^{UP} = \gamma_2^{DOWN}$

$\gamma_2^{UP} - \gamma_2^{DOWN}$	-1.058
Chi-square	14.06
Prob > F	0.0002

Source: Author's estimation from Stata 11 software

With the Chi-square p-value being 0.00 the present study rejected the null hypothesis at 1 percent level of significance and concluded that γ_2^{UP} and γ_2^{DOWN} are different.

5.4.2 HERD BEHAVIOUR DURING HIGH AND LOW TRADING VOLUME

The present study tested the asymmetric effects of high and low trading volumes on herding, as formulated in Equations 4.30 and 4.31.The results are shown in Table 5.15. and 5.16.

Table5.15: Results of CCK Regression Equation for High Trading Volumes (Equation 4.31)

	Coefficient	Standard Error	t-statistics	p-value
α	1.176	0.023	50.79	0.000
γ_1^{V-HIGH}	0.243	0.084	2.89	0.004
γ_2^{V-HIGH}	0.087	0.053	1.66	0.098
R^2	0.116			
Adjusted R^2	0.114			

Source: Author's estimation from Stata 11 software

Table 5.16: Results of CCK Regression Equation for Low trading Volumes (Equation 4.32)

	Coefficient	Standard Error	t-statistics	p-value
α	1.14	0.021	55.91	0.000
γ_1^{V-LOW}	0.325	0.113	2.88	0.004
γ_2^{V-LOW}	0.117	0.115	1.02	0.309
R^2	0.1301			
Adjusted R^2	0.127			

Source: Author's estimation from Stata 11 software

Tables 5.15 and 5.16 show that there are asymmetric effects of trading volumes on herd behaviour. As is the case in previous equations however, the γ_2 coefficients are positive but less that unity and are not statistically significant. By fitting a time trend and removing a constant the following results were obtained.

Table 5.17: Results of CCK regression Equation for High Trading Volume (Equation 4.31) with Trend but no Constant

	Coefficient	Standard Error	t-statistics	p-value
trend	0.002	0.000	0.000	0.000
γ_1^{V-HIGH}	2.64	0.119	17.34	0.000
γ_2^{V-HIGH}	-0.732	0.084	-8.72	0.000
R^2	0.809			
Adjusted R^2	0.809			

Source: Author's estimation from Stata 11 software

Table 5.18: Results of CCK Regression Equation for Low Trading Volume (Equation 4.32) with Trend but no Constant

	Coefficient	Standard error	t-statistics	p-value
trend	0.002	0.000	0.000	0.000
γ_1^{V-LOW}	3.129	0.183	17.07	0.000
γ_2^{V-LOW}	-2.032	0.208	-9.79	0.000
R^2	0.831			
Adjusted R^2	0.830			

Source: Author's estimation from Stata 11 software

Tables 5.17 and 5.18 indicate that there is asymmetric effect with regard to trading volumes in the JSE. Herding is more prevalent during periods of low trading volumes than periods of high trading volumes. The coefficient of the squared market return during low trading volumes (γ_2^{V-LOW}) is -2.032 as to opposed as -0.732 for high trading volume (γ_2^{V-HIGH}). The explanation is that during quiet trading periods, the information that drives the behaviour of investors is not diverse enough and investors are dealing with a limited pool of information to allow them to make individual investment decisions. The results do not agree with those of Tan *et al*. (2008), who examined the asymmetric effect of volume in Shanghai and Shenzhen A- and B-share markets in China and found that herding by B-share investors is unrelated to trading volume and that herding by A-share investors occurs only in the high volume state.

