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Testing the influence of herding behaviour on the Johannesburg Securities Exchange

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Commerce (Finance) in the School of Business and Finance, Faculty of Economic and
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**UNIVERSITY of the
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i

Declaration

I, **Raramai Patience Munetsi** hereby declare that this thesis, titled, **Testing the evidence of herding behavior on the Johannesburg Securities Exchange**, is my own original work which has not previously been tendered by me for a degree at this or other university or institution, all materials contained herein have been duly acknowledged.

Raramai Patience Munetsi

November 2018



Dedication

I dedicate my thesis to Shine Muringai (Munetsi)



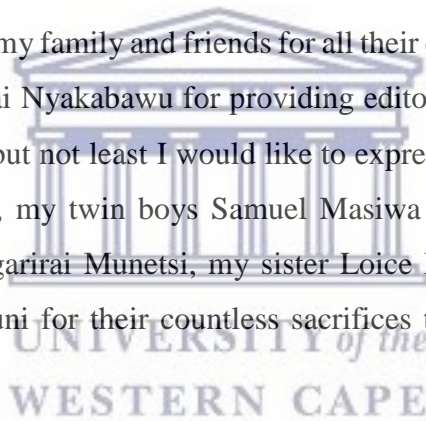
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Abstract

Since the discovery of herding behaviour in financial markets in the 1990s, it has become an area of interest for many investors, practitioners and scholars. Herding behaviour occurs when investors and market participants trade in the same direction during the same time period, as a result of the influence of other investors. Studies on herding behaviour have been undertaken in both the developed and developing economies and majority of these studies have confirmed the existence of herding behaviour in the stock markets. Despite its tremendous growth, the South African financial markets are not immune to such market anomaly.

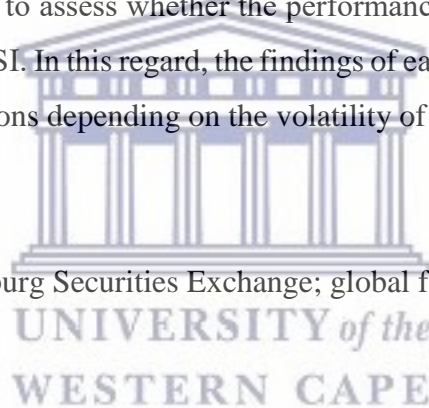
Herding behaviour on the JSE was first investigated in 2002 focusing in the unit trust industry on the South African stock market. Motivated by this, this study assessed the presence of herding behaviour using the Johannesburg Securities Exchange tradable sector indices. Four indices were employed, namely Financials, Industrials and Resources and were benchmarked against the JSE All Share Index for the period from January 2007 to December 2017. The industrials index ((FINI₁₅) constitutes of 25 largest industrial stocks by market capitalization, the financials index (FINI₁₅) comprises of 15 largest financial stocks by market capitalization, the resources index (RESI₁₀) which represents 10 largest resources stocks by market capitalization and lastly the FTSE/JSE All Share Index defined as a market capitalization-weighted index which is made up of 150 JSE listed companies and is the largest index in terms of size and overall value JSE. The FTSE/JSE All Share Index was used as a benchmark for investors to check how volatile an investment is.

The South African economy experienced the effects of the 2008 global financial crisis from 01 July 2007 to 31 August 2009. This study split the examination period into three categories namely before the global financial crises which was the period starting from 1 January 2007 to 30 June 2007, then the period during the global financial crisis which was from 1 July 2007 to 31 August 2009 and lastly the period after the global financial crises which was from 1 September 2009 to 31 December 2017. Apart from the diversity of the indices, the length of the examination period also had a significant influence towards the magnitude of herding behaviour on the JSE.

The study builds upon the efficient market hypothesis, portfolio theory and behavioural finance to provide evidence of the herding behaviour on the JSE tradable indices in an emerging market. The study adopted the conventional measures of herding behaviour by Christie and Huang (1995) and Chang, Cheng, and Khorana (2000). This research overall found evidence of herding behaviour on the indices RESI₁₀, INDI₂₅ and FINI₁₅ indices during the global financial crisis. Conversely no herding behaviour was documented during normal periods. These findings were also documented by was recorded by Angela, Miruna and Andreea (2015) on the study that was done on Czech Republic, Poland, Hungary, Romania and Bulgaria using the measure by Chang, Cheng, and Khorana (2000). The performance of the indices was compared against the JSE ALSI to deduce the cross-sectional standard deviation of returns and cross-sectional absolute deviation of returns. An in-sample composite return graph for the three indices was plotted against the benchmark which is the JSE ALSI index. Statistical inference was run in the form of a t-test to assess whether the performance of the indices is statistically significant against the JSE ALSI. In this regard, the findings of each time frame assists investors to make more informed decisions depending on the volatility of the markets.

Key words:

Herding behaviour; Johannesburg Securities Exchange; global financial crisis; bull markets; bear markets



List of Tables

Table 2.1 Comparison of the MPT models.....	26
Table 3.1 Names and codes of companies in the tradable sector indices from 2007 to 2017	69
Table 5.1 Average daily returns and standard deviations before the global financial crises...79	
Table 5.2 Average daily returns and standard deviations during the global financial crises...80	
Table 5.3 Average daily returns and standard deviations after the global financial crises.....80	
Table 5.4 Average daily returns and standard deviations for the whole period of study.....82	
Table 5.5: CSSD for the period before the global financial crises.....84	
Table 5.6: CSSD for the period during the global financial crises.....85	
Table 5.7: CSSD for the period after the global financial crises.....86	
Table 5.8: CSSD for the 11-year period of study.....87	
Table 5.9: CSAD for the period before the global financial crises.....92	
Table 5.10: CSAD for the period during the global financial crises.....93	
Table 5.11: CSAD for the period after the global financial crises.....94	
Table 5.12: CSAD for the 11-year period of study.....95	

List of figures

Figure 2.1 Forms of Efficient Market Hypothesis.....	11
Figure 2.2 Random Walk	14
Figure 2.3 Systematic and unsystematic risk.....	17
Figure 2.4 Minimum variance portfolio.....	20
Figure 2.5 Capital Market Line (most efficient portfolio).....	23
Figure 2.6 Security market line.....	24
Figure 2.7 Prospect theory.....	33
Figure 5.1: RESI Comparative returns for the 2007 to 2017 period.....	89
Figure 5.2: INDI Comparative returns for the 2007 to 2017 period	90
Figure 5.3: FINI Comparative returns for the 2007 to 2017 period.....	91



List of abbreviations and acronyms

ALSI	All Share Index
APT	Arbitrage Pricing Theory
BVB	Romanian Bucharest Stock Exchange
CAPM	Capital Asset Pricing Model
CASD	Cross-sectional absolute deviation of returns
CSSD	Cross-sectional standard deviation of returns
CML	Capital Market Line
E(r)	Expected Return
FDI	Foreign Direct Investment
FINI	SA Financial Index
FTSE	Financial Times Stock Exchange
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
ICB	Industry Classification Benchmark
IMP	Impact Developer and Contractor
INDI	SA Industrial Index
JSE	Johannesburg Securities Exchange
MAD	Mean Absolute Deviation
MPT	Modern Portfolio Theory
MV	Minimum Variance
NSE	Nepalese Stock Exchange
PMPT	Post Modern Portfolio Theory
RESI	SA Resources Index
SA	South Africa
S &P	Standard and Poor
STDEV	Standard Deviation
USA	United States of America

Table of contents

Abstract.....	v
List of Tables.....	vii
List of figures.....	viii
List of abbreviations and acronyms	ix
Chapter One – Introduction and Background	1
1.1 Research Background	1
1.2 Overview of the Johannesburg Securities Exchange	4
1.3 Problem Statement.....	5
1.4 Aim.....	6
1.5 Research objectives.....	6
1.6 Research questions.....	7
1.7 Justification of the study	7
1.8 Ethical statement.....	9
1.9 Structure of the dissertation	9
Chapter Two – Theoretical Overview	11
2.1 Introduction.....	11
2.2 Traditional Finance:	11
2.2.1 Efficient Market Hypothesis (EMH)	11
2.2.2 Random Walk.....	14
2.2.3 Modern Portfolio Theory (MPT)	15
2.2.4 Separation Theorem	22
2.2.6 Arbitrage Pricing Theory (APT)	25

2.2.7 Comparison of the MPT models	27
2.3 Rolls Critique	28
2.4 Behavioural Finance	29
2.4.1 Background of Behavioural Finance	29
2.4.2 Assumptions and attributes of behavioural finance	31
2.4.3 Prospect Theory	32
2.4.4 Limits to arbitrage.....	35
2.4.5 Overreaction Hypothesis and Investor Irrationality.....	35
2.4.6 Traditional Finance versus Behavioural Finance.....	36
2.5 Herding behaviour	38
2.5.1 Types of herding behaviour.....	39
2.5.2 Reasons for herding behaviour	40
2.5.3 Causes of herding behaviour.....	41
2.5.4 Consequences of herding behaviour	43
2.5.7 Herding behaviour on the Johannesburg Securities Exchange.....	43
2.6 Conclusion	45
Chapter Three – Review of Prior Literature	46
3.1 Introduction.....	46
3.2 Herding in the developed markets	46
3.2.1 Herding behaviour in developed markets during normal periods.....	46
3.2.2 Herding behaviour in developed markets during normal periods.....	50
3.3 Herding in the developing market.....	57
3.3.1 Herding behaviour in developing markets during normal periods	57
3.3.2 Herding behaviour in developing markets during periods of market volatility.....	59
3.4 Conclusion	65
Chapter Four – Research Methodology	67

4.1 Introduction.....	67
4.2 Research design	67
4.3 Possible Biases in Research and Their Remedies.....	69
4.5 Population / sample description and data sources.....	70
4.6 Data Collection	73
4.7 Data used and analysis.....	74
4.7.1 Data analysis	74
4.7.2 Herding during normal periods- pre and post global financial crisis.....	75
4.7.3 Herding during periods of market stress-during the global financial crisis.....	77
4.8 Conclusion	78
Chapter Five – Results and Analysis	79
5.1 Introduction.....	79
5.2 Restatement of research objectives	80
5.3 Results.....	80
5.3.1 Descriptive statistics	80
5.3.2 Descriptive statistics before the global financial crisis.....	81
5.3.3 Descriptive statistics during the global financial crisis.....	82
5.3.4 Descriptive statistics after the global financial crisis.....	84
5.3.5 Descriptive statistics for the entire study period.....	85
5.4.1 Herding behaviour on the JSE tradable indices	86
5.4.2 CSSD before the global financial crisis	86
5.4.3 CSSD during the global financial crisis.....	87
5.4.4 CSSD after the global financial crisis.....	88
5.4.5 CSSD for the entire period of study.....	90
5.4.6 Herding behaviour on the JSE indices during the global financial crisis period using CSAD.....	95

5.4.7 CSAD before the global financial crisis	95
5.7.8 CSAD during the global financial crisis	96
5.4.9 CSAD after the global financial crisis	97
5.4.10 CSAD for the entire period of study	98
5.5 Conclusion	99
Chapter Six – Conclusion	101
6.1 Introduction.....	101
6.2 Summary of findings.....	101
6.3 Significance of this research outcome to investors.....	102
6.4 Recommendations for future research	106
Chapter Seven - Bibliography.....	108



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Chapter One – Introduction and Background

1.1 Research Background

In developed and developing economies, the volatility of financial markets is a major concern to scholars, stock market investors and practitioners in the finance field. The South African (SA) financial market is not immune to such volatilities as it is integrated with other global markets. It is influenced by both micro and macro-economic factors such as inflation, interest rates, oil prices and exchange rates (Szczygielski & Chipeta, 2015). In this regard, these market volatilities tend to influence investors to follow each other's investment decisions in search for profitable returns.

Herding behaviour is a phenomenon that is found when investors follow each other's investment decisions. It can also be defined as the tendency by investors to imitate the actions of other market participants (Angela, Miruna & Andreea, 2015). This idea is located on the border between the theory of market efficiency and behavioural finance. The theory of market efficiency coined by Fama in 1960 is the base of most financial literature and will be discussed in detail in chapter two. The market efficient hypothesis is based on the idea that prices of a stock fully reflect all new information. Even when an uninformed investor buys a diversified portfolio at a price given by the market, returns obtained will be as generous as those achieved by the investment experts (Gupta, Preetibedi & Poonamlakra, 2014).

Critics emerged to counter this school of thought with the behavioural aspect of investors in the stock market to expose the irrationality of capital market participants (efficient market hypothesis). They revealed that there is a psychological principle on investor's decision making, which is decisions to buy or sell stocks (Gupta, Preetibedi & Poonamlakra, 2014).

Herding behaviour is a branch of behavioural finance. Herding behaviour is a mindset that is described by the lack of individual decision-making, causing investors to think and act in the same way as the majority of those around them (Bikhchandani & Sharma, 2001). Herding behaviour was exhibited in the 1990s when private investor's excitedly invested large amounts of money into internet related companies (Bikhchandani & Sharma, 2001). This was done

irrespective of the financial performance of the companies. Boortz and Jurkatis (2013) assumed that the driving force was the reassurance the investors got from seeing so many other market participants doing the same thing. Another good example to explain herding behaviour is when Warren Buffett buys a stock, it is reported as news, and that news affects the stock prices. The impact of such news may be rational, but investors are often regarded as irrationally because of the presence of the herding behaviour (Hirshleifer & Hong Teoh, 2003).

Ouarda, El Bouri and Bernard (2013) argue that since behavioural finance assumes that investors are irrational and markets are inefficient, herding behaviour has different types of irrationality which reflects why investors tend to follow what others do. These two forms are irrational and rational herding behaviour. Irrational herding behaviour refers to a set-up of collective actions that are taken by an investor in uncertain market conditions. Irrational behaviour occurs when traders ignore the information available to them, and refuse to make their own decisions, in order to follow the conclusions of others, even if they do not agree (Christie & Huang, 1995). Investors benefit from such behaviour since it reduces the uncertainty and the fear of the unknown that some investors possess (Devenow & Welch, 1996). Rational herding behaviour is seen in situations where investors, are unable to fulfill their expectations and then replicate the actions of investment experts they believe to be better informed. These investment experts are believed to possess a source of more reliable information, which makes the investors to obtain returns above the market (Demirer & Kutan, 2006).

This research focuses on the rational herding behaviour and provides an analysis of herding behaviour on the JSE tradable indices. Amongst the 22 African stock exchanges the Johannesburg Securities Exchange is the biggest. It is among the top 20 security markets in the world JSE (2017) and more than 800 securities with different risk-return characteristics trade daily on the JSE equity market (JSE, 2018). In 2017 the JSE stock market recorded number of trades that amounted to 26 081 with a yearly reported volume of 5 359 000 000 (JSE, 2017).

JSE has a wide range of products and services which include commodities, currencies and resources. The JSE sector indices provide an easy way to determine the overall performance of

the stock market or a segment of the stock market over a period of time (JSE, 2017). Of all the indices on the JSE the Top40 index is the largest. It comprises of 40 largest listed companies on the JSE by market capitalization (JSE, 2017). The JSE has a number of sub-indices such as the Mid Cap, Small Cap and Tradable indices. The MidCap index comprises stocks ranked from 41 to 100 on the market by market capitalization, after the Top40 index. Small caps are the companies with values smaller than the top 100 listed companies by market capitalization. The tradable indices which include the industrials index (INDI₂₅) constitutes of 25 largest industrial stocks by market capitalization, the financials index (FINI₁₅) comprises of 15 largest financial stock by market capitalization and lastly the resources index (RESI₁₀) which represents 10 largest resources stocks by market capitalization.

With so many investments opportunities to choose from and also so much trading activities, an average investor may face challenges in order to decide where to invest (Baker & Haugen; 2012; Blitz & van Vliet; 2007; Haugen & Baker, 1991; Jagannathan & Ma, 2003). In order to make the process of choosing an investment simple, investors can consider the past and present performance of the desired stock. However, a challenge comes in not knowing whether the stock will produce profitable returns (Lombard; 2015). In order to rectify this a benchmark normally represented by a market index can be used to evaluate the performance of the chosen investment (Elton & Gruber, 1999; Lombard, 2015).

This study uses a market index as the FTSE/JSE All Share Index (ALSI), defined as a market capitalization-weighted index which is made up of 150 JSE listed companies and is the largest index in terms of size and overall value (JSE, 2017). This index was formed after JSE had tied up with the London FTSE to form the JSE/FTSE indices. The companies included in this index constitutes to the top 99 percent of the total pre free-float market capitalization of all listed companies on the Johannesburg Securities Exchange (JSE, 2017).

The FTSE/JSE All Share Index as a benchmark for investors assisted this research to check how volatile an investment is and the investment's performance against a benchmark (Lombard, 2015). According to Cairns (2016), the volatility of the SA market as measured by the South African Volatility Index (SAVI) for the period 2007 to 2016 ranged from as low as

12 to 60 and this high volatility of the SA market is due to the weakening rand, political instability and a series of rating downgrades recently.

1.2 Overview of the Johannesburg Securities Exchange

The JSE was formed on 8 November 1887 after the discovery of gold in Witwatersrand to raise the ample desired capital to invest in the mining sector (Smith, Jefferis & Ryoo, 2002). The first trading done on the JSE started in a small tent which was later upgraded to an automated electronic trading system in the early 1990s. Back then the JSE was known as Johannesburg Stock Exchange because only shares were being traded, but in 2000 it changed its name to Johannesburg Securities Exchange (JSE, 2017). To date, the JSE is among the world's top twenty largest stock markets with a market capitalisation \$1,007 billion at the end of 2013.

Among the developments of the JSE is its agreement with the London Stock Exchange in 2001, which permitted the cross-trading between the two securities exchanges (JSE, 2014). This was followed by the acquisition of the Bond Exchange of South Africa (BESA) in 2009 which formed debt market has allowed in the inclusion of South African government and corporate bonds as well as interest rate derivatives on the JSE. In 2012, the JSE together with other exchanges founded the United Nations Sustainable Stock Exchanges as an initiative to explore how exchanges can operate with stakeholders such as investors, regulators and companies so as to create more conducive capital markets. The JSE was re-branded in 2017 in order to show its identity as a modern African securities market that links investors to growth opportunities in both the SA market and the global market. In 2017 the JSE also changed its logo following the re-branding (JSE, 2017).

According to the Industry Classification Benchmark (ICB), the SA sector categorizes all listed instruments into one of three sectors, namely Resources, Financials and Industrials, based on their revenue (JSE, 2017). As mentioned earlier, the industrials index (INDI₂₅) constitutes of 25 largest industrial stocks by market capitalization, the financials index (FINI₁₅) comprises of 15 largest financial stock by market capitalization and lastly the resources index (RESI₁₀) which represents 10 largest resources stocks by market capitalization. JSE (2017) shows that the industrial sector is the most represented sector in terms of market capitalization on the JSE.

This research will focus on the JSE tradable indices which are RESI₁₀, FINI₁₅ and INDI₂₅.

1.3 Problem Statement

Financial research incorporates human behaviour in describing the actions of investors in financial markets. Herding behaviour is a behavioural anomaly which defies the efficient market hypothesis. Herding behaviour is known to influence the investors buy and sell decisions. It has implications on investor trading, financing choices, managerial investment, market prices and market regulation. Investors are shown to follow herding behaviour because they undertake risky speculations without adequate information and appreciation of the risk-reward trade-offs (Demirer & Kutan, 2006).

Friedman (1953) first examined the relationship between investor behaviour and market volatility, arguing that irrational investors destabilize stock prices. Irrational investors are believed to buy stocks when the prices are high and sell when the prices are low which is in contrast to rational investors that buy low and sell high (Messis & Zapranis, 2014). According to De Long, Shleifer, Summers and Waldmann (1990), the presence of irrationality on investors in financial markets can increase price volatility and the risk related with investing. In addition, Froot, Scharfstein, and Stein (1992) demonstrates that investors imitate one another by this means increasing the instability in the financial markets. Wang (1993) accounts that uninformed investors are likely to follow the market trend and such behaviours are considered to be the same as herding.

On the JSE, Seetharam and Britten (2013) studied the impact of herding behaviour on the market cycle focusing on the assumption that herding behaviour dramatically fluctuated before a market contraction. Monthly data was collected for all shares listed on the JSE and the All Share Index (ALSI) from 1995 to 2011. Seetharam and Britten (2013) found evidence that a negative market reaction was led by an increase in herding during a South African market contraction. Ababio and Mwamba (2017) examined evidence of herding behaviour on South Africa's financial industry. They collected data from January 2010 to September 2015 and used the quantile regression model in order to evaluate the effects of herding behaviour. Results

showed evidence of herding behaviour in the banking and real estate sectors during the sample period.

Angela, Miruna and Andreea (2015) note that nothing has been tested on the JSE Limited tradable indices. After the occurrence of global financial crisis, herding behaviour could cause stock prices to deviate from their fundamental value. The presence of herding behaviour could provide useful information for financial models that are used to estimate evolution of stock prices. Research by Ababio and Mwamba (2017) showed that real estate sector investors presented herding behaviour to be present during periods when the market is rising. Angela, Miruna and Andreea (2015) show that investors followed herding behaviour more during periods of downward trend. This research focuses on herding behaviour on the JSE focusing on the tradable indices. It looks at the presence of herding behaviour before global financial crisis, during global financial crisis and after global crisis. This study uses the convectional measures namely the Cross-sectional standard deviation of returns measure by Christie and Huang (1995), and Cross-sectional absolute deviation of returns measure by Chang et al. (2000) to analyze if the herding behaviour was evident on the JSE tradable indices.

1.4 Aim

The aim of the study is to investigate whether investors follow herding behaviour based on the SA tradable sector index namely the industrials index (INDI₂₅), the financials index (FINI₁₅) and lastly the resources index (RESI₁₀). The measures of herding behaviour by Christie and Huang (1995) and Chang et al. (2000) used to determine the presence of herding behaviour on the JSE tradable indices using JSE ALSI as a benchmark for comparison and results analysis.

1.5 Research objectives

In order to guide this study, the following research objectives are stated:

1. To establish whether the JSE tradable sector index (RESI₁₀, INDI₂₅, FINI₁₅) had evidence of herding behaviour before the global financial crisis
2. To establish whether the JSE tradable sector index (RESI₁₀, INDI₂₅, FINI₁₅) had evidence of herding behaviour during the global financial crisis

3. To establish whether the JSE tradable sector index (RESI₁₀, INDI₂₅, FINI₁₅) had evidence of herding behaviour after the global financial crisis

1.6 Research questions

1. Does evidence of herding behaviour exist on the JSE tradable indices (RESI₁₀, INDI₂₅, and FINI₁₅) before the global financial crisis during the study period 2007 to 2017?
- 2 Does evidence of herding behaviour exist on the JSE tradable indices (RESI₁₀, INDI₂₅, and FINI₁₅) during the global financial crisis during the study period 2007 to 2017?
- 3 Does evidence of herding behaviour exist on the JSE tradable indices (RESI₁₀, INDI₂₅, and FINI₁₅) after the global financial crisis during the study period 2007 to 2017?

1.7 Justification of the study

The issue that investors follow herding behaviour is the rationale for carrying out this research (Nofsinger & Sias, 1999). Herding behaviour is related to investor's psychology in which different investors follow each other in the financial world rationally or irrationally. The existence of herding behaviour shows that markets are inefficient. Asset prices may be misleading and the markets are inefficient and enough consideration should be taken by local and foreign investors in order to attain a higher number of securities to diversify their investment (Sarpong & Sibanda, 2014).

Studies conducted by Ababio and Mwamba, (2017) also presented evidence that herding behaviour is present in financial markets and it influences how investors buy and sell stocks. The implication of this study was therefore to determine if herding behaviour existed at the JSE before the global financial crisis, during the global financial crisis and after the global financial crisis using the three major JSE tradable sector indexes. This study makes a comparison with the JSE ALSI as a benchmark. The global market crash in 2008 affected the JSE stock performances (Venter, 2011). The outcome of this study will provide investors with the knowledge on the influence of herding behaviour and this will ultimately help investors when making investment decisions.

According to Coetzee (2017), the SA local index performance for the last 10 years recorded that the INDI₂₅ index (25 largest industrial stocks on the JSE) outperformed major global markets and even the S&P500 (an American stock market index which is based on the market capitalizations of 500 large companies having common stock listed on the NASDAQ) by 143 percent. Coetzee (2017) documented that the FINI₁₅ index (comprises of 15 largest financial stocks) gained 34.4 percent in its overall performance while the SA-listed property retained 87.9 percent of its value. Conversely, the RESI₁₀ index (which represents 10 largest resources stocks) lost 59.9 percent of its overall performance over the past decade. With such a performance trend of the local indices, it is essential for this research to investigate if these indices performances are in any way influenced by herding behaviour.

Furthermore, investigating herding behaviour aids to analyze the more complex elements of the market by identifying biases in human behaviour and using such findings to explain some of the observed anomalies such as market crashes (Dangi & Rathore, 2011). Research that has been done both in developed and developing economies has showed overwhelming evidence that investors make major systematic inaccuracies and there is evidence that psychological biases affect market prices significantly (Dangi & Rathore, 2011).

Studies of herding behaviour on the SA stock market had been done focusing on component indices, mutual funds, financial industry and property industry and found herding behaviour present (Gilmour & Smit, 2002; Seetharam & Britten, 2013; Sarpong & Sibanda, 2014; Ababio & Mwamba, 2017). This research deviates from the empirical studies on the JSE by focusing on the JSE tradable sector indices. South Africa tradable sector indices are a representation of all the JSE listed instruments, classified according to their sector categories, which are Resources (RESI₁₀), Financials (FINI₁₅) and Industrials (INDI₂₅) (JSE, 2018). Using the JSE tradable sector indices will permit a comprehensive investigation of the performance of JSE stocks as a whole. The present study focuses on three different market volatility periods in South Africa namely before, during and after the global financial crisis period in order to capture herding behaviour during different market periods. In order to address this hypothesis, two major testing measures (cross-sectional absolute deviation of returns and cross-sectional

standard deviation of returns) of herding behaviour by Christie and Huang (1995) and Chang et al. (2000) are used.

1.8 Ethical statement

The main purpose of the study is not to make any critical remarks against any investor. Since information on JSE ALSI index constituents are publicly available and the study does not use private information, there are no major ethical issues that arise during the study.

1.9 Structure of the dissertation

The rest of the dissertation is structured as follows:

Chapter 2: Theoretical Overview

This chapter opens by discussing the basic theory of the Markowitz model and explain the derivation of behavioural finance and ultimately leading to herding behaviour, its causes and consequences.

Chapter 3: Literature review

Chapter three reflects on the past studies that were done both in developed and developing markets on herding behaviour, leading to studies that have been done the JSE.

Chapter 4: Research methodology

The chapter discusses the methodological issues employed to achieve the stated objectives, the data employed, as well as the measures on how to calculate herding behaviour. Daily data of closing share prices of the main three tradable sector indices on the JSE was collected as well as the JSE ALSI, which was used as a benchmark. Research objectives were restated and potential research biases relating to this study will also be discussed in this chapter.

Chapter 5: Research findings and discussion

This chapter presents descriptive statistics, results on the analysis of herding behaviour during normal periods and periods of market stress. Also empirical findings on herding behaviour in both international and domestic economies were discussed in relation to the findings of this research.

Chapter 6: Conclusion

The final chapter concludes the study. It presents a summary of findings from the examination results performed in this research and ends by proffering recommendations, the significance of this study and suggestions for further research.



Chapter Two – Theoretical Overview

2.1 Introduction

This chapter discusses the theoretical underpinnings of herding behaviour starting from the efficient market hypothesis (EMH) until behavioural finance leading to herding behaviour. Behavioural finance is the study of the influence of psychology on investors and how they invest as a result of thereof. Behavioural finance arises due to the inefficiency of the Capital Asset Pricing Model (CAPM) which was developed from the Efficient Market Hypothesis (EMH) (Malkiel, 1989). Behavioural finance helps explain how and why markets might be inefficient and herding behaviour is a branch of behavioural finance. This chapter discusses the logical development of herding behaviour, traditional and behavioural finance with a rational and irrational explanation as to why they both exist. Lastly, this chapter will discuss how behavioural finance leads on to the development of herding behaviour.

2.2 Traditional Finance:

Traditional finance explains financial markets using mathematical models that assume the rationality of investors. Nofsinger (2001) states that the field of finance has progressed over the past years based on the assumption that investors make rational decisions. A rational investor is defined as an investor that always makes choices that are normatively acceptable and upgrade their knowledge consistently with new information (Thaler, 2005). Traditional finance consists of Efficient Market Hypothesis (EMH), Random Walk and Modern Portfolio Theory. To elaborate on the development herding behaviour this chapter will start by discussing EMH and all its forms, CAPM, Rolls Critique on CAPM and the Arbitrage Pricing Theory (APT).

2.2.1 Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH) theory was introduced by Eugene Fama in 1960. This school of thought is central to all financial literature and is used by both academics and practitioners. EMH postulates that it is impossible for market participants to outperform the market in a consistent manner and earn abnormal risk-adjusted returns (Malkiel, 1989). It

contends that markets are efficient and current prices reflect all information, therefore attempts to outperform the market are a game of chance rather than a skill (Fama & French, 2004). With the objective of wealth maximisation, investors use all accessible information when trading securities. As a result, stocks always trade at their fair value on the market exchange thereby eliminating opportunities of arbitrage (Fama & French, 2004). LeRoy (2010) argues that it is impossible to beat the market on a constant basis through stock selection or market timing variables and the only way investors can obtain higher returns is through acquiring riskier stocks. This is because investors are rational and they are compensated for the amount of risk they bear.

2.2.1.1 Forms of EMH

Fama (1970) suggests that a stock price fully reflects all information at any given time as markets are efficient. Efficient Market Hypothesis (EMH) exists in three forms which are the strong, semi-strong and weak.

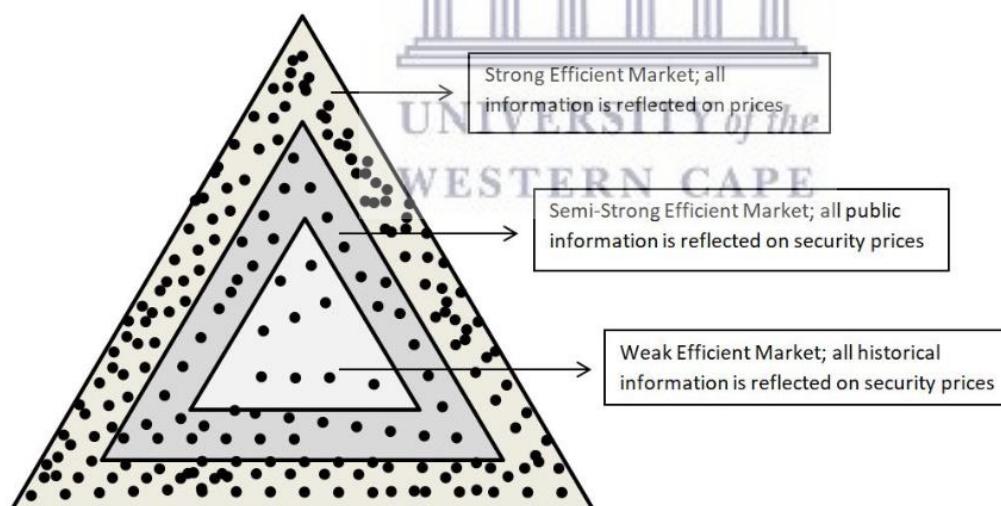


Figure 2.1: Forms of Efficient Market Hypothesis

Source: Timmermann and Granger, (2004)

The diagram above presents the detailed sequence of these levels of market efficiency. The first form of market efficiency, the weak-form of EMH implies that the market is efficient, based on historical information. Stock prices are believed to reflect all information, derived by

examining market trading data such as the history of past prices and trading volumes (Malkiel, 1989). This form of EMH stresses that trend analysis commonly used by technical analysts is ineffective because it cannot be used to predict and outperform the market. Technical analysis uses charts and trading volumes when deciding which stocks to purchase. If there are signals of market inefficiencies, investors would have found them and exploited them, resulting in movements in the shares price towards its intrinsic value (Fama, 1970). The rates of return on the market should be independent, meaning the past rates have no effect on future rates. With the help of the numerous techniques, technical analysts attempt to time the markets and sell or buy stocks when stocks are considered to be overbought or oversold, in relation to the overall market trends. Goodspeed (2013) agrees with Marshall and Cahan (2005) that technical analysis, involves observing and analyzing past asset price series and trading volume data in attempt to gain from periodic deviations in these trends. By these definitions, technical analysis can be seen to fall under the weak form of the EMH.

The second form of market efficiency, the semi-strong form states that all publicly available information concerning the prospects of a firm is reflected in the stock price. This information also incorporates the weak-form hypothesis. Semi strong form uses fundamental data on the company's product which include quality of management, balance sheet structure, patents, earning forecasts, and accounting practices amongst others. This implies that a fundamental analyst, who analyses macro-economic variables and the firm's performance, will not be able to beat the benchmark on a consecutive basis. Warren Buffet uses his entrepreneurship skills to find mispriced securities so as to outperform the market (Bruner, 2003).

The last and final form of market efficiency, strong-form of EMH views the market as efficient, reflecting all information both public and private. It incorporates the weak-form EMH and the semi-strong form EMH (Fama, 1992). Strong form, suggests that corporate insiders and specialists have access to pertinent information long before it is publicly released, and enables insiders and specialists to gain from trading with the information. The Securities and Exchange Commission (SEC) is directed toward preventing insiders from profiting by disabling their advantaged position (Malkiel, 1989). Thus, trading by all corporate officers, directors and owners is required to be reported to the SEC. Although there is evidence that contradicts EMH

whereby specialists use controlling information to earn profits. Fama (1970) proves that management of mutual funds do not earn abnormal returns, the fund risk-reward is below market line over the period. As stated by efficient market hypothesis under the weak form that past and future returns are independent and evenly distributed, that is past and future returns are not correlated. This belief agrees to the idea of the random walk model. Fama (1970) supports that the theory of random walk leads to the evidence of weak-form EMH.

2.2.2 Random Walk

The random walk theory argues that stock price changes are independent of each other and as a result, the past trend of a stock price cannot be used to predict its future movement (Kendall, 1953). The theory of random walk supports the efficient market hypothesis's weak form which argues that stock markets are believed to be efficient since the historical information of the stock price is available to all investors. Thus, individuals that buy and sell stocks consist of a large number of rational investors with access to this information (Van Horne & Parker, 1967).

Kendall (2005) argues that stock prices follow a random walk because investors cannot predict the future market prices of a stock. In other words, the price changes are independent of another. Past news or information does not influence stock prices tomorrow (Fama, 1965). Applying the random walk theory to finance and stocks suggests that a follower of the random walk theory believes it's impossible to outperform the market without assuming additional risk. This complements what advocates of the efficient markets suggests that it is impossible for an investor to constantly outperform the market. Below is graph that shows how stock prices are random:

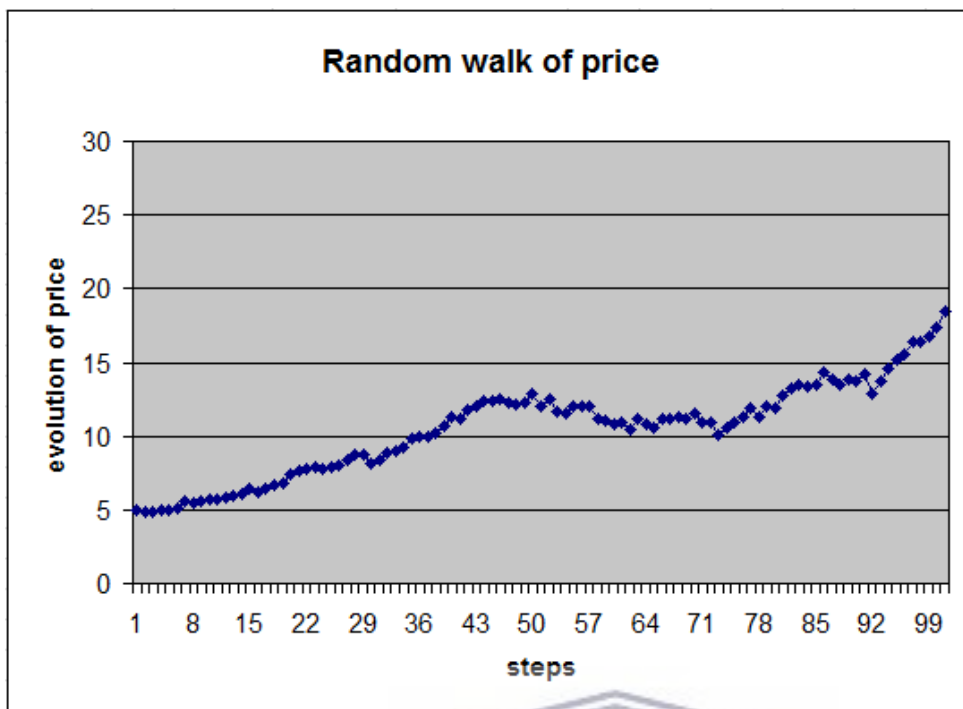


Figure 2.2: Random Walk

Source: Lo and MacKinlay, (2002)

The graph above shows that stock price trends are independent of each other. In other words stock prices follow a random walk. Since the past price movements of a stock price cannot be used to predict its future movements, this complements the notion of market efficiency that stock prices disclose all relevant information on that particular day.