The present study also examined whether herding coefficients γ_2^{V-HIGH} and γ_2^{V-LOW} have the same effect in Equations 4.31 and 4.32. In this regard the Joint Wald test was used, where the null hypothesis of H_0: $\gamma_2^{V-HIGH} = \gamma_2^{V-LOW}$ was tested against the alternative hypothesis of H_1: $\gamma_2^{V-HIGH} \neq \gamma_2^{V-LOW}$. The results are given in Table 5.19

Table 5.19: Wald Test for the Null Hypothesis of H_0: $\gamma_2^{V-HIGH} = \gamma_2^{V-LOW}$

γ_2^{V-HIGH} - γ_2^{V-LOW}	1.30
Chi-square	118.44
Prob > F	0.000

Source: Author's estimation from Stata 11 software

With the Chi-square p-value being 0.00 the current study rejects the null hypothesis at 1 percent level of significance and concludes that γ_2^{V-HIGH} and γ_2^{V-LOW} are different.

5.4.3 HERD BEHAVIOUR DURING HIGH AND LOW MARKET VOLATILITY

In order to test the asymmetric effect of herding during high and low market volatility the current study estimated Equations 4.34 and 4.35. Tables 5.20 and 5.21 display the estimates of Equations 4.34 and 4.35

Table 5.20: Results of CCK Regression Equation for High Market Volatility (Equation 4.34)

	Coefficient	Standard Error	t-statistics	p-value
α	1.146617	0.1102502	32.00	0.000
$\gamma_1^{\sigma^2 HIGH}$	0.271873	0.0648591	2.47	0.014
$\gamma_2^{\sigma^2 HIGH}$	0.0801321	0.0358307	1.24	0.217
R^2	0.1007			
Adjusted R^2	0.0977			

Source: Author's estimation from Stata 11 software

Table 5.21: Results of CCK Regression Equation for Low Market Volatility (Equation 4.35)

	Coefficient	Standard error	t-statistics	p-value
α	1.162485	0.0137364	84.63	0.000
$\gamma_1^{\sigma^2 LOW}$	0.2761632	0.1083214	2.55	0.011
$\gamma_2^{\sigma^2 LOW}$	0.4203037	0.1454012	2.89	0.004
R^2	0.2218			
Adjusted R^2	0.2193			

Source: Author's estimation from Stata 11 software

Tables 5.20 and 5.21 show that there is asymmetric effects of volatility on herd behaviour. However, as is the case in previous equations, γ_2 coefficients are positive, but less than unity and are not statistically significant. By fitting a time trend and removing a constant the following results are obtained:

Table 5.22: Results of CCK Regression Equation (Equation 4.34) for High Market Volatility without Constant but with Trend

	Coefficient	Standard Error	t-statistics	p-value
trend	0.001364	0.0001018	13.40	0.000
$\gamma_1^{\sigma^2 HIGH}$	2.237953	0.1138435	19.66	0.000
$\gamma_2^{\sigma^2 HIGH}$	-0.7959163	0..0794987	-10.01	0.000
R^2	0.8327			
Adjusted R^2	0.8319			

Source: Author's estimation from Stata 11 software

Table 5.23 Results of CCK Regression Equation (Equation 4.35) for Low Market Volatility without Constant but with Trend

	Coefficient	Standard Error	t-statistics	p-value
trend	0.0017053	0.0000786	21.71	0.000
$\gamma_1^{\sigma^2 LOW}$	4.288852	0.2314624	18.53	0.000
$\gamma_2^{\sigma^2 LOW}$	-3.693935	0.3451934	-10.70	0.000
R^2	0.8441			
Adjusted R^2	0.8434			

Source: Author's estimation from Stata 11 software

The results in the above tables indicate that there are asymmetric effects with regard to market volatility in the JSE. Market volatility is more significant during low market volatility than during high market volatility. The coefficient of the squared market return during low market volatility ($\gamma_2^{\sigma^2 LOW}$) is -3.694, as opposed to -0.759, the coefficient of squared market during high market return volatility ($\gamma_2^{\sigma^2 HIGH}$). These results are in conflict with those of Tan *et al*. (2008), who analysed the asymmetric effect with regard to market volatility in two

Chinese equity exchange markets and noted that herding occurs only during periods of high volatility.