Some scholars argue that there is no distinct difference between the random walk theory and the efficient market hypothesis. However, LeRoy (1973) and Lucas (1978) suggest that there is a clear distinction between the two. The distinction comes from one of the central ideas of modern financial economics mentioned above, the necessity of some trade-off between risk and expected return. Furthermore, prices move only with the introduction of new information and this information is random and unpredictable (Jiang & Tian, 2012)

2.2.3 Modern Portfolio Theory (MPT)

The Modern Portfolio Theory is a passive portfolio management approach based on the portfolio risk-return profile for portfolio selection and construction, constituting three portfolio theories (Garaba, 2000; Vukovic & Bjerknes, 2017). These three theories include the mean-

variance analysis (MVA) by Markowitz (1952), the CAPM independently developed by Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966) as well as the arbitrage pricing theory (APT) by Ross (1976). The pioneering research by Markowitz (1952) on portfolio optimisation qualified him to be the father of modern portfolio theory (Darko, 2012). The research by Markowitz is considered as the foundation of portfolio optimisation. In this regard, Markowitz's MVA is explained as the root theory of MPT, followed by Tobin's (1958) separation theorem, which extends upon the works of Markowitz. In order to cater for the shortcomings of the previous theories, the CAPM was introduced and lastly, the APT, which forms the final block of the MPT.

Markowitz (1952) is the pioneer of MPT, which was the first theory to include risk into the portfolio management process. A combination of diversification for risk reduction and efficient capital markets resulted in an increase in expected returns of a portfolio. The MPT theory placed portfolio selection scenario into steps starting with observing and experiencing and ending with the belief in the future performance of available stocks. The second step on the MPT theory began with relevant beliefs about prospect performance and ends with selection of assets that would be incorporated into a portfolio. Markowitz (1952) developed the efficient frontier, with the function to maximise expected returns at the given level of risk in a portfolio. In order to manage portfolio, risk investors should include a proportion of risk-free assets into their portfolio to ensure a certain level of return. This usually is a risk free asset which has a high level of liquidity with almost no chance of defaulting. Any point on the efficient frontier that contains both risky and risk free assets is referred to as the optimal portfolio. This allows investors to select portfolios with high expected returns given a certain level of risk (Markowitz; 1952).

Prior to Markowitz's work, the calculation of the rewards and risks of portfolios was carried out through the analysis of specific securities individually. By formalizing the concept of diversification, Markowitz suggested that investors should focus on selecting portfolios based on their joint risk-reward features instead of merely compiling individually attractive securities (Bera & Park; 2008). Using past returns of each asset on a portfolio and statistical measures

such as standard deviation and average return, the expected return and volatility of any portfolio is constructed. Markowitz used volatility and expected return as proxies for risk and reward.

Previously MPT investors used to calculate performance of individual securities based on judgement and experience. The standard pattern for investing was to construct a portfolio by first identifying the securities that hold great probabilities for gain with the low risk chances (Brown, 2012; Marx, Mpofu, De Beer, Nortje & Van de Venter, 2010). In this regard, investors would think that bank stocks have good risk return characteristics and construct an entire portfolio using only the bank stocks. By doing so, the investors will be omitting the effect of unsystematic risk which can be eliminated by diversification. With the vastness of securities available on stock markets, it can be tedious and challenging for investors to pick stocks individually that would yield the investors' desired outcomes.

The MPT theory hypothesises on diversification benefits (Joshiyura & Joshiyura, 2015). By formalising the concept of diversification, Markowitz proposes that investors should consider portfolios based on their collective risk - return characteristics rather than focusing on individual securities without considering how they will perform collectively as a portfolio (Brown, 2015). According to Markowitz (1952), the process of selecting a portfolio can be divided into two stages. The first stage deals with observation, experience and ends with the beliefs about the future performances of available securities. The second stage on the other hand started with the relevant beliefs about future performances and ends with choice of portfolio. Therefore, the collective performance of assets in a portfolio can be estimated by using the individual assets historical returns, the standard deviation and their covariance to calculate the portfolio risk and return. Joshiyura and Joshiyura (2015) note that since return and risk (mean and variance) relationship is the main backbone of this theory, the model was then referred to as the mean- variance portfolio model.

There are two types of risk namely systematic and unsystematic risk (Rutterford & Sotiropoulos, 2016). Systematic risk is related to an economy as a whole and macro in nature for example inflation and interest rate (Rutterford & Sotiropoulos, 2016). Systematic risk is also referred to as undiversifiable risk since nothing can be done by investors in order to reduce

systematic risk. Conversely, unsystematic risk is firm specific and is also referred to as diversifiable risk (Fragkiskos, 2014). Diversification can be used to eliminate unsystematic risk (Markowitz, 1952). According to the MPT theory, as the number of securities in a portfolio increase, the level of portfolio risk decreases (Yahaya, Abubakar & Garba; 2011). This can be diagrammatically presented in Figure 1 below:

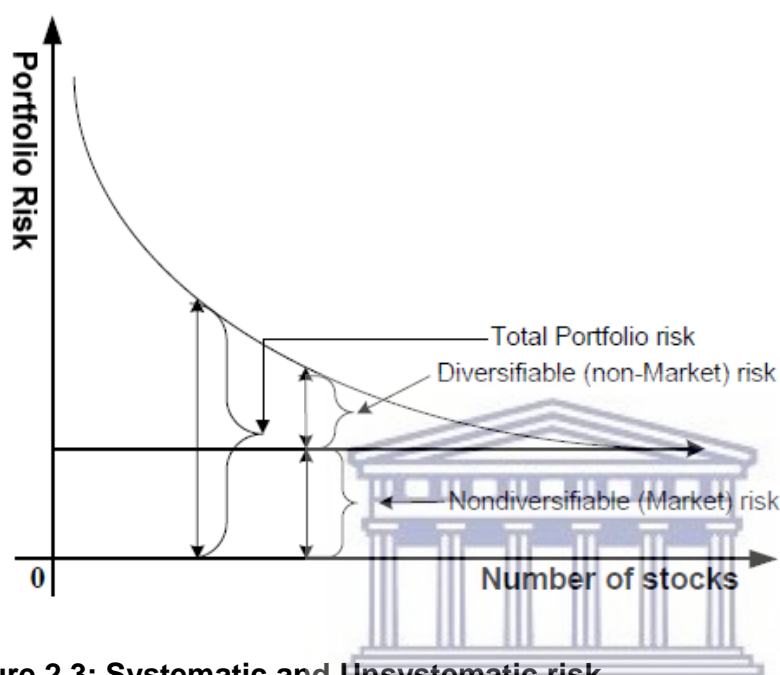


Figure 2.3: Systematic and Unsystematic risk

Source: Yahaya *et al.*, (2011)

The graph above shows that portfolio risk is made up of both systematic and unsystematic risk. From the graph, diversifiable risk is subjective to the risk appetite of the investor and non-diversifiable risk is constant to every investor irrespective of the risk appetite. Markowitz (1952) argued that for diversification to be effective, there must be a correlation between the different investment vehicles, thus the securities in a portfolio must have a different reaction to certain market events. In order to obtain superior diversification benefits investors should select assets from different industries and asset classes that are uncorrelated (Popina & Martyniuk, 2016). Different asset classes such as bonds and stocks react differently to hostile negative market events. The sensitivity of the entire portfolio will be reduced as a favourable movement in one asset class will offset an unpleasant movement in another asset class. Thus the more uncorrelated the stocks are, the less the portfolio risk (Popina & Martyniuk, 2016).

Markowitz (1952) notes that the law of large numbers states that an investor can diversify many several assets at the same time maximising returns whereby the actual return of the portfolio will be almost the same as the expected return. In other words, the rule argues that there is a portfolio which gives a maximum return at the same time having a minimum variance. However, Markowitz overlooked the rule based on the fact that the portfolio with the maximum return is not necessarily the one with the lowest variance hence diversification does not eliminate portfolio risk exclusively since there is always systematic risk which cannot be diversified away (Markowitz, 1952).

2.2.3.1 Expected return measurement - The Capital Asset Pricing Model (CAPM)

The value of a security is best evaluated by its mean, variance, and its correlation to other securities in a portfolio (Markowitz, 1952). Optimal results within an infinite number of possible alternatives that an investor has to construct a portfolio can be yield by balancing the risk and return features of the portfolio.

Portfolio return refers to the anticipated earnings generated from the invested securities. Markowitz (1999), Mossin (1966), Sharpe (1964) and Lintner (1965) all independently contributed towards the development of CAPM which is an extension on Markowitz's (1952) portfolio theory. CAPM is a one-factor model which illustrates the relationship between risk and return associated with assets within a portfolio. It is constructed with an understanding that diversifiable risk is mitigated through diversification therefore an investor's portfolio is only exposed to its market risk.

CAPM builds on the Markowitz mean, variance and efficiency model in which focused on risk-averse investors. These investors choose only efficient portfolios with maximum expected return with minimum variance. CAPM believes that unsystematic risk can be mitigated through diversification (Hsieh & Hodnett, 2012; Sharp, 1964; Lintner, 1965; Mossin, 1966). Investors only require to be rewarded for bearing systematic risk. Systematic risk is measured by beta (β) which is the sensitivity of either assets or portfolios returns in relation to the market and has a market beta of 1. This implies that stocks with high beta coefficients are subject to higher risk and higher expected returns compared to those with low betas. However, investors have

different degrees of risk aversion and adjust their exposures by altering their proportions invested in risk-free and risky assets. According to Markowitz (1999) the assumptions of CAPM are listed below:

1. The wealth of individual investors is small in comparison to the market, which means an individual investor cannot impact prices with trades.
2. Investors plan for identical holding period (no rebalancing during the period).
3. The investment universe is limited to that of publicly traded financial assets.
4. Investors pay neither tax nor transaction costs.
5. All portfolios are constructed on basis of the efficient frontier and they are seen as mean-variance optimizers.
6. All investors analyse securities similarly and share the same economic view of the world which results in investors holding the same approximations of the probability distribution of future cash flows from investing in the available securities.

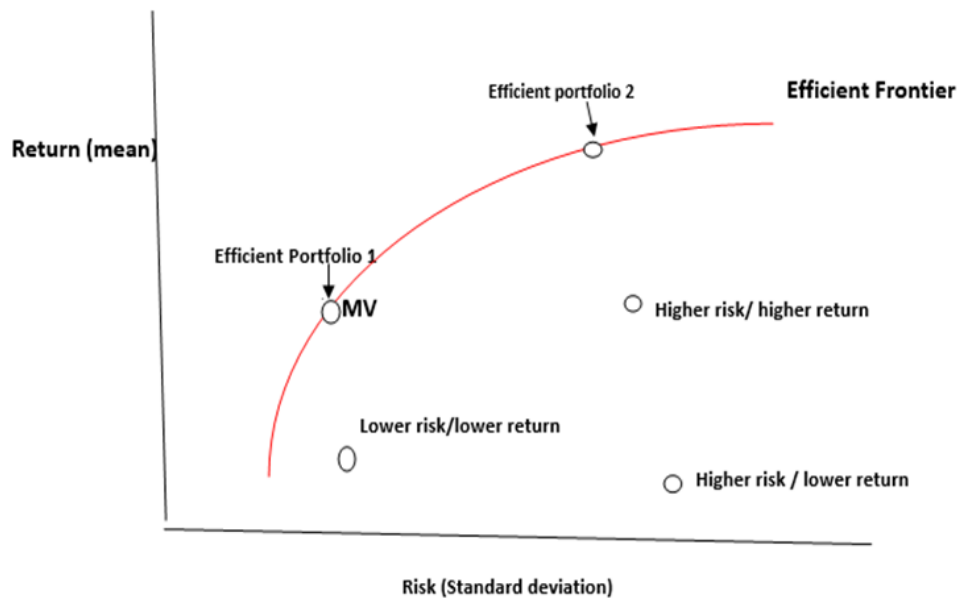
All investors' use the same expected returns, standard deviations and correlations to generate the efficient frontier and the unique optimal risky portfolio. Its computation comprises finding the weighted average return of securities included in a portfolio by multiplying individual securities by their respective weights (Nawrocki, 1999).

2.2.3.2 Variance and covariance calculation

Markowitz (1999) states that the portfolio variance (risk) is a measure of how returns of a set of securities constituting a portfolio fluctuate and deviate from the expected rate of return, that is the chance of unfavorable events happening. Covariance is a measure of how the assets in a portfolio can move in relation to each other Markowitz (1959).

The portfolios constructed in this optimal manner follow Markowitz's efficient frontier. Any point below the efficient frontier is attainable and efficient; however, portfolios below the frontier are inefficient. Depending on the investors risk averse they should select a portfolio that lies on the efficient frontier. Below is an example of the efficient frontier

Y



X

Figure 2.4: Minimum variance portfolio

Source: Ayodeji and Ingram (2015:44)

The graph above shows that investors with low risk appetite will invest in efficient portfolio 1 on the efficient frontier and conversely investors with high risk appetite will invest in efficient portfolio 2. The essence of MPT is that even very risky assets can reduce a portfolio's total risk if the covariance of returns between the risky asset and other assets in the portfolio is low. A vital assumption of Minimum Variance Portfolio is that all investors desire to maximize return and minimize risk. Markowitz's work established that a mean-variance efficient frontier exists for any collection of risky assets. Thus rational investors tend to choose their optimal portfolios along the efficient frontier depending on their personal risk tolerances and preferences (Msimanga, 2010).

Additionally, there is a rule which implies that an investor should diversify and maximise expected return. The rule states that an investor does or should diversify their portfolio amongst various securities which would in return produce maximum expected return. However, the expected or anticipated returns rule is insufficient alone. If the returns from securities are too

inter-correlated diversification cannot eliminate all variance. Markowitz (1952) states that one should consider the expected returns-variance (E-V) rule. The E-V rule states that an investor should or does want to select a portfolio which gives rise to the E-V, which are those portfolios with minimum Variance (V) for a given Expected return (E). This hypothesis implies the right kind and reason of diversification, and shows the necessity of avoiding to invest in securities with high covariance among themselves. Sharpe (1964) states that in equilibrium, capital assets prices have adjusted so that an investor, if he follows rational procedures such as diversification, is able to obtain a desired point along the Capital Market Line (CML). An investor may gain a higher expected return by acquiring additional risk.

2.2.4 Separation Theorem

In 1958 Tobin extended on Markowitz's work by adding a risk-free asset to the analysis. This theory is referred to as called the Separation Theory. Tobin assumed that by adding a risk free asset such as a government asset to a portfolio, it is possible to outperform a risky portfolio in terms of both risk and return. In this regard if an investor seeks to avoid risk they can lend at the risk-free rate and if the investor is risk seeking, they can borrow at the risk-free asset rate and invest into market at their desired level of risk (Kroll & Levy, 1992).

The Separation theory proposes that investors should separate their portfolios choices by identifying the mean-variance efficient risky portfolio, also known as the market portfolio and allocating capital to a combination of the risk-free asset and the market portfolio (Kroll & Levy, 1992). By combining a risk free asset with a portfolio on the efficient frontier, a portfolio with superior risk-return profiles as compared to those on the efficient frontier can be constructed. Tobin (1958) argues that using the risk free asset, investors who hold the super-efficient portfolio may leverage their position by shorting the risk free asset and invest the proceeds in additional holdings in the super-efficient portfolio or deleverage their position by selling some of their holdings in the super-efficient portfolio and investing the proceeds in the risk free asset (Trammell, 2006).

Holding a risk free asset will also protect investors from losing all of their investments during market crashes. One of the key assumptions brought by Tobin (1959) was that in the world

there is only one safest asset, which is the risk free asset. Therefore, portfolio choice by any risk averse portfolio holder can be described as a choice between the safe asset and the same portfolio of risky assets. In summary Tobin believed that investors should not put all their eggs in one basket, which clearly shows the need for diversification and the incorporation of risk free within a portfolio (Tobin, 1958).

The Separation theory provides a better understanding of how to diversify risk profiles and it also provides a comprehensive standard of how to allocate capital in efficient markets. This perspective aided to the development of the CAPM. According to Tobin (1958) the assumptions of the separation theorem are listed below:

1. At least one asset is riskless (has a zero return variance).
2. Investors can borrow or lend at the riskless rate of interest.
3. A set of assets with known means, variances and pairwise covariance's.
4. Investors are risk averse.
5. Every investor should the optimal portfolio.

With all the explanation above, Tobin used the Capital Market Line (CML) to identify efficient portfolios. The CML is used in conjunction with the efficient frontier in order to show the rates of return for efficient. The level of risk an investor would accept is dependent on their risk tolerance. Fig 2.5 shows an example of the CML together with the efficient frontier.

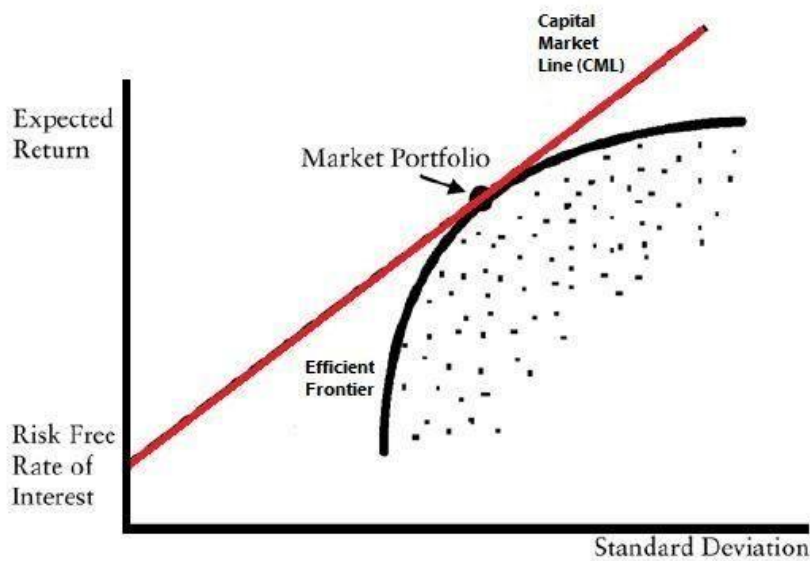


Figure 2.5: Capital market line

Source: Ayodeji and Ingram (2015:46)

Figure 2.5 above shows the capital market line drawn tangent to the efficient frontier. The efficient portfolio is shown by the point super-efficient portfolio. According to Dayala, (2012) CML intercepts at the risk free return which has a standard deviation of zero and is tangent at Markowitz' efficient frontier, as a result it dominates the remainder of Markowitz efficient frontier in terms of risk reward features. The efficient portfolio with all risky assets held by all investors at equilibrium is reflected by point of tangency.

This single factor model ignores real world complexities but give us an intuitive insight into the nature of equilibrium within capital markets. Subsequently, leading to development of the Security Market Line (SML) which describe the equilibrium relationship between risk and expected return for both individual assets and portfolios respectively. Below is an SML graph which shows the risk and return relationship. Investors should buy undervalued stocks and sell overvalued stocks.

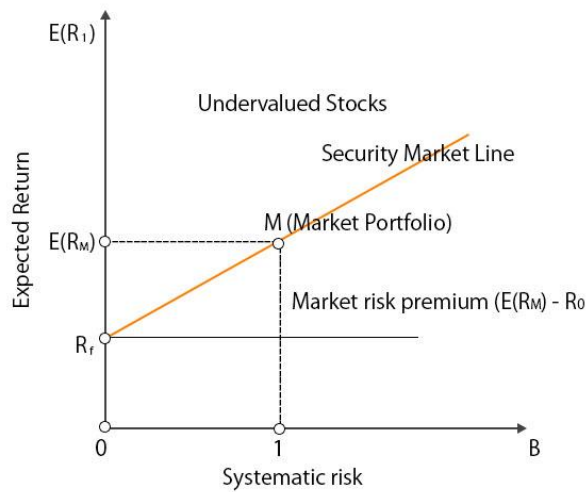


Figure 2.5: Security market line

Source: Dybvig, P. H., & Ross, S. A. (1985:16)

According to Mossin (1966) asset prices that are in equilibrium will adjust so that investors can achieve their desired point on the market line however, this is only if the portfolio is completely diversified. The SML focuses on individual stocks and the appropriate measure would be beta as it relates to an asset contribution of risk to a portfolio. The beta of a security is calculated by using covariance returns of the underlying asset i and the market. The SML uses beta to model the relationship between expected return and risk of asset. Alternatively, the CML concentrates on a portfolio of risky assets by measuring the total risk of a portfolio relative to the total risk of the market.

The CAPM was developed to determine the impact of risk adjusted returns on stocks in efficient financial markets. It predicts what a particular asset expected return should be relative to its risk and the market return. CAPM is a single factor model because there is only one relevant risk measure of this model which is the beta coefficient. Herding behaviour is witnessed when then beta coefficient is either high or low.

2.2.6 Arbitrage Pricing Theory (APT)

Arbitrage pricing theory argues that there are arbitrage opportunities when markets are

inefficient, allowing investors to make riskless profits without making an initial investment. For example, if a stock is overpriced in the market, an arbitrageur will sell the overpriced stock and purchase a similar lower priced stock in the market. This results in asset prices reverting back to equilibrium whereby mispriced stocks adjust for market inefficiencies. This theory contradicts CAPM which states that holding the market portfolio is the optimal mean-variance portfolio.

The Arbitrage Pricing Theory (APT) was developed predominantly by Ross (1976). It is an asset pricing model in which every investor believes that the returns of capital assets can be modeled as a linear function of various macro-economic factors. Ross argues that if equilibrium prices offer no arbitrage opportunities over fixed portfolios of the assets, then the expected returns on the assets are approximately linearly related to the macro-economic factors.

The APT theory suggests that rational investors undo price deviation (Ross, 1976). The arbitrage earned by investors is derived from the discrepancies between the fundamental values of a stock with its market price. It is an alternative method for the pricing of securities which addresses issues of identifying the market proxy. APT separates risk components that find that market risk is not the only systematic risk and explain long-term average returns. It seeks to identify which systematic factors of market risk determine the variation in assets returns thereby assisting investors and managers in understanding which variables are most powerful in explaining assets returns. The APT model provides investors with the opportunity to develop intuitive models that are absent from CAPM due to its restrictive assumptions. Chen, Ross and Roll (1986) suggest the various macro-economic factors that should be incorporated into the model. The significant risk factors when determining stock market returns are listed below:

1. The industrial production (indication of future cash flow).
2. Inflation.
3. The yield spread between low yield and government bonds.
4. The slope of the term structure of the interest rate (yield curve).

The APT permits businesses and investors to recognise various attributions of securities returns and their relative impact in determining these asset returns (Modigliani & Pogue, 1988). APT

follows the law of one price which states that two assets that tolerate identical levels of risk cannot sell at dissimilar prices.

A benefit of APT is that it identifies the unexpected portion of returns that are not explained by CAPMs beta. Portfolio managers are faced with the decision of what their preferred risk exposures are for their clients. In this regard, Roll and Ross (1984) argue that if all investors were to use the same investing strategy, markets would not function. This permits portfolio managers to segment risk and actively manage uncertainties through predicting stock price movements.

The above models are based on the notion of the efficient market hypothesis. These theories suggest that investors or managers can only outperform the market if they diversify their portfolios by using assets which are perfectly uncorrelated. However, Damodaran (2010) suggests that managers have got two kinds of abilities, selectivity (stock picking) ability and timing ability. Managers or investors can acquire potential gains if they time the market correctly so as to switch between asset classes, investment styles or sectors.

2.2.7 Comparison of the MPT models

Model	MVO	CAPM	APT
Originator(s)	Markowitz (1952)	Treynor (1961), Sharpe (1964), Linter (1965) and Mossin (1966) (independently)	Ross (1976)
Contributions	-The first model on portfolio theory which conceptualises on diversification	-An expansion of the MVO which introduced valuation of systematic risk -Was later modified by Sharpe (1964) to make it more practically easier and operational	-In addition to market risk, there are more variables to consider when pricing assets such as investor confidence, inflation and interest rates -The model is based on less restrictive assumptions
Risk measure	Standard deviation	Beta	Beta

Similarities	-Based on the assumptions of EMH -Single model for asset pricing	- Based on the assumptions of EMH -Single model for asset pricing	-Based on the assumptions of EMH though less restrictive -Multi-factor model for asset pricing
Differences	-Formula: $E(rp) = \sum w_i r_i$	-Formula: $(r) = r_f + b(r_m - r_f)$	-There is no arbitrage -Formula: $(r) = r_f + b_1(\text{factor 1}) + b_2(\text{factor 2}) + b_3(\text{factor 3})$

2.3 Rolls Critique

CAPM and APT are based on the belief that investors are rational and consider all available information when making decisions. Investment markets are therefore efficient, reflecting all available information in security prices (Fama & French, 2004). In this regard Roll (1977) studies have found that it is impossible to create or rather observe a truly diversified market portfolio. CAPM has been criticized because of its restrictive assumptions that expected returns are based on historical variables. For that reason, it cannot be used reliably to predict an assets performance in the future. Studies on CAPM have mostly been conducted on stock markets including the Morgan Stanley Capital International (MSCI) world index and Standard and Poor's 500 (S&P500) index when constructing market proxies. Roll (1977) pointed out that the market portfolio does not only include equities and other tradable assets for example, bonds and property, and non-tradable assets which include human capital.

In addition, Roll (1977) argues that unless the market portfolio is known with confidence, CAPM cannot be accurately tested. This is primarily due to the inaccuracy of beta coefficients which can be attributed to either an incorrect specified market portfolio or to a weak model. Roll (1978) believes that an incorrect beta coefficient results in problems with the benchmark proxy which is used to price an asset. The equations that make up the CAPM are highly sensitive to the initial variables hence a small change in the market rate of return can have a large impact on the solution set.

Evidence has been found which contradicts the Efficient Market Hypothesis (EMH) and these are referred to as market anomalies. Various anomalies have shown results inconsistent with the implying that EMH failed to depict trading operations in real world. The presence of these market anomalies has been documented extensively for the last two decades in financial markets. Behavioural finance is a market anomaly which led to the development of herding behaviour.

2.4 Behavioural Finance

2.4.1 Background of Behavioural Finance

Efficient Market Hypothesis (EMH) is the base for many financial theories. EMH is an investment theory based on the belief that investors are rational and consider all available information when making investment decisions. Investment markets are efficient, reflecting all available information in security prices (Fama & French, 2004). Traditional finance theorists hold a perspective that any mispricing created by irrational traders, will create attractive investment opportunities which will be quickly capitalized by the rational traders and the mispricing will be corrected (Boortz & Jurkatis, 2013). Behavioural finance theorists argue that the strategies required to correct the mispricing can be costly thus, resulting the mispricing to be unattractive.

Many studies have found long-term historical variables in securities markets that contradict the efficient market hypothesis and cannot be captured reasonably in models based on perfect investor rationality. These researchers have discovered evidence of irrationality amongst investors and behavioural finance tries to fill the gap (Shiller, 1995). De Bondt and Thaler (1985) introduced the phenomena of behavioural finance. Behavioural finance models were developed to explain investor behaviour and market anomalies when rational models provide insufficient explanations. The theory of behavioural finance has tested the existence of overreaction in the market and found that investors systematically overreact to unexpected news resulting in weak form inefficiencies in the stock market (Thaler. 2005).

Behavioural finance believes in the existence of limits to arbitrage in the stock market, which allows investor irrationality to have long lived impact on stock prices (Shleifer, 2000). In an

attempt to explain investor irrationality, behavioural finance puts forth evidence of the psychology and biases that arise when investors are influenced by beliefs (Barberis & Thaler, 2003). Thus, psychology and limits to arbitrage are reviewed as the two main factors that result in the standing of behavioural finance (Shleifer, 2000). Arbitrage is an investment strategy that offers profit at no cost; it allows investors to benefit from differences between the fundamental value and the market value (Thaler, 2005).

Behavioural finance attempts to understand the market implications of human emotion on investment decisions through the study of psychology and sociology. During the 1960's and 1970's psychologists began to examine economic decisions based on human behaviour. This psychology based financial analyses coincided with the start of many empirical findings that cast doubt on some of the key foundations in standard finance, namely the EMH and the CAPM (Baker & Nofsinger, 2010). Studies were conducted in order to examine different security prices and evidence was found that either markets were not as efficient as purported and also that the capital asset pricing model was inadequate. These studies found that the behaviour of market participants had an effect on their investment decisions (Baker & Nofsinger, 2010).

The field of behavioural finance was established in an attempt to better understand and explain how emotions and cognitive errors influence investor decision making. Leading researchers such as have used theories of psychology and social sciences to better explain the efficiency of financial markets and stock market anomalies such as stock market bubbles and crashes (Kahneman & Tversky, 1979; Thaler, 1985). Behavioural finance is a moderately new branch to the decision making process which analyses how investors make irrational decisions concerning their investment portfolios due to psychological biases.

In their article, "Does the stock markets overreact?" De Bondt and Thaler (1985) introduced the phenomena of behavioural finance. The authors found that investors systematically overreact to unexpected and dramatic news and events resulting in substantial weak form inefficiencies in the stock market. In this regard Barber and Odean (2000) added on the findings of De Bondt and Thaler (1985) that individual investors are loss averse and trade too much. These authors found that investors are overconfident which leads to too much trading.

Overconfident investors overestimate the value of their private information triggering them to trade too actively and earn below average returns.

Herding behaviour branched from behavioural finance. According to Bikhchandani and Sharma (2001), herding defines the tendency of institutions or individuals to display resemblances in their behaviour and hence act like a herd. Herding behaviour of investors is explained as the trend to gather on the same side of the market, which is seen as a threat towards the stability and efficiency of financial markets (Hwang & Salmon, 2004). It was strongly exhibited in the 1990s when a lot of private investors invested large amounts of money into internet related companies. The motivating factor for these investors seemed to be the reassurance they received from seeing many other investors doing the same (Boortz & Jurkatis, 2013).

The way investors behave has been an area of interest for portfolio managers and academic researchers. Past literature reveals that irrationalities in investment behaviour have been the reason behind major booms and busts in the market (Kim, 2005). Herding behaviour is a behavioural anomaly which defies the efficient market hypothesis (EMH). In the case of herding behaviour, investors copy the actions of the crowd. They do not decide on their own judgment but follow the way other investors invest. Hence herding behaviour is mostly seen in periods of market extremes (Christie & Huang, 1995). This could be due to social pressure and the common thought that the crowd cannot be wrong and it knows better than individual investors (Hwang & Salmon, 2001). In addition, Hirshleifer and Hong Teoh (2001) argues that in the absence of opportunities for herding, there is a potential incentive for individuals, acting on their own, to invest in such manipulative strategies. If investors are allowed to trade at an arbitrage, it is not clear whether in equilibrium opportunities can persist. This raises the question of whether there are incentives for herding or an indirect means of manipulation.

2.4.2 Assumptions and attributes of behavioural finance

Below are some of the underlying assumptions of behavioural finance (Baker & Nofsinger, 2010).

1. Information structure and characteristics of the market participants systematically influence individuals' investment decisions and ultimately the market's outcome. The psychology behind this theory found that the human brain often processes information using emotional filters as well as shortcuts. This causes investors to act in an irrational manner, routinely violating traditional theory of risk aversion and making forecasts with predictable errors. These problems are pervasive in investment decisions, financial markets and corporate managerial behaviour
2. There are limits to arbitrage which allows the irrationality of investors to impact prices. This has led to further developments, the most notable of these being prospect theory
3. Investors maximize their own utility or well-being
4. Investors base their preferences between choices of outcome of their investments
5. Investors use past performance as an indicator of future performance in stock purchase decisions
6. Investors behave parallel to each other and
7. Investors are influenced by historical high or low trading stocks

Shiller (2003) describes behavioural finance under the following four key principles which includes the prospect theory, limits to arbitrage, overreaction hypothesis and investor irrationality.

2.4.3 Prospect Theory

The prospect theory was developed by Kahneman and Tversky in the late 1970's. This theory argues that investors value gains and losses differently and, as such, will base decisions on perceived gains rather than perceived losses. Kim and Nofsinger (2005) indicates how prospect theory describes investors framing and valuing of decisions involving uncertainty. In particular, investors underweight outcomes that are merely probable in comparison with outcomes that are obtained with certainty. This tendency is referred to as the certainty effect and it contributes to risk aversion in choices involving sure gains and to risk seeking in choices involving sure losses (Ricciardi & Simon, 2000).

Investors may combine the net effect of the gains and the losses associated with any choice of

asset class in order to produce a well-diversified portfolio (Kahneman & Tversky, 1979). This is viewed academically as the concept of utility and is often used to describe desirability or enjoyment and logical that investors should prefer those decisions which are believed to maximize utility (Kahneman & Tversky, 2013). Many illogical financial behaviours can be well explained by prospect theory since when an investor is faced with two equal choices that are presented differently, one in terms of possible gains and other in terms of possible losses it is likely to choose the one suggesting gains, even if the two choices yield the same end result (Kahneman & Tversky, 2013).

One of the fundamental components of prospect theory is the S-shaped value function. According to Kahneman and Tversky (2013) the value function is mainly justified by experimental investigation of the certainty equivalents of prospects confined either to the positive or to the negative domain, but not of mixed prospects, which characterize most actual investments.

Below is a graph that explain the prospect theory

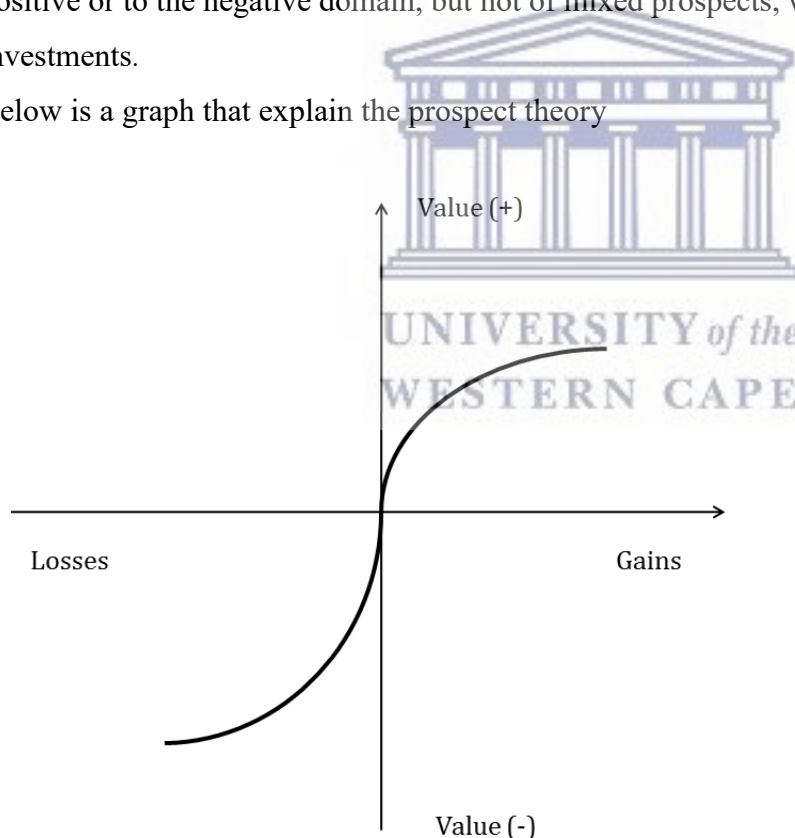


Figure 2.5: Prospect theory

Source: Kahneman, & Tversky, (2013:72)

The S-shaped function in figure 2.5 shows how investors value gains and losses (Kim & Nofsinger, 2005). The graph above shows that value function is steeper for losses than it is for gains because an investor feels more pain with a loss compared to the joy experienced with an equivalent gain (Kahneman & Tversky, 2013). Ricciardi and Simon (2000) argues that the convex shape for the losses describes how investors get disappointed when they make losses. The reference point, where the two axes (value; gains and losses) intersect is where the s-shaped value function is at its steepest (Kahneman & Tversky, 1979). The difference in these two curves leads to different responses by investors to losing and winning positions which are the disposition effect and mental accounting. Shefrin and Statman (1985) argues that mental accounting and the disposition effect mainly contribute to what appears to be irrational behaviour.