As a robust test, the current study investigated whether herding coefficients $\gamma_2^{\sigma^2 HIGH}$ and $\gamma_2^{\sigma^2 LOW}$ have the same effect in Equations 4.34 and 4.35. In this regard, the current study used the Joint Wald test, where the null hypothesis of H_0: $\gamma_2^{\sigma^2 HIGH} = \gamma_2^{\sigma^2 LOW}$ is tested against the alternative hypothesis of H_1: $\gamma_2^{\sigma^2 HIGH} \neq \gamma_2^{\sigma^2 LOW}$. The results are given d in Table 5.24

Table 5.24 Joint Wald Test for the Null hypothesis of H_0: $\gamma_2^{\sigma^2 HIGH} = \gamma_2^{\sigma^2 LOW}$

$\gamma_2^{\sigma^2 HIGH} - \gamma_2^{\sigma^2 LOW}$	3.011
Chi-square	47.05
Prob > F	0.000

Source: Author's estimation from Stata 11 software

With the Chi-square p-value being 0.00 the present study rejected the null hypothesis at 1 percent level of significance and concluded that $\gamma_2^{\sigma^2 HIGH}$ and $\gamma_2^{\sigma^2 LOW}$ are different.

5.5 TESTING FOR LAGS IN HERDING

In order to test whether herd behaviour occurs immediately or with a lapse in time, in other words, whether the relationship between equity returns dispersions and market return in the CCK model is instantaneous, the current study employed an ARDL approach to cointegration as specified in Equation 4.43. First the present study tested cointegration by carrying out a bound test. The bound test is based on the Wald-test (F-statistic). The asymptotic distribution of the Wald-test is non-standard under the null hypothesis of no cointegration among the variables (Dritsakis, 2011). Then the bounds test compares the calculated F-statistics against the critical values generated using stochastic simulations. Table 5.25 shows the results where each variable taken as a dependent variable in the calculation of the F test. Table 5.25 shows that the F-statistics of the models that have CSAD as the dependent variable $F_{CSAD}\left(CSAD \backslash \left|R_{m,t-i}\right|, R^2_{m,t-i}\right) = 29.684$, $\left|R_{m,t-i}\right|$ as the dependent variable $F_{\left|R_{m,t-i}\right|}\left(\left|R_{m,t-i}\right| \backslash CSAD, R^2_{m,t-i}\right) = 21.037$ and $R^2_{m,t-i}$ as the dependent variable $F_{R^2_{m,t-i}}\left(R^2_{m,t-i} \backslash CSAD, \left|R_{m,t-i}\right|\right) = 11.989$ are greater than the critical values in all cases. This means that the variables are I(1) at 1 percent 5 percent and 10 percent levels of significance. The results therefore indicate that the null hypotheses of no long-run relationship are rejected. In other words, the results support the existence of a long-run relationship among the variables in the model.

Table 5.25 Test for Cointegration Relationships

Critical value bounds of the F-statistic: unrestricted intercept and no trend					
99% level		95% level		90% level	
I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
5.15	6.36	3.79	4.85	3.17	4.14
Calculated F-statistic					
$F_{CSAD}\left(CSAD \backslash \left|R_{m,t-i}\right|, R^2_{m,t-i}\right) = 29.684$					
$F_{\left|R_{m,t-i}\right|}\left(\left|R_{m,t-i}\right| \backslash CSAD, R^2_{m,t-i}\right) = 21.037$					
$F_{R^2_{m,t-i}}\left(R^2_{m,t-i} \backslash CSAD, \left|R_{m,t-i}\right|\right) = 11.989$					

Source: Author's estimation from Microfit 4.1 software

Having detected the long-run cointegration relationship, the present study proceeded to run Equation 4.43. The coefficients for the short-and long-run are displayed in Tables 5.26 and 5.27, respectively. For the short-run, the herding coefficient c_i is -0.428, which is statistically significant at 1 percent level of significance. The negative c_i coefficient suggests the presence of herd behaviour in the short-run. As for the long-run model, the herding coefficient γ_3 is -1.5576 and is statistically significant at 1 percent level of significance. The coefficient γ_3 is negative suggesting the present of herding in the long-run.