The prospect theory is also useful in explaining the disposition effect which is the tendency that investors hold on to losing stocks for too long and sell winning stocks too soon (Shefrin & Statman, 1985). According to Kahneman and Tversky (2013), when an investor is risk averse over gains, they should be inclined to sell a stock that is trading at a gain, this has been used by many researchers to link the prospect theory and the disposition effect. The prospect theory has proved compelling as the commonly mentioned explanation for this particular pattern of trading (Shefrin & Statman, 1985). To better explain the disposition effect, consider an investor who bought stocks a year ago for R100, and it is now worth R60. An investor has to decide whether sell at a loss or hold for long and sell when it is profitable. Because this decision lies at the loss (convex) portion of the value function, the theory implies that the investor will hold onto the stock in an attempt to recover their losses.

In addition, mental accounting is an economic concept that was developed by Thaler (1999) which refers to a set of cognitive operations used by investors to organize, evaluate and keep track of financial activities. This theory argues that individual investors classify personal funds differently and therefore are inclined to irrational decision-making. Investors are believed to assign different functions to each asset group and the result of which can be an irrational and detrimental set of behaviours (Kahneman & Tversky, 1979). If an investor suffers a loss on a

stock, they need to realize their losses and consequently close the mental account for that particular stock instead of trying to recover losses (Shefrin & Statman, 1985). For example, if an investor sold a stock at a profit however after selling they still monitor its performance and only to realize that the price of the stock is going up, that leads investors to suffer mental accounting (Kahneman & Tversky, 2013).

2.4.4 Limits to arbitrage

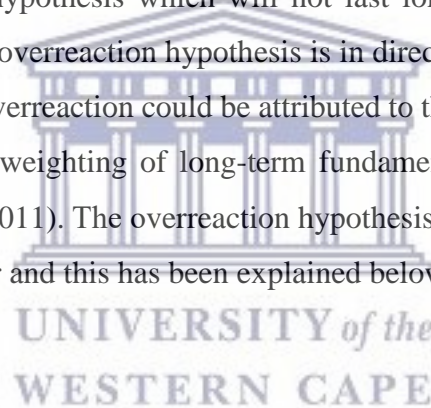
At any given time, there are arbitrage opportunities in the market that do not disappear quickly and it is not easy to beat the market. Actually, there are many instances where trained arbitrageurs may not be able to profit from market under valuations or overvaluations (Herschberg, 2012). Arbitrage is critical to the maintenance of efficient markets, since it is through the arbitrage process that fundamental values are kept aligned with market prices reference. In effect, arbitrage entails costs as well as the assumption of risk, and for these reasons there are limits to the effectiveness of arbitrage in eliminating certain security mispricing (Gromb & Vayanos, 2010). There is sufficient evidence for such limits to arbitrage. Limits to arbitrage exist because of risks and costs (Shleifer & Vishny, 1997). The main risk is from new negative information that might arrive in the market after an investor has made an investment. Even if hedging is possible, they risk receiving bad news that might affect an entire industry (Bodie, Kane & Marcus, 2013).

2.4.5 Overreaction Hypothesis and Investor Irrationality

The contrarian hypothesis also known as the overreaction hypothesis implies the simultaneous buying of previous losers and selling of previous winners in order to realize excess returns (Antoniou, Galariotis & Spyrou, 2005). This occurs based on the belief that extreme previous losers are undervalued due to investor overreaction possibly caused by some bad events and news. If given adequate time, previous losers will outperform the market and on the contrary, the overvalued previous extreme winners will underperform the market in subsequent periods (Gromb & Vayanos, 2010).

In addition, Thaler (2005) argued that investors react disproportionately to new information of a given security which leads to the discovery of investor irrationality as a result of the overreaction hypothesis. Hodnett and Hsieh (2012) stated that an irrational explanation as to why anomalies exist is the existence of psychological biases which results in investors making irrational predictions due to the irrationality of the investor. De Bondt and Thaler (1985) define overreaction as when investors have a habit of overweighting recent information and underweighting historical data. As a result of investor overreaction, stock prices tend to be biased as they may temporarily deviate from their underlying fundamental values, allowing for arbitrage opportunities when the correction of the stock market takes place.

According to Hodnett and Hsieh (2011), abnormal earnings can be generated from the temporary overshooting of asset prices before the market corrects itself. The price changes as a result of the overreaction hypothesis which will not last long, as the stock prices adjust towards their fair values. The overreaction hypothesis is in direct contradiction to the efficient market hypothesis. Investor overreaction could be attributed to the persistent overweighting of recent information and underweighting of long-term fundamental information by irrational investors (Hsieh & Hodnett, 2011). The overreaction hypothesis may happen as a result of the presence of herding behaviour and this has been explained below.



2.4.6 Traditional Finance versus Behavioural Finance

Traditional finance argues that investors think rationally and thus their financial decisions result in a maximization of wealth for any given level of risk (Bodie, Kane & Marcus, 2010). Behavioural finance takes a different approach. It relaxes the assumptions of investor rationality and investor risk aversion in the market as proposed by traditional finance. It recognizes cognitive errors and emotions habitually influence investors in their financial decisions. Traditional and behavioural finance theories have evolved with time (Bodie, Kane & Marcus, 2010).

Traditional finance is largely based on modern portfolio theory (MPT) as well as the EMH.

Markowitz (1952) established the modern portfolio theory. Modern portfolio theory revolutionized the way the capital markets operate. The MPT and EMH findings show that the correlations of securities are more important than the amount of securities that is held in a portfolio. However, modern portfolio theory argued that all investors are wealth maximizers and rational.

Another important concept in traditional finance is the EMH. The EMH, developed by Eugene Fama in 1970, which states that all information has already been reflected in a securities price and the current price of the stock, is its fair value. It also assumes that there are no trading strategies that produce positive excess returns thus EMH investors make unbiased decisions and maximize self-interest (Baker & Nofsinger, 2010). On the other hand, behavioural finance attempts to understand and explain the market implications of human emotion on investment decisions. It studies financial markets and is used to explain some of the stock market anomalies (Ricciardi & Simon, 2000). Behavioural finance emerged as a field that could explain some of the difficulties that traditional finance theory (EMH) was not able to explain. Behavioural finance attempts to understand the investment market by relaxing some of the assumptions made by the traditional finance theory (Damodaran, 2012). The way investors behave has been an area of interest for portfolio managers and academic researchers. Irrationalities in investment behaviour have been shown to be the reason behind major booms and busts in the market (Latif, Arshad, Fatima & Farooq, 2011). EMH believes that investors make informed decisions and expected returns of stocks are based on equilibrium models such as the Capital Asset Pricing Model (CAPM) (Damodaran, 2012)

Traditional finance (EMH) states that all decisions made by investors are rational and that no biases are found within research conducted. Traditional finance theorists are of the view that, any mispricing created by irrational traders, will create attractive investment opportunities which will be quickly capitalized by the rational traders and the mispricing will be corrected (Boortz & Jurkatis, 2013). However, behavioural finance theorists argue that the strategies required to correct the mispricing can be costly thus, resulting the mispricing to be unattractive. Therefore, investors are irrational and markets are inefficient.

Behavioural finance believes that there are limits to arbitrage in the stock market, which allows investor irrationality to have long lived impact on stock prices. In an attempt to explain investor irrationality, behavioural finance puts forth evidence of the psychology and biases that arise when investors are influenced by beliefs (Barberis & Thaler, 2003). These psychology biases and limits to arbitrage are reviewed as the three main factors which include heuristic simplification, self-deception and emotions. Heuristic simplification is the simplification of the decision making process as individuals' attention span and memory tend to be limited. Whereas, self-deception is the illusion of knowledge, felt by investors due to overconfidence in their decision making and lastly, emotions which investors tend to base their decisions on (Hirshleifer, 2001).

Arbitrage is an investment strategy that offers profit at no cost; it involves investors benefiting from differences between the fundamental value and the market value. Hodnett and Hsieh (2012) asserts that investors make decisions based on their emotions in addition to the mean, variance and covariance of asset returns upon making investment decisions. In addition, behavioural finance also debates that there are limits to arbitrage which allows the irrationality of investors to impact prices. Behavioural finance has led to further developments, the most notable of these being the theory of herding behaviour.

2.5 Herding behaviour

The theory of behavioural finance has led to the generation of research in relation to behavioural patterns on herding. Behavioural finance is a field of research that uses psychological, emotional and social factors to explain stock market anomalies (Baker & Nofsinger, 2010). This theory seeks to provide reasons why investors make irrational decisions and it also helps explain why and how markets might be inefficient. In other words, this field of behavioural finance was established in an attempt to explain how emotions influence investors when making investment decisions (De Bondt & Thaler, 1985). Some leading researchers such as Kahneman and Tversky (1982) and Thaler (1985) have used theories of psychology to explain the irrationality and the inefficiency of financial market Sewell (2007).

Herding behaviour is a branch of behavioural finance, which is a mindset that is described by

the lack of individual decision-making, which causes investors to mimic one another (Trueman, 1994). In this regard, the theory of herding behaviour tries to connect the traditional finance anomaly and behavioural finance anomaly relating to investors. A good example to explain herding behaviour is when Warren Buffett buys a stock, it is reported as news, and that news affects the stock prices. Some investors tend to buy the same share with the belief that since the share has been bought by an investment guru then the probability of earning above market returns is high. The impact of such news may be rational, but investors are often regarded as irrationally because of the presence of the herd behaviour (Hirshleifer & Hong Teoh, 2003).

Bikhchandani and Sharma (2000) define herding behaviour as an evident intent by investors to replicate the behaviour of other investors. Herding behaviour branched from behavioural finance. In the financial field, herding behaviour was discovered in the 1990s when private investor's anxiously invested large amounts of money into internet related companies. The driving force that seemed to influence these investors to invest their money into such an uncertain venture was the reassurance they got from seeing so many other investors doing the same thing (Boortz & Jurkatis, 2013). Herding behaviour generally believed to be a critical element of investor behaviour in financial markets however there is little empirical evidence that exists in its favor. Herding behaviour is mostly seen in periods of market extremes (Christie & Huang, 1995). This could be due to social pressure and the common thought that the crowd cannot be wrong and it knows better than individual investors (Hwang & Salmon, 2001).

2.5.1 Types of herding behaviour

Bikhchandani and Sharma (2001) describes herding as the tendency of institutions or individuals to show connection in their behaviour and thus act like a herd. Herding exists in two forms unintentional and intentional herding. Unintentional herding is fundamentally motivated and rises when institutions observe the same factors and receive correlated private information, leading them to attain similar decisions concerning individual stocks (Hirshleifer, Subrahmanyam & Titman, 1994). According Kremer and Nautz (2013), intentional herding occurs whenever traders intentionally follow the crowd and ignore their own private information. This is a result of the belief that other investors possess superior information. Also, experts may create a relatively homogenous group in which they share related professional

qualifications and educational background and they have a tendency of interpreting informational signals similarly (Walter & Weber, 2006). Intentional herding may destabilize stock prices and thus impair the proper functioning of financial markets.

With intentional herding investors are sentiment-driven and it encompasses the imitation of other market contributors, causing the concurrent buying or selling of the same stocks irrespective of preceding beliefs (Walter & Weber, 2006). This form of herding can result asset prices not to reveal the fundamental information and as a result contributing to the creation of bubbles and crashes on financial market (Morris & Shin, 1999; Persaud, 2000). However economic theories by Avery and Zemsky (1998) and Scharfstein and Stein (1990) demonstrates that even intentional herding can be rational from the trader's perspective.

The models of intentional herding believe that there is a slight consistent of information in the financial markets and as a result some traders are not certain to make their own decisions and therefore they follow the crowd (Walter & Weber, 2006). On the other hand, unintentional herding traders recognize public information as dependable and take it as the market ending up on the same side of the market. Looking at the two categories of herding, the extant of herding is related to the uncertainty or availability of information

2.5.2 Reasons for herding behaviour

This section of this study looks at the reasons of herding behavior. Investors and financial managers are concerned about the way information is reflected in stock market prices. The efficient market hypothesis claims that market participants form rational expectations of future prices discounting all market information into expected prices (Cipriani & Guarino, 2005). Nonetheless, the existence of herding can intensify volatility of returns thereby disrupting financial markets (Demirer & Kutan, 2006). In addition, investors follow herd behaviour because of the social pressure of conformity; investors are sociable beings and have a natural desire to be accepted by other investors as a result following a group of investors is an ideal way of following herd behaviour (Demirer & Kutan, 2006).

Moreover, it is less likely that a large group of investors could be wrong. The ultimate goal of

an investment manager is to maximize a client's invested wealth and risk minimization. Even though these investment managers (individual investors) are convinced of the existence of irrationality in investment decision making, they are likely to still follow the herd. This is because these individual investors believe that investment guru's know something those others investors do not (Demirer & Kutan, 2006). It is usually common in situations where individual investors have no or little investments experience. More so, investors become part of a group and follow the herd when they know and feel that they cannot voice their own opinions alone (Kim, 2005). In this way, following a herd provides sense of security to individual investors. Thus, by nature investors finds it easy to conform to what the investment specialist (guru) opinion is saying rather than losing profits due to rebellious behaviour (Demirer & Kutan; 2006).

2.5.3 Causes of herding behaviour

Distinguishing between the different causes or types of herding behaviour is vital for regulatory purposes and for determining whether herding leads to market inefficiency (Clement & Tse, 2005). Past research has investigated the determinants of herding using the relationship between herding and information by allowing for variables that proxy, for example the availability of information. Some of the causes of herding are size, trading volume and risk management systems, feedback trading and the volatility of returns.

Lakonishok et al.. (1992) studied herding behaviour of investor within a quarterly time span using a sample of US equity funds. The author separated the stocks by size because the market capitalization of firms commonly reflects the quantity and quality of available information (Clement & Tse, 2005). As a result, one would expect higher levels of herding behaviour in trading small stocks to be significant against intentional herding. On the contrary, since institutions have a higher commonality in information unintentional herding is more likely to occur in stocks with larger market capitalization. In actual fact, Lakonishok et al.. (1992) found evidence of herding being more intense among small companies compared to large stocks. Choi and Sias (2009) and Venezia et al.. (2011) documented a greater extent of herding behaviour in small stocks.

In addition, literature on herding behaviour also highlights the relationship between information quality, information asymmetries and market liquidity. For example, Diamond and Verrecchia (1991) predict higher information asymmetry in less liquid markets. Suominen (2001) model proposes that better information quality is shown by higher trading volume. Intentional herding concept implies higher herding levels are associated with lower trading volumes.

Unintentional herding happens due to simultaneous reaction to a common signal, the presence of this kind of herding behaviour is a momentum investment (Clement & Tse, 2005). If herding behaviour is driven by past returns, this would be interpreted as evidence of unintentional herding (Froot et al., 1992; Sias, 2004). In this regard, Lakonishok et al., (1992) and Grinblatt et al., (1995) recorded positive feedback strategies that contribute towards herding behaviour. Wylie (2005) documents that UK funds herd out of stocks that have performed well in the past. In addition, even though correlated positive feedback trading may result unintentional herding, it may have a destabilizing impact on financial markets (De Long et al., 1990). With reference to past research, feedback trading is typically captured by returns (r_i) of stock i .

The volatility of stock return has visible effects on herding behaviour. The impact of return volatility is often assumed to show the extent of discrepancies amongst market participants and thus, the degree of uncertainty in the market (Clement & Tse, 2005). Using the intentional herding model, higher degree of herding behaviour in stocks that experienced a higher degree of volatility. Looking at both the buy and the sell side it is important to emphasize that higher information uncertainty should induce intentional herding in a symmetric way (Clement & Tse, 2005). Conversely, same risk measure could also result higher levels of herding in more volatile stocks (Persaud, 2000). Volatility sensitive models which are commonly used for risk management purposes and regulatory requirements may induce common sell activity (Persaud, 2000). In particular, the market risk capital and as a result more unintentional herding behaviour is expected in stocks with higher volatility of returns (Clement & Tse, 2005).

2.5.4 Consequences of herding behaviour

This section discusses the effects that may be caused by the existence of herding behavior. Institutional herding behaviour may exact pressure on the price of stocks. For example, Lakonishok et al.. (1992) argues that unintentional herding can be an efficient outcome, if it produces results that causes a simultaneous reaction to fundamental values which in turn speeds up price adjustment and makes the market more efficient (Clement & Tse, 2005). On the contrary herding behaviour can lead to inefficient outcomes if not based on fundamentals. A well-known example is unintentional herding behaviour due to positive feedback strategies that aggravate downward or upward pressures (De Long et al., 1990).

Furthermore, Dani'elsson (2008) and Persaud (2000) emphasized on the destabilizing effects of unsystematic risk regulation that forces common reaction on volatility and thus the indigeneity of risks. Scharfstein and Stein (1990) and Barberis and Schleifer (2003) documented that if herding behaviour drives prices away from fundamentals then the price movements should reverse subsequently. The IMF (2007) argues that the destabilizing impact of return volatility if institutions employ similar risk models and to this end, empirical analyses have been conducted to discover whether the impact of herding on prices continues or reverses in the future (Choi & Sias, 2009). Empirical evidence on the consequences of herding is mixed, looking at quarterly data, Lakonishok et al.. (1992), Wermers (1999) and Sias (2004) documented no return reversals following herds. However, more recent studies, including Puckett and Yan (2008) and Brown et al.. (2010) found herding-related return reversals using weekly data.

2.5.7 Herding behaviour on the Johannesburg Securities Exchange

Since Johannesburg Securities Exchange began its operations in early 1880s, it has been expanding dramatically and became one of the world's 20 largest exchanges by its market capitalization of just over \$1 billion and the largest exchange in Africa. It is anticipated that JSE's stock market will continue to grow due to the nation's strong savings habits (JSE, 2017).

JSE has a wide range of products and services which includes commodities, currencies and resources. The JSE sector indices provide an easy way to determine the overall performance of

the stock market or a segment of the stock market over a period of time (JSE, 2017). Of all the indices on the JSE the Top40 index is the largest, it comprises of 40 largest listed companies on the JSE by market capitalization (JSE, 2017). The JSE has a number of sub-indices such as the Mid Cap, Small Cap and Tradable indices. The MidCap index comprises stocks ranked from 41 to 100 on the market by market capitalization, after the Top40 index. Small caps are the companies with values smaller than the top 100 listed companies by market capitalization. The tradable indices which include the industrials index (INDI₂₅) constitutes of 25 largest industrial stocks by market capitalization, the financials index (FINI₁₅) comprises of 15 largest financial stock by market capitalization and lastly the resources index (RESI₁₀) which represents 10 largest resources stocks by market capitalization.

Despite its tremendous growth, the South African financial markets may not be characterized by the depth and maturity of a stock exchange observed in this developing country. Evidence has shown that South African's interest rates are controlled and kept low for government enterprises to borrow loans at below market rates. The central government has solid interests in the ability of the stock market to finance state-owned enterprise hence investors facing only a few alternatives and heavy government involvement, such as regulation tend to speculate the stock market, causing significant market volatility (Yartey, 2008). An additional distinct characteristic of the stock market is ownership; researchers have found that about 60 percent of outstanding shares are not publicly tradable (Sareewiwatthana, 2011).

In addition, most traders are facing political risk, law and order and these determinants enhance the viability of external finance. The resolution of this political risk is an important factor in the development of the South Africa market. For example, the abrupt cabinet reshuffling for which led to the removal of the Minister of Finance Nhlanhla Nene in December 2015 might also have contributed to the present depreciation of the rand to the dollar, as there were mixed views about his removal. The xenophobic attacks in South Africa might also be a deterrent to investors. In this regard, since there is the political uncertainty and market volatilities in the SA market, this research is likely to document evidence of herding behaviour during the sample. This part of the study provided an overview of how herding behaviour was discovered. Herding behaviour is found on the border between the traditional finance and behavioural finance.

Herding behaviour discredits the efficient market hypothesis that markets are efficient and that investors are rational.

2.6 Conclusion

This chapter discussed the theoretical underpinnings of the herding behaviour, starting from the mean variance analysis by Markowitz (1952), to the separation theorem by Tobin (1958), CAPM by Treynor (1961), Sharpe (1964), Linter (1965) and Mossin (1966) independently as well as the APT by Ross (1976) and behavioural finance which argues on the irrationality of investors leading to herding behaviour. The three main branches of the MPT have been compared and a discussion on how they complement each other followed. The causes of herding behaviour, types of herding behaviour, and consequences of herding behaviour were discussed. Herding behaviour was also briefly discussed in the context of South Africa. Chapter 3 considers the empirical studies that have been done on herding behaviour both in developed and developing countries.



Chapter Three – Review of Prior Literature

3.1 Introduction

This chapter discusses the theoretical underpinnings of herding behaviour. A comparison of the different studies is done in order to elucidate how the findings link and complement each other. Past studies on herding behaviour in developed economies, in developing economies as well as on the JSE are also discussed. A developing country is a country with a less developed industrial base and vice versa for developed countries.

According to Vieiraa and Pereirab (2015), past and present academic scholars have dedicated considerable effort in understanding the behaviour of market participants when investing and ensuing its influence on security prices. The investment behaviour of market participants has been linked to factors such as the behaviour of other market participants, the degree of underlying market volatility and the presence speculative trading activity in the financial markets. Hence, it is imperative to understand the investment styles as they aid to the risk and return maximization (Clement & Tse, 2005).

3.2 Herding in the developed markets

This section discusses past studies that have been done on herding behaviour in developed markets. With that in mind, this research categorized past literature into two; that is studies done on herding behaviour during normal periods and periods of market volatility.

3.2.1 Herding behaviour in developed markets during normal periods

Normal periods are defined as market periods where security's value does not fluctuate dramatically. These periods are associated with low market volatility, which is measured statistically by beta. The studies discussed below are on herding behaviour during market periods characterized by steady security values.

Shiller and Pound (1989) observed the economics rational of herding behaviour in financial markets. The authors observed 250 stocks on the US market and found that herding was

common in financial markets due to the presence of large institutional investors. Findings showed that herding was subject to information in the market especially prices. In conclusion investors placed huge emphasis on actions of investment professionals when they were buying and selling volatile stocks.

Adding to the research by Shiller and Pound (1989), Lakonishok, Shleifer, Thaler and Vishny (1991) analyzed herding behaviour in financial markets looking at investors' portfolio holdings. In order to calculate herding behaviour, the authors used a methodology that mainly aimed to evaluate if investors were trading more on either the sell side or the buy side of the market than what they would normally be expected when market participants traded independently (Lakonishok et al., 1991). In other words, Lakonishok et al. (1991) investigated to see if institutional investors' trades influence stock prices. With the main focus on the existence of herding behaviour and positive-feedback trading the authors empirically observed the trading patterns of institutional investors, which are associated with the popular belief that institutional investors destabilize stock prices. They used a sample of 769 all-equity tax-exempt funds with the majority of which as pension funds which were being managed by 341 different institutional money managers. Data was collected from SEI on the NYSE stock markets. The authors found that neither the stabilizing nor the destabilizing image of institutional investors was truthful. Little evidence was found that pension fund managers in large stocks followed herding behaviour. This was where over 95% of the pension fund managers trading was concentrated. Also evidence of more herding in smaller stocks was recorded, however, the magnitude of herding behaviour was insignificant. In summary, little evidence of herding behaviour was recorded and also weak evidence of a simultaneous relationship between price changes and excess demand by institutions.

Stirred by two previous studies by Grinblatt and Titman (1993) in Grinblatt, Titman & Werners (1995) studied and analyzed the scope of the purchasing mutual funds relying on their previous returns and the tendency to reveal herding behaviour. The authors aimed to provide empirical evidence on the trading patterns of fund managers. They observed quarterly portfolio holdings for 274 mutual funds that existed on December 31, 1974, which were purchased from CDA Investment Technologies, Inc. of Silver Springs, Maryland and 155 funds that existed on the

Center for Research in Security Prices (CRSP) monthly returns for each NYSE- and AMEX-listed stock during the period December 1974 to December 1984 (Grinblatt & Titman, 1993). Their aim was to observe the extent to which herding behaviour and momentum investing affected the performance of the funds. Grinblatt, Titman and Werners (1995) concluded that the investment funds on momentum showed better performance than other funds on average. The authors figured out that the tendency of funds are buying and selling in the same stocks in the same time period. They also established that the stocks bought by the mutual funds had more same period and lagged earnings.

Furthermore, Lobao and Serra (2003) tested the existence of herding behaviour on the Portuguese mutual funds during the period of from 1998 to 2000. The authors used the measure of herding behaviour suggested by Lakonishok et al.. (1992). Lobao and Serra (2003) found significant evidence of herding behaviour for Portuguese mutual funds. These results advocated that the level of herding was stronger than the herding behaviour that was found for institutional investors on the same stock market. Conversely, herding behaviour was shown to decrease when the stock market was more volatile Lobao and Serra (2003).

Furthermore, Demirer, Kutanand and Chen (2006) examined individual stock returns for firms and sector returns. The study was done between 1999 and 2002 to inspect the presence of herd behaviour in the Chinese stock market. The article extended the research on investor herds to American Depository Receipts (ADRs) and using daily price data on 305 ADRs traded in U.S. exchanges issued by corporations from 19 countries. In addition to that these authors examined herding behaviour in the market for ADRs within country-based portfolios. Daily ADR data and the stock market index data were collected from Datastream and CRSP. The period of study was from January 1995 to January 2011, amounting to 4030 listing days for most ADR issues. The authors classified ADRs in two groups one based on industry classification and the other based on the country of origin. This was to follow the suggestion by Bikhchandani and Sharma (2001) that testing herding behaviour within a homogeneous groups of investors where they experience similar decision problems and uncertainties yield more comparable results.

In addition, Walter and Weber (2006) evaluated the trading activity of German mutual funds in the 1998–2002 periods to study whether mutual fund managers in German followed herding behaviour. The period of study was from 31 December, 1997 to 31 December, 2002 since this period incorporates both bull and bear market. By applying the measure of herding developed by Lakonishok et al.. (1994) to their dataset, the authors found that herding behaviour was present. Periods of bull stock markets (January 1998 until March 2000) and the preceding bear market (April 2000 until December 2002) both showed the presence of herding behaviour. In conclusion evidence was found that a substantial portion of herding detected in the German market is related with spurious herding as a consequence of changes in benchmark index composition. Hence investigating the effect of mutual fund herding on stock prices seems to neither destabilize nor stabilize stock prices Walter and Weber (2006).

Agudo, Sarto and Vicente (2008) analysed the presence of herding behaviour phenomenon in the management style of Spanish equity funds. Monthly returns data was collected of all Spanish equity funds investing mainly in the domestic stock market from July 1994 to June 2002. This data was assessed using the herding behaviour measure by Lakonishok et al.. (1992) and Sharpe's style analysis (1992). Documented results showed significant evidence of herding behaviour in the value stocks and growth stocks during the period of study.

In addition, Hachicha, Bouri and Chakroun (2008) studied the herding behaviour and its measurement problem in the Toronto stock market. The authors introduced a further measure for herding, the Dynamic Herding measure based on the cross sectional dispersion of trading volume in order to examine the herding behaviour on Toronto stock exchange. This was based on the findings of Hwang and Salmon (2001). The new herding behaviour measure was used to detect the degree of which investors follow herding behaviour in the financial market. This research used monthly data on volumes and prices from Toronto stock exchanges main index which is the S&P/TSX60 index and it contains the largest companies. The study period was from January 2000 to December 2006, and in total a number of 5124 observations were made.

The Dynamic Herding method was successfully tested on the Toronto Stock Exchange. Hachicha et al. (2008) concluded that the herding hypothesis had three components. Firstly, the

constant term which proved the existence herding behaviour in different market conditions. This is consistent with reality since it is probable that there is at least one investor who imitates the actions of other investors. The second component deals with the anticipation error of the investors. Lastly, the current herding behaviour depends on the previous one (Hachicha et al., 2008).

In addition, Duasa and Kassim (2008) used daily price from Thomson Reuters Data Stream. Data was collected from Malaysian stock exchange from 1 January 1990 until 31 December 2010 encompassing of 846 listed firms. This study was done with the objective of testing the role of herd behaviour in determining the day-of-the week anomaly. Research was centered on the Christie & Huang (1995) CSSD model. Authors concluded that herd behaviour materialized during periods of market anomalies since investors are more likely to suppress their own belief opting the market consensus.

3.2.2 Herding behaviour in developed markets during normal periods

Periods of market volatility are defined as market periods where security's value fluctuates dramatically. These periods are associated with high market volatility, which is measured statistically by beta. The studies discussed below are on herding behaviour during market periods characterized by unstable security values.

Following up on the herding behaviour by Lakonishok et al.. (1991), Christie and Huang (1995) studied listed firms in the United State (New York Stock Exchange) during the period 1925 to 1988. This study focused on measures of dispersion during periods of significant variations in stock prices, with that in mind the authors developed an intuitive herding measure utilizing cross-sectional standard deviation (CSSD) of single stock returns with regards to market returns. CSSD was developed as a measure of average proximity of individual asset returns to the realized market average.

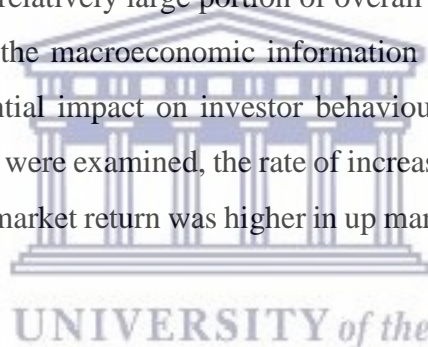
Christie and Huang (1995) analysed the market alternatives between normal and extreme phases and whether herding behaviour existed during periods of financial distress. Data was defined and tested as daily and monthly return data. The authors debated that when investors followed herding behaviour toward the market then individual asset returns would not diverge much from the overall market return hence value of CSSD gets reduced. Christie and Huang (1995) found that herding behaviour was absent during the sample period and concluded that periods are uniquely informative. Hence there was a high probability for investors to follow herding behaviour in stressful markets as individual investors are likely to discard their own beliefs and follow the market consensus.

In addition, Devenow and Welch (1996) expanded on the research by Wermers (1994); Lakonishok et al.. (1992) by describing the economics of the herding behaviour in financial markets. The authors used past literature by Lakonishok et al.. (1991) and Wermers (1994) to analyze if herding behaviour was present NYSE stock market. The authors concluded that investors on the NYSE leave their beliefs and follow the actions of other investors during periods of stress, thus following the herding behaviour. On the other hand, Christie and Huang (1995) proposed that it is optimal for investors to follow herding behaviour during periods of extensive movements in the markets. In summary, Devenow and Welch (1996) discovered that when investors ignore their own asset price predictions to use the market behaviour, then the individual asset returns will not diverge significantly with overall market returns.

Kaminsky and Schmukler (1999) addressed herding behaviour as the reason for chaotic financial environment. Daily data of changes in stock prices was collected on the Malaysian stock exchange during 1997 to 1998 crisis. This data was examined using Christie and Haung (1995) CSSD measure of herding behaviour. The authors believed that because of the bad news from neighboring countries, herding behaviour was present on the Malaysian stock exchange. Kaminsky and Schmukler (1999) analyzed the type of news that moved the markets in those days of market jitters. The authors found the presence of herding behaviour during the financial reforms in Malaysia. These movements were triggered by both local and neighboring-country news, with credit rating agencies and news about agreements with international organizations

and having the most impact Kaminsky and Schmukler (1999). However, some of those large changes were believed not to be enlightened by any important news, but seemed to be caused by herding behaviour instincts of the market investors Kaminsky and Schmukler (1999).

Chang, Cheng and Khorana (2000) extended the findings of Christie and Huang (1995) and established a nonlinear relationship between equity return and the overall market return. Cross-sectional absolute deviations (CSAD) were taken as a measure for dispersion. The authors examined the presence of herding hypothesis in five financial markets including developing and developed. These financial markets were US, Hong Kong, Japan, South Korea, and Taiwan. The authors concluded that herding was not present in developed (US & Hong Kong) economies but present in emerging economies (South Korea and Taiwan). Chang et al. (2000) also documented that in South Korea and Taiwan, where the evidence in favor of herding, systematic risk accounts for a relatively large portion of overall security risk. This evidence is consistent with the view that the macroeconomic information relatively to the firm specific information had more substantial impact on investor behaviour in markets which exhibited herding. In all the markets that were examined, the rate of increase in security return dispersion as a function of the aggregate market return was higher in up markets, relative to down markets days (Chang et al., 2000).



Extending on the studies by Chang et al. (2000) and Christie and Huang (1995), Hwang and Salmon (2001) introduced a new measure of herding that looked at the dispersion of a share's beta relative to the market beta. This measure focused on the risk-return relationship rather than the cross section variation of returns. The incorporation of beta made the cross sectional variability of beta to be interpreted in terms of irrational pricing due to herding. This measure captures market wide biases as opposed to individual biases which arise from systematic risk. The authors argued that the degree of dispersion in beta over time was not expected to change in response to share fundamentals. The study observed herding behaviour on the US, UK, and South Korean stock markets.

Hwang and Salmon (2001) findings showed that herding is present at a relatively lower degree in the developed countries and at a relatively higher degree in developing countries during the financial crises of 1997 and 1998. The authors also concluded that, herding behaviour in developed markets is not as prominent as in developing markets. They evaluated the direction towards which the market may be herding and their measure accounted for the fundamentals of the firms and the influence of time series instability. Using this they could distinguish intentional herding from spurious herding. Contrary to the findings of Christie and Huang (1995) they found herding in normal market conditions relative to market stress. This could be due to the larger information asymmetry present in emerging markets (Hwang & Salmon, 2001). Furthermore, Hwang and Salmon (2001) also concluded that the degree of distribution in beta over time is not expected to vary in response to either idiosyncratic news or share fundamentals. Their outcomes show that herding behaviour is present in the United States and United Kingdom at lower degree and in South Korea at a higher degree during the Asian and Russian financial crises of 1997 and 1998, respectively. In developing markets herding behaviour is prominent not as it is in developed markets. This may possibly be resulted by the higher information asymmetry existing in developing markets. In a nutshell herding was discovered to be greater before a crisis and becomes relatively weaker once the crisis appears as investors appear to lose confidence in the market. By using the multifactor models, the authors established that during a crisis, investors tend to focus more on value rather than growth shares and size plays a significant role as well Hwang and Salmon (2001).

Hwang and Salmon (2004) tested their previously derived method in 2001 for the South Korea and United States. The authors suggested a new approach to identify and measure herding behaviour which was based on the cross-sectional dispersion of the factor sensitivity of assets within a given market. This method enabled the researchers to evaluate if there was herding behaviour in the direction of particular sectors. They included macroeconomic factors to try and explain herding behaviour. The market of study was the US (S&P500) with 500 stocks and South Korean stock markets (KOSPI index) and 657 ordinary stocks. The findings showed that herding behaviour towards the market shows significant movements and persistence independently from and given market conditions and macro factors. The study concluded that

herding cannot be described by macroeconomic factors and was also present in both bull and bear markets in both countries examined.