Table 5.26 Estimated Short-run Coefficients ARDL Model

Regressor	Coefficient	Standard Error	T Ratio [Prob.]
constant	0.84374	0.059180	14.2572[0.000]
$\Delta CSAD_{t-1}$	0. 23383	0.042918	5.4483[0.000]
$\Delta \left\| R_{m,t-i} \right\|$	0.575	0.125	4.587[0.00]
$\Delta R^2_{m,t-i}$	-0.428	0.124	-3.4625[0.01]

Source: Author's estimation from Microfit 4.1 software

Table 5.27 Estimated Long-run Coefficients ARDL Model

Regressor	Coefficient	Standard Error	T Ratio [Prob.]
constant	1.1012	0.0323	34.0813[0.000]
$\left\| R_{m,t-i} \right\|$	0.7507	0.1717	4.3718[0.000]
$R^2_{m,t-i}$	-0.559	0.1664	-3.3568[0.001]

Source: Author's estimation from Microfit 4.1 software

To measure the speed of adjustment after herding has taken place, the error correction coefficient ECM_{t-1} was calculated and is displayed in Table 5.28.

Table 5.28 Error Correction Results for the ARDL

Regressor	Coefficient	Standard Error	T Ratio[Prob]
$\Delta CSAD_{t-1}$	0.234	0.0429	5.4483[0.000]
Δa	0.844	0.059180	14.2572[0.000]
$\Delta \left\| R_{m,t-i} \right\|$	0.575	0.12540	4.5866[0.000]
$\Delta R^2_{m,t-i}$	-0.428	0.12363	-3.4625[0.001]
ECMt-1	-0.76617	0.042918	-17.8519[0.000]

Source: Author's estimation from Microfit 4.1 software

The coefficient of the error correction ECM_{t-1} in Table 5.28 is negative and is statistically significant; this means that the series is non-explosive and that long-run equilibrium i.e. market adjustment is attainable. The ECM_{t-1} coefficient is -0.7717 suggesting a rather high speed of adjustment. Indeed, the ECM_{t-1} coefficient means that nearly 77 percent of the previous day's herding adjusts back in the current day. These findings reinforce the argument that herd behaviour is confined to a short time horizon as suggested by Chang et al. (2000).

5.6 SUMMARY

This chapter applied the analytical framework designed to address the objectives formulated in Chapter 1. The first objective was to detect herd behaviour indirectly. This was achieved by testing the presence of volatility clustering among stock returns in the JSE. Using a GARCH-type model it was found that volatility clustering is prevalent in the financial time series data at the JSE. However, asymmetric effects of news on conditional volatility could not be detected.

To achieve the second objective the current study tested the presence of herding directly, by demonstrating that the variation in market returns is not only due to the arrival of new information. This was achieved by using the CCK model. The CCK model tests the nature of the relationship between equity returns dispersions and market returns. It was found that the relationship is negative and non-linear. The conclusion was thus that herd behaviour is present at the JSE.

To achieve the third objective the present study examined whether or not herd behaviour in the JSE varies with market conditions. This was achieved by using modified CCK models to test whether herding exhibits asymmetric effects associated with market returns, trading volume and return volatility. It was found that herding is more prevalent in bear markets than in bull markets; it was also found that herding is more intense in low trading volume than high trading volume; and lastly herding was found to be more severe in low market volatility than high market volatility.

Finally, the fourth objective was to determine if herd behaviour is an instantaneous phenomenon or occurs with lapse of time. Using the ARDL approach to cointegration, it was found that herding was not instantaneous. However it has a rather high speed of adjustment, implying that herding is a short-lived phenomenon.