Furthermore, Caparrelli, D'Arcangelis and Cassuto (2004) investigated the presence of herding in Italian stock market. Data was collected from the Italian Stock Exchange to test the presence of herding as described in Christie and Huang (1995). The findings supported the conclusion by Christie and Huang (1995) that herding is present in extreme market conditions. They also discovered the nonlinearity in herding pattern using methodology given by Chang et al. (2000). In conclusion the authors determined the degree of herding in order to distinguish between spurious and intentional herding. Intentional herding is indicated by a decreasing H-statistics and spurious herding is vice versa

Demirer, Kutan and Chen (2006) adopted the methodology that was originally proposed by Chang et al. (2000) to investigate herding behaviour. This methodology focuses on the cross-sectional behaviour of returns (CSAD) within a group of similar securities in order to make interpretations on investor's herding behaviour. They provided evidence from sector-based portfolios. There is significant evidence of herding behaviour in the market for ADRs from Chile only regardless of alternative model specifications. The authors found that during the Asian crisis cross-sectional standard deviations did not significantly affect stock returns and sector returns. Hence their results found no evidence of herding behaviour in the Chinese market. These findings of herding behaviour are consistent with other studies that investors are more anxious about potential losses than potential gains (Kahneman & Tversky, 1979; Kahneman, Knetsch, & Thaler, 1990).

Extending on Demirer, Kutan and Chen (2006), Demirer, Gubo and Kutan (2007) tested the presence of herding in stock markets of Western Europe, the U.S.A, Asia, Central and Eastern Europe, Latin America, Middle East and Africa using methodology first proposed by Chang et al. (2000). The authors investigated the presence of herding toward three anchor S&P 500 index, MSCI world market index and oil prices instead of using only market return. The authors found evidence of herding behaviour in Middle East and Asia and no evidence of herding in all the remaining regions. For Middle East and Asia results showed that investors were following

herding behaviour towards the MSCI index. So in line with Demirer, Gubo and Kutan (2007) there is no evidence of herding behaviour towards the S&P 500 index, MSCI world market index and oil prices in stock markets of Central and Eastern Europe, including Ukraine too.

Furthermore, Nativida and Sandra (2008) examined the intentional herding behaviour of market participants within different international markets (Germany, United Kingdom, United States, Mexico, Japan, Spain and France) using a new approach which accommodated for the detection of moderate herding over the whole range of market return. This method compares the cross-sectional deviation of selected stocks with the “artificially created” market free of herding effects. Nativida and Sandra (2008) suggested that intentional herding is likely to be better revealed when we analyze familiar stocks. The findings show that only Spain showed a substantial herding effect.

Herding behaviour has different types of irrationality which reveals why investors tend to follow what others do rather than believe in their own judgment (Dangi & Rathore, 2011). The two forms of herding behaviour are irrational and rational. Under the irrational perception, herding behaviour refers to a scenario of collective actions that are taken by an investor in uncertain market conditions. It occurs when traders ignore the information available to them, and refuse to make their own decisions, in order to follow the conclusions of others, even if they do not agree (Christie & Huang, 1995). Investors benefit from such behaviour since it reduces the uncertainty and the fear of the unknown that some investors possess (Dangi et al., 2011).

Hsieh (2013) observed the presence of herding behaviour for both institutional and individual investors on the Taiwanese stock market. Data was collected from the Taiwanese stock market ranging from May 2002 to October 2003 and used the LSV measure of herding behaviour introduced by Lakonishok et al. (1992) and was later modified by Zhou and Lai (2009). The author documented evidence that the institutional investors followed herding behaviour more than the individual investors. Both institutional and individual investors followed herding behaviour more in the case of companies with a low market capitalization. Hsieh (2013) also

recorded positive returns for institutional investors that practiced a herding behaviour, while individual investors recorded losses from such behaviour.

Moreover, Vieiraa and Pereirab (2014) studied the presence of herding behaviour on the European market, by evaluating the stocks that instituted to the Portuguese stock PSI-20 index, for the period between 2003 and 2011. The authors used two methods to evaluate herding behaviour, the first one applied a measure of herding, based on the methodology used in Chang et al.. (2000) CSAD measure and Christie and Huang (1995) CSSD measure. Secondly the authors followed the methodology proposed by Patterson and Sharma (2006), this method captured intraday order sequences, generally considered to offer the ideal frequency for testing the presence of herding behaviour. Once news is conveyed to the market on an intraday basis, investors may not have time to apply analytical models to interpret the news and, subsequently, to predict future price movements. Additionally, the study analyses the relationship between herd behaviour and investor sentiment, an area that has been little explored. In applying causality tests to the impact of sentiment on herd behaviour, only weak evidence is found that sentiment influences herding (Vieiraa & Pereirab, 2014).

The CSAD and CSSD measures of herding behaviour intensity led to different results, signifying that measurements of the herding behaviour are profound to the method used. The results showed that herding intensity is negative and statistically significant, concluding that investors follow each other in an organized way. Using Chang et al.. (2000) and Christie and Huang (1995), no evidence of herd behaviour was found, which advocates some evidence for the market efficiency hypothesis. These results are consistent with Chang et al.. (2000), Demirer and Kutan (2006) and Patterson and Sharma (2007), among others, whose findings support rational asset pricing models (Vieiraa & Pereirab, 2014).

Furthermore, Huang, Wu and Lin (2015) investigated the impact of institutional herding on the relationship between risk and return and the influence of the global financial crisis on this connection. Data of 25 individual stocks traded on the Taiwan Stock Exchange from January 2005 to Dec 2013 was collected and analyzed using Nofsinger and Sias (1999) method that changes in institutional ownership of individual stocks will be a proxy for the institutional

herding on each stock. The authors documented results that showed a weak relationship between institutional herding and risk-return. A strong relationship between institutional herding and risk-return was found on foreign institutional investors.

Looking at the studies of herding behaviour above, the phenomenon has been found to be present in developed markets both during normal periods (as documented by Agudo, Sarto and Vicente (2008), Lakonishok et al. (1992) and periods of market volatility (as concluded by Hsieh (2013), Hwang and Salmon (2004)). It is important to note that herding behaviour also exists in developing markets, below is a discussion of the studies on herding behaviour that were done in developing markets.

3.3 Herding in the developing market

The presence of herding behaviour in financial markets is worth to be observed and recorded because investors and financial managers are concerned about the way information is reflected in stock market prices. Below is a discussion of literature on herding behaviour in developing markets and on the South African stock market.

3.3.1 Herding behaviour in developing markets during normal periods

As mentioned above, normal periods are defined as market periods characterized by steady security values. These periods are associated with low market volatility, which is measured statistically by beta. The studies discussed below are on herding behaviour during market periods where security's value does not fluctuate dramatically.

Hachicha, Bouri and Chakroun (2008) studied the herding behaviour and its measurement problem in the Toronto stock market. The authors introduced a further measure for herding, the Dynamic Herding measure based on the cross sectional dispersion of trading volume in order to examine the herding behaviour on Toronto stock exchange. This was based on the findings of Hwang and Salmon (2001). The new herding behaviour measure was used to detect the degree of which investors follow herding behaviour in the financial market. This research used monthly data on volumes and prices from Toronto stock exchanges main index which is the

S&P/TSX60 index and it contains the largest companies. The study period was from January 2000 to December 2006, and in total a number of 5124 observations were made.

The Dynamic Herding method was successfully tested on the Toronto Stock Exchange. Hachicha et al. (2008) concluded that the herding hypothesis had three components. Firstly, is the constant term which proved the existence herding behaviour in different market conditions. This is consistent with reality since it is probable that there is at least one investor who imitates the actions of other investors. The second component deals with the anticipation error of the investors. Lastly, the current herding behaviour depends on the previous one Hachicha et al. (2008).

In addition, Duasa and Kassim (2008) used daily price from Thomson Reuters Data Stream. Data was collected from Malaysian stock exchange from 1 January 1990 until 31 December 2010 encompassing of 846 listed firms. This study was done with the objective of testing the role of herd behaviour in determining the day-of-the-week anomaly. Research was centered on the Christie & Huang (1995) CSSD model. Authors concluded that herd behaviour materialized during periods of market anomalies since investors are more likely to suppress their own belief opting the market consensus.

On the South African stock market, Gilmour and Smit (2002) made use of the herding behaviour measure proposed by Lakonishok et al. (1991) to test institutional herding phenomenon in the unit trust industry in South Africa. The authors recorded the presence of comparatively low levels of herding behaviour among institutional investors. The authors also documented the highest level of herding on aggressive growth funds, suggesting a substantial positive connection existed between the risk profile of funds and the level of herding on the JSE. Over the period 1992 to 1999, herding behaviour occurred both on the sell side and buy side. However, only international mutual funds were allowed in South Africa in 1998 and since then the industry has recorded remarkable growth Gilmour and Smit (2002).

The section above discussed herding behaviour in developed countries during normal market periods.

3.3.2 Herding behaviour in developing markets during periods of market volatility

As discussed earlier, periods of market volatility are defined as market periods characterized by unstable security values. These periods are associated with high market volatility, which is measured statistically by beta. The studies discussed below are on herding behaviour during market periods where security value fluctuates dramatically.

Kaminsky and Schmukler (1999) addressed herding behaviour as the reason for chaotic financial environment. Daily data of changes in stock prices was collected on the Malaysian stock exchange during 1997 to 1998 crisis. This data was examined using Christie and Haung (1995) CSSD measure of herding behaviour. The authors believed that because of the bad news from neighboring countries herding behaviour was present on the Malaysian stock exchange. Kaminsky and Schmukler (1999) analyzed the type of news that moved the markets in those days of market jitters. The authors found the presence of herding behaviour during the financial reforms in Malaysia. These movements were triggered by both local and neighboring-country news, with credit rating agencies and news about agreements with international organizations and having the most impact Kaminsky and Schmukler (1999). However, some of those large changes were believed not to be enlightened by any important news, but seemed to be caused by herding behaviour instincts of the market investors Kaminsky and Schmukler (1999).

Tan, Chiang, Mason & Nelling (2008) studied the presence of herding behaviour in the Shanghai and Shenzhen Stock Exchanges. Their period of study was from 1996 to 2003. They used the linear test by Christie and Huang (1995) and the nonlinear test by Chang et al. (2000). Tan et al. (2008) found evidence of herd behaviour in the Shanghai and Shenzhen markets for A-shares. The authors concluded that herding behaviour was present in both the exchange markets in bull and bear phases. Tan et al. (2008) also found strong evidence of herding behaviour in the Shanghai market when there is high volatility and when markets are rising. Furthermore, Tan, Chiang, Mason and Nelling (2010) studied herding behaviour of investors on the Chinese stock market. Since December 1990 when the Shanghai Stock Exchange

(SHSE) and the Shenzhen Stock Exchange (SZSE) was established, two classes of shares have been issued. First the A shares that can be purchased and traded only by domestic investors (i.e. only the Chinese investors) using the local currency, the Renminbi (RMB). Secondly are the B shares which were sold only to foreign investors (i.e. only non-Chinese investors) before February 2001, and have been sold to both foreign and domestic investors since then Tan et al. (2010). Both A and B shares traded concurrently on the Shanghai and Shenzhen stock markets even though the features of their investors were very different. Share B was dominated by foreign institutional investors who seemed knowledgeable about financial markets than share. An investor who were mainly local individual investors who had little experience and knowledge in investments Tan et al. (2010).

Data on stock prices, trading volume, and earnings per share for all firms listed on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) was collected from July 1994 to December 2003. There were 746 Shanghai A-share firms (SHA), 54 Shanghai B-share firms (SHB), 489 Shenzhen A-share firms (SZA), and 57 Shenzhen B-share firms (SZB). There are 44 firms that are dual-list A and B shares on the Shanghai exchange inside this sample, and 43 firms that dual-list A and B shares on the Shenzhen exchange and both were used. Tan et al. (2010) used daily data are from July 1997 to December 2003 which comprised of 1569 daily return observations for Shanghai A and Shenzhen A shares, and 1534 observations for both B shares Tan et al. (2010). Also weekly and monthly data from January 1996 to December 2003 were used. The authors found evidence of significant herding behaviour among share that were listed on both the Chinese A and B shares. Herding behaviour by A-share investors in the Shanghai market showed very strong asymmetric characteristics that is high market volatility and high trading volumes Tan et al. (2010).

In addition, evidence of herding over weekly and monthly time intervals was found to much weaker, signifying that herding behaviour is a phenomenon that is confined to short periods time. In summary herding behaviour was found to be present in all four markets examined, in all the circumstances when markets are rising, and when volume and volatility are high Tan et al. (2010).

In their study Lao and Singh (2011) examined herding behaviour in the Chinese and Indian stock markets. India and China have a number of fundamental factors which are the same these includes large labor forces, supportive government policies. These fundamentals are important as they aid long-term economic growth and the ability to become giant economies. As a result, that has exerted pressure on the stock markets of India and China. Lao and Singh (2011) used the methodology of Christie and Huang (1995) and Chang et al. (2000) to tested herding in the Chinese and Indian stock markets.

The aim of their article was to develop a clearer understanding of some forces that leads to the irrationality by proposing herd behaviour as the determinant force. A model was developed for herding behaviour using the Christie and Huang (1995) approach. In a nutshell, this research on herding behaviour bridges the gap between traditional finance and its contender by using the behavioural approach. Moreover, it recommends that the efficiency in the market actually can be achieved as long as there is no psychological bias in the investor trading behaviour. Secondly, it caters for the implication to practitioners by revealing the fear and regret aversion of the individual investor Lao and Singh (2011).

Their findings suggest that herding behaviour exists in both markets, and the level of herding depends on market conditions. In the Indian market the study finds that it occurs during up-swings in market conditions whereas in the Chinese market, herding behaviour is greater when the market is falling and the trading volume is high. In a nutshell herding in the Chinese market, herding was greater when the market was in a bear phase or when the market was falling and the trading volume is high. In India market herding was greater when the market was in a bull phase thus during up-swings in market conditions Lao and Singh (2011).

Moreover, Messis and Zapranis (2014) investigated the presence of herding in the Athens Stock Exchange over the 1995-2010 periods and studied its effects on market instability. The authors examined portfolios formed on beta and size of the selected stocks and used the state space model of Hwang and Salmon (2004) to test herd behaviour. This method focuses on the cross-sectional variability of factor sensitivities. According to Hwang and Salmon's model, betas of

individual assets will be biased and away from their equilibrium values when investors' herding towards market portfolio is present Messis and Zapranis (2014).

In conclusion, Messis and Zapranis (2014) findings depicted the presence of herding however large differences were observed among the portfolios regarding the herding periods. The results confirmed linear effects of herding on all volatility measures considered. Stocks displaying higher levels of herding also presented higher volatility, and from this point of view, herding can be regarded as an additional risk factor Messis and Zapranis (2014).

Moreover, Angela, Miruna and Andreea (2015) investigated the existence of herding behaviour of investors from emerging markets. This was done using industry level data of daily returns for the companies listed on stocks markets of the following countries Czech Republic, Poland, Hungary, Romania and Bulgaria for the period from January 2008 to December 2010. Herding behaviour was calculated using the CSAD statistical method proposed by Chang et al.. (2000) at industry level i.e construction, energy, pharmaceutical, banks, financial and hotels. The authors also analysed the presence of herding behaviour for both upward and downward trends on the market and during the market crisis. Angela, Miruna and Andreea (2015) documented results that investors followed herding behaviour more during periods of downward trend and the behaviour was different during the pre-crisis and post crisis periods compared with the crisis period. In summary, Angela, Miruna and Andreea (2015) found evidence of herding behaviour of investors on all the stock markets, except for Poland hence investors from CEE stock markets tend to base their investing decisions based on those of other market participants (brokers, field practitioners etc), thus herding behaviour is exhibited in both upward and downward trends.

Furthermore, Huang, Wu and Lin (2015) investigated the impact of institutional herding on the relationship between risk and return and the influence of the global financial crisis on this connection. Data of 25 individual stocks traded on the Taiwan Stock Exchange from January 2005 to Dec 2013 was collected and analyzed using Nofsinger and Sias (1999) method that changes in institutional ownership of individual stocks will be a proxy for the institutional herding on each stock. The authors documented results that showed a weak relationship

between institutional herding and risk-return. A strong relationship between institutional herding and risk-return was found on foreign institutional investors.

In the South African context, Seetharam and Britten (2013) studied herding behaviour together with market cycles in South Africa. The authors observed herding behaviour from 1995 to 2011 which encompassed both the bear and bull markets. When studied together with the market cycle, herding behaviour has appeared to dramatically fluctuate before a market contraction. Theoretically, herding behaviour can be seen as an explanatory factor for the presence of a nonlinear market model. Monthly data was collected for all shares listed on the JSE and the All Share Index (ALSI) from 1995 to 2011. Data was gathered in order to incorporate the 2007 financial crisis thus this sample period provided a sufficient framework to examine the market cycle, especially given the global recession since 2007 Seetharam and Britten (2013). In this regard, Seetharam and Britten (2013) used three different methods proposed by Christie and Huang (1995), Chang et al. (2000) and Hwang and Salmon (2001) to analyse their data. Seetharam and Britten (2013) found evidence that a negative market reaction was led by an increase in herding during a South African market contraction can thus impact financial forecasts and volatility estimates of the market. Furthermore, it could possibly designate the level of confidence of market participants, both experienced and inexperienced individuals tend to follow the group consensus in times of a market downturn, yet deviate from the group consensus in times of a market upturn. In summary Seetharam and Britten (2013) found evidence of herding behaviour during bear market periods only.

In addition, Sarpong and Sibanda (2014) studied herding behaviour in the midst of equity mutual fund managers and the performance of mutual funds that in South Africa. The authors investigated herding behaviour among 41 domestic equity mutual fund managers and the performance of mutual funds that trade against the herd in South Africa. The activities of mutual funds have an effect on the stability and volatility of stock markets and ultimately investors return. This study builds upon the efficient market hypothesis, behavioural finance

and portfolio theory to provide endorsement of the herding behaviour of mutual funds in developing market context using the Johannesburg Stock Exchange.

Looking at the measure of herding behavior by Lakonishok et al. (1991), the authors used it to determine the behaviour of mutual funds over the period 2006 to 2012. Most investors in South Africa are vulnerable to bias of herding behavioural and this influences the ultimate performance of their funds. These outcomes suggest that following investment waves does not terminate in superior returns in the stock market and subsequently, mutual funds that take contrary direction to herd funds aid towards stabilizing the stock market. In summary Sarpong and Sibanda (2014) managed to classify mutual funds into herding and contrarian providing an understanding on the performance of each category. Investors who compete against herding behaviour tend to realize greater returns over time at the same time stabilizing the markets. The authors documented evidence of herding behaviour among mutual fund managers and concluded that institutional investors in South Africa are prone to herding behaviour bias and that this phenomenon influences the performance mutual funds.