CHAPTER 6

SUMMARY, CONCLUSION AND POLICY IMPLICATIONS

6.1 SUMMARY AND MAJOR CONCLUSIONS

In the current study, the investment behaviour among market participants at the JSE was examined. The focus was on their tendency to imitate each other's actions, a behaviour commonly known as herd behaviour. The purpose of the current study was to address four main issues, namely:

(1) to test the presence of herd behaviour in the JSE indirectly, by investigating whether or not the stock returns at the JSE exhibit volatility clustering, (2) to test the presence of herding directly, by demonstrating that the variation in market return is not only due to the arrival of new information, (3) to investigate whether herd behaviour in the JSE varies with market conditions (4) to examine whether herd behaviour occurs instantaneously or with a lapse of time.

The review of the existing theoretical literature was done in the fields of social psychology and of behavioural finance. The theoretical review in the field of social psychology focused the concept on of social influence. The present study noted that there are two types of social influence: the normative and the informational social influences. Normative social influence is a form of the conformity that results from an internal motivation to conform to the perceived rules of others. Informational influence is centred on the acceptance of information from others because individuals view others as a source of valid information. The theoretical review in behavioural finance highlighted the two main types of herd behaviour as the rational and the irrational herd behaviours. Rational herd behaviour occurs when investors faced with the same problems and information arrive at the same conclusions. Irrational herding takes place when investors ignore their earlier beliefs and blindly follow the crowd.

The review of empirical literature on herd behaviour revealed that various empirical models have been used to detect and measure herd behaviour. Five measures of herd behaviour were discussed which can be divided in two categories: the first analyses herding on a particular subset of market participant, it includes (1) the LSV and (2) PCM measures the other three use a market wide approach to detect herding; they are (3) the measure of beta herding, (4) the CH measure of herding and (5) the CCK measure of herding.

After applying the methodology, empirical results were presented. The results from GARCH-type models indicated the presence of herd behaviour at the JSE, given the fact that stock returns in the JSE exhibit volatility clustering. However, the results for asymmetric effect of news on conditional volatility were inconclusive.

To test the presence of herd behaviour directly, the CCK model was applied. It was established that herd behaviour is indeed present at the JSE. It was also revealed that herd behaviour is more prevalent during bull markets than during bear markets, that it is more intense during low trading volume than it is during high trading volume and that it is more prevalent during low market volatility than it is during high market volatility. Finally, using the ARDL approach to cointegration, it was shown that herd behaviour takes place with a lapse of time. However, the results revealed a high speed of adjustment, and it was conclude that herd behaviour at the JSE is a short-lived phenomenon.

6.2 POLICY AND INVESTMENT IMPLICATIONS

The current study found strong evidence of herd behaviour in the South African financial market. This is an indication that the JSE, in particular, is not efficient. Therefore the South African authorities should put in place policies that will help to prevent herd behaviour the JSE. These policies should involve:

1. Educating investors on how to make rational investments and how to detect false information in the market.
2. Creating policies and regulations that discourage irrational investors from distorting the efficiency of the financial markets.
3. Strengthening the control of the market and encouraging effective reporting of Companies' information.

4. Improving the information dissemination mechanism and making sure that investors can get enough information to prevent the spreading of misleading information.
5. Reviewing the compensation of institutional fund managers in order to avoid instances where their compensation and remuneration are tied to the performance of benchmarks.

6.3 LIMITATIONS AND SUGGESTED AREA FOR FURTHER RESEARCH

It was observed in Chapter 2 that there is no direct link between the theoretical arguments on herd behaviour and the empirical specifications used to test it. Empirical models on herd behaviour do not clearly demonstrate to what extent the statistical analysis can help to differentiate between ‘intentional’ and ‘spurious’(or unintentional) herding. Further research should focus on how to formulate new herding measures that will help to differentiate irrational from rational herd behaviour.

Herding behaviour on African financial markets remains under-researched. The current study only analysed herd behaviour on the South African stock market. Further studies should broaden the scope to include other African countries and a comparative analysis should be carried out to compare the similarities that might exist and are specific to African markets.

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