Niyitegeka (2013) observed the existence and the nature of the volatility clustering phenomenon in the Johannesburg Stock Exchange (JSE). Volatility clustering is one of the most common stylized facts in financial time series it has captivated many researchers. This study used the Autoregressive Distributed Lag (ARDL) approach to examine the short- and long-term dynamics of investors' herd behaviour on top 100 stocks on the JSE by market capitalisation. Autoregressive Distributed Lag (ARDL) approach is a GARCH-type models which was used by the authors to detect volatility clustering. The authors study period was from August 2006 to August 2011. Results showed that negative shocks to stock prices produced more volatility than positive shocks of equal magnitude. In a nutshell, the outcomes of this study showed the presence of volatility clustering on the JSE during bull market periods and conversely there was no proof of herding behaviour during bear market periods.

In addition, Ababio and Mwamba (2017) conducted a study to investigate if there was evidence of herding behaviour in South Africa's financial industry using an alternative approach. Using the quantile regression model in assessing daily data on stock returns on the JSE from January

2010 to September 2015. As an alternative measure of average market portfolio returns the median was used in their study in order to evaluate the evidence of herding behaviour in the banking and real estate sectors during the sample period (Ababio & Mwamba, 2017). The authors found herding behaviour in the banking during bear phase ie when the market is falling. Conversely, the real estate sector investors showed herding behaviour to be present during bull phase ie when the market is rising. In summary, the whole financial industry recorded evidence of herding behaviour only during the bull phase ie during the period of extreme market stress (Ababio & Mwamba, 2017).

3.4 Conclusion

In summary, literature on developed countries during normal periods by Lakonishok et al. (1991) found evidence that pension fund managers in both large stocks and small stocks followed herding behaviour. Christie and Huang (1995) found that herding behaviour was absent during periods characterized by high market volatility in developed countries. Chang et al. (2000) also documented that in South Korea and Taiwan, there was evidence in favor of herding behaviour during periods characterized with high market volatility. Tan et al. (2008) also found strong evidence of herding behaviour in the Shanghai market when there is high volatility and when markets are rising. Hwang and Salmon (2001) findings showed that herding was present at a relatively lower degree in the developed countries and at a relatively higher degree in developing countries during the financial crises of 1997 and 1998.

Even though the literature in this field is plentiful, empirical studies on the JSE are not numerous. In the existing literature, most of the empirical studies on the JSE have mostly employed the autoregressive distributed lag measure, the dynamic herding measure and quantile regression model in testing for herding behaviour on stocks and mutual funds (Gilmour & Smit, 2002; Seetharam & Britten, 2013; Sarpong & Sibanda, 2014; Niyitegeka & Tewari, 2015; Agyarko & Ababio, 2017). The documented findings on the JSE of are consistent to other related studies on developed markets for example studies by (Lakonishok et al., 1991; Chang et al., 2000; Tan et al., 2008).

It is evident from the above studies on the JSE that there is no literature on herding behaviour, focusing on the JSE tradable indices. This research seeks to fill this gap and to contribute towards the existing literature on herding behaviour on the JSE. This is done by observing the evidence of herding behaviour before the global financial crisis, during the global financial crisis and after the global financial crisis on the JSE tradable indices. This research identified that after the occurrence of global financial crisis herding behaviour could have caused stock prices to deviate from their fundamental value. With that in mind, testing evidence of herding behaviour could provide useful information for financial models that are used to estimate evolution of stock prices.



Chapter Four – Research Methodology

4.1 Introduction

Behavioural finance combines sociology and psychology to describe investors' behaviour, providing a more holistic theoretical basis for financial decision making (Demirer & Kutan, 2006). Amongst the various behavioural theories, this paper studied herding behaviour together with market cycles in South Africa. Seetharam and Britten (2013) defined herding behaviour as the relationship captured between share price movements with the market.

The purpose of this study is to apply the cross-sectional standard deviation of returns (CSSD) measure postulated by Christie and Huang (1995), and cross-sectional absolute deviation of returns (CSAD) measure proposed by (Chang et al., 2000) to examine if there was evidence of herding behaviour on the JSE tradable indices (RESI₁₀, INDI₂₅, FINI₁₅). The industrials index (INDI₂₅) constitutes of 25 largest industrial stocks by market capitalization, the financials index (FINI₁₅) comprises of 15 largest financial stock by market capitalization and lastly the resources index (RESI₁₀) which represents 10 largest resources stocks by market capitalization JSE (2017). This research used the CSSD and CSAD herding behaviour measures since they have been tested and validated by most literature (Chang et al., 2000; Tan et al. 2010; Angela, Miruna and Andreea; 2015). This chapter discusses the research design that was utilized, the methodological issues involved such as sample data, data analysis adopted as well as the possible biases and their remedies are explained.

4.2 Research design

There are two research approaches that can be used for research, namely qualitative and quantitative. A quantitative design tests relationship and examines cause and effect relations on a subject while a qualitative research method is used to obtain an in-depth understanding of the subject (Merriam & Tisdell, 2015). In order to obtain a quality and reliable study result, an effective and appropriate research design and methods must be used. Testing herding behaviour using the Christie and Huang (1995) and Chang et al. (2000) models requires a calculation of variables i.e the arithmetic mean and standard deviation.

The model is a form of quadratic problem, which makes it ideal to use of quantitative research methods for this research to investigate and analyse the CSSD and CSAD models on the JSE. According to Walliman (2017) a quantitative research design allows a systematic investigation, measuring, quantifying, and testing of the hypotheses as well as establishment of the relationship between financial variables. This assisted the researcher to find evidence in support of or to contradict whether herding behaviour is present on the JSE tradable sector index. The relationship between herding behaviour and market cycles was also able to be analysed using the quantitative approach. The financial data was analysed and interpreted using Stata version 14 and the Microsoft Excel software package. A comparison was made with a chosen benchmark, namely the JSE ALSI.

Using quantitative research methods allows the research to be replicated, analysed and compared with similar studies. That is information from various sources can be analysed through the use of mathematical models, summarised and compared against one another. In addition, quantitative research approach gives room for a comprehensive study of the subject and is ideal for studying subjects when huge quantities of data are involved at the same time, permitting generalisation of results (Creswell, 2002). According to Williams (2007), quantitative research is also regarded as a way of obtaining the true facts about a subject since it uses standard means, predictions and controls are made possible and cause and effect relationships can be identified.

Quantitative research design does not relate to the views of each individual investor, as a qualitative research method does. The results obtained using a quantitative approach are limited, as they provide numerical descriptions rather than detailed narrations with elaborations on how the result came into being (Williams, 2007). Therefore, quantitative research strategy on its own does not address the complexity of a phenomenon and quite a large sample of the population must be studied for the results to be more accurate (Williams, 2007).

Having considered both the advantages and disadvantages of the quantitative research design method, this research found that the quantitative method was the most ideal for this research.

Statistical inference was used to ensure that the data were a true representative of the whole population and that the results were statistically significant. Looking at the CSSD and CSAD measures Angela, Miruna and Andreea (2015) investigated the existence of herding behaviour of investors from emerging markets focusing on the Czech Republic, Poland, Hungary, Romania and Bulgaria stock markets using the CSAD statistical method proposed by Chang et al.. (2000). Lao and Singh (2011) examined herding behaviour in the Chinese and Indian stock markets using the CSSD measures.

4.3 Possible Biases in Research and Their Remedies

In order to ensure that this research has rational economic reasoning and valid expectable results, research data and sample periods were carefully examined. Usually research findings are subject to possible research biases, the biases which are relevant to this research include data mining, survivorship amongst others and their measures are discussed below.

Data mining bias refers to the mismanagement of data which occurs where data is repetitively used to find statistically significant patterns, that otherwise could be insignificant. Thus data mining bias is reliant on the effectiveness of the data collection and computer processing. Since sample data will be used in this study, this research is subject to data mining bias. In order to eradicate this bias, this research made sure that substantial levels for test samples are high enough to boost the validity of, and provide some degree of continuity to the research findings (Keogh & Kasetty, 2003).

Survivorship bias refers to a scenario where company's data that no longer exist maybe due are excluded due to their poor performance This bias tends to skew research findings higher as companies that are performing well tend to increase the actual results (Hodnett & Hsieh, 2012). Relating to this study moderately low number of stocks at the very early stage of the sample can cause survivorship bias problems. Keogh and Kasetty (2003) argue that survivorship bias can be mitigated through the exclusion of smaller and larger firms. In order to observe the possible effects associated with survivorship bias, this research used data until the last day of

listing since this bias can be eliminated if companies that are delisted are included as part of the sample up until the month of delisting.

4.5 Population / sample description and data sources

A population is an entire group of the subjects being studied. The relevant target population of this study was all the tradable indices on the JSE. According to the JSE equity market statistics (JSE, 2018), there are more than 800 potential investments, of which approximately 300 are tradable indices and sub-indices on the JSE. However, not all the tradable indices are active on the JSE. The top JSE indices comprise of the Top 40, JSE ALSI (which include some 150 JSE-Listed companies and the largest index in terms of size and overall value (JSE, 2018)), the industrials index (INDI₂₅) constitutes of 25 largest industrial stocks by market capitalization, the financials index (FINI₁₅) comprises of 15 largest financial stock by market capitalization and lastly the resources index (RESI₁₀) which represents 10 largest resources stocks by market capitalization.

Since tradable sector indices constitutes assets from all the South African sectors they form an integral part of the financial world on the JSE. According to Yu (2008), those investment vehicles or assets derive their prices from other instruments and they trade intra-day on the JSE. The tradable sector indices allow investors access to hold value of a number of companies from the same South African sector pooled together in one big basket. Investors can monitor these indices for decision making with respect to their portfolios.

According to Walliman (2017), a sample is a subset or a representation of the entire population with the same characteristics as the population. Practically, it would not have been feasible to focus on the entire JSE with the vastness of securities trading daily, hence this study made use of the three JSE tradable sector indices, which comprise of 50 companies. There are two types of sampling methods, namely probability and non-probability. With non-probability sampling, samples are grouped in a process that does not give all the individuals in the population equal chances of being selected while with probability each unit will stand an equal chance of being selected. This research employed the non-probability sampling using a technique called

purposive sampling. According to Tongco (2007) purposive sampling is a sample that is picked based on a certain criterion depending on the qualities that the units to be studied possess. For the purpose of this study, the sample was the three indices that constitute the JSE tradable sector, namely the INDI₂₅, FINI₁₅ and RESI₁₀ indices. The index codes for the 3 indices are J211, J210 and J212 respectively. All three indices had a base date of 1 February 2002.

This study purposively chose the INDI₂₅, FINI₁₅ and RESI₁₀ indices as the sample. The three indices represent different South African market sectors, which facilitates sector diversification onto the constructed portfolio. According to the Industry Classification Benchmark (ICB) of South Africa, the JSE ALSI was sub divided into three South African sectors, which are SA Resources, SA Financials and SA Industrials. SA Resources constitutes 12%, SA Financials 24% while SA Industrials constitutes 64% of the JSE ALSI (JS Exchange Regulatory Report, 2013). The three indices capture the most liquid, tradable instruments in their respective sectors.

Each sector index comprises of a number of different companies that are pooled together to maintain their values as one. The SA Resources sector constitutes the JSE listed companies that belong to the ICB Sectors of Oil & Gas Producers (0530) and Mining (1770). The second sector, which is SA Financials comprises of JSE-listed companies that belong to ICB Financials (8000). Finally, the SA Industrials sector comprises of all remaining companies, that is the JSE listed companies that do not belong to ICB Industry Financials (8000) or ICB Oil & Gas Producers (0530) and Mining (1770). The companies in each index are not static; they change daily to accommodate the top companies into their respective indices. The INDI₂₅ index holds the daily top 25 companies from the industrial sector by market capitalization, the FINI₁₅ index the daily top 15 from the financial sector by market capitalization while the RESI₁₀ index holds the value of the daily top 10 companies from the resources sector by market capitalization. Table 4.1 below shows a list of some of the companies (and the company codes) that existed on the first day of this study (1 January 2007) and were also present on the last day of the study (31 December 2017).

Table 4.1: Names and codes of companies in the tradable sector indices from Jan2007 to Dec 201 7

INDI₂₅	FINI₁₅	RESI₁₀
Afrocentric Investment Corporate Ltd (ACT)	Capitec Bank Holding Ltd (CPI)	AECI Ltd (AFE)
Astral Foods Ltd (ARL)	Coronation Fund Managers Ltd (CML)	Anglo American Platinum Ltd (AMS)
Barloworld Ltd (BAW)	Hammerson PLC (HMN)	Anglo American PLC (AGL)
Cashton CTP Publishers and Printers (CAT)	Hosken Consolidated Investments Ltd (HCI)	Anglogold Ashanti Ltd (ANG)
Clicks Group Ltd (CLS)	Intu Properties (ITU)	Assore Ltd (ASR)
EOH Holdings Ltd (EOH)	Investec Plc (INP)	Harmony Gold Mining Company Ltd (HAR)
Grindrod Ltd (GND)	Liberty Holdings Ltd (LBH)	Northam Platinum Ltd (NHM)
Hudaco Industries Ltd (HDC)	MMI Holdings Ltd (MMI)	Omnia Holdings Ltd (OMN)
Lewis Group Ltd (LEW)	Nepi Rockcastle PLC (NRP)	Impala Platinum
MTN Group Ltd (MTN)	PSG Konsult Ltd (KST)	Sappi Ltd (SAP)
Murray and Roberts Holdings Ltd (MUR)	Peregrine Holdings Ltd (PGR)	
Nampak Ltd (NPK)	Redefine Properties Ltd (RDF)	
Naspers Ltd (NPN)	Texton Property Fund Ltd (TEX)	
Netcare Ltd (NTC)	Sanlam Ltd (SLM)	
Oceana Group Ltd (OCE)	Standard Bank Group Ltd (SBK)	
RCL Foods Ltd (RCL)		
Reunert Ltd (RLO)		
Shoprite Holdings Ltd (SHP)		
Spur Corporation Ltd (SUR)		
Super Group Ltd (SPG)		
The Foschini Group Ltd (TFG)		
Tiger Brands Ltd (TBS)		
Tongaat Hulet Ltd (TON)		
Truworths International Ltd (TRU)		
Wilson Bayly Homes Ovcon Ltd (WBO)		

However, the constituents of the indices shown in Table 3.1 are not fixed since they keep on changing daily and the index will automatically pick the top companies to make up its constituents.

The period under consideration for the study was from 1 January 2007 to 31 December 2017 (a period of 132 months). This period was selected because of the different market phases experienced due to the global financial crisis of 2008, the continuous fluctuations of interest rates and the devaluation of the South African Rand (ZAR) against the United States Dollar (U.S Dollar). Therefore because of the in volatility during the period of study the examination of the existence of herding behaviour will be tested during the different market phases.

4.6 Data Collection

Daily data was used in the study obtained from Bloomberg, a website which provides a comprehensive and continuously updated information resource. The present study focused on the tradable sector indices in South Africa by assessing the evidence of herding behaviour using tradable sector indices on the JSE. Daily closing prices for each of the four indices were downloaded in order to compute daily returns and volatilities. Considering these three tradable sector indices to under study, a total of 50 shares was included in the indices. Each of the three tradable sector indices had a base date of 24 June 2002. The data collected from Bloomberg included the historical price records for the three indices, namely INDI₂₅, FINI₁₅ and RESI₁₀. The data were first filtered and cleaned to get rid of any irregularities. The study period was divided into three periods, starting with the period from 1 January 2007 to 30 June 2007 which was before the global financial crises, then the period from 1 July 2007 to 31 August 2009 which was the period during the global financial crisis and lastly from 1 September 2009 to 31 December 2017 which was the period after the global financial crises.

This research used two major testing measures of herding behaviour by Christie and Huang (1995) and Chang et al. (2000). According to past research, herding was investigated based on return data to hypothesize that herding behaviour is captured by examining either return

dispersions or relative dispersion of the time-varying betas for assets. This research employed the CSSD measure among individual indices and CSAD. These models differ because the first focuses on the cross-sectional variability of returns, while the last one focuses on the cross-sectional variability of factor sensitivities (Vieiraa & Pereirab, 2014). Therefore, understanding the contributions and use of each model will help to yield consistent results with herding behaviour.

4.7 Data used and analysis

The objectives of this research is to examine if there is evidence of herding behaviour using data from the JSE tradable indices RESI₁₀, INDI₂₅, FINI₁₅). The industrials index (INDI₂₅) constitutes of 25 largest industrial stocks by market capitalization, the financials index (FINI₁₅) comprises of 15 largest financial stock by market capitalization and lastly the resources index (RESI₁₀) which represents 10 largest resources stocks by market capitalization (JSE, 2017). This will be done by using the CSSD measure proposed by Christie and Huang (1995) and CSAD measure postulated by Chang et al. (2000). Having said that, this section discusses the methodological procedure that is employed in order to achieve the research. In order to clearly demonstrate the methodological procedure, this section is segmented into two main sub-section namely the investigation of herding behaviour during normal periods (which includes the period before the global financial crisis and after the global financial crisis) and during periods of market stress.

4.7.1 Data analysis

This study used Microsoft Excel and Stata version 14 to run the estimations and calculate the CSSD and CSAD for a period of 132 months (11 years). Daily downloaded stock prices for each index were arranged in ascending order based on dates and the average rate of return and standard deviation for each index were then estimated for the four indexes which include RESI₁₀, INDI₂₅, FINI₁₅ and JSE ALSI. Using the same daily data, the average return dispersion and standard deviation of dispersion were estimated. With that in mind this research used the volatility and average rate of return estimates together with dummy variables on Microsoft

Excel and Stata version 14 to calculate the CSSD and CSAD values as done by other scholars (Vieiraa & Pereirab, 2014; Angela, Miruna & Andreea, 2015).

The period of study was categorized into three parts; before the global financial crisis period, during the global financial crisis period and after the global financial crisis period. According to Reinhart and Rogoff (2008) the global financial period in South Africa transpired from July 2007 to August 2009. With that in mind, the period before the global financial crisis will start from 1 January 2007 to 30 June 2007. On the other hand, the period during the global financial crisis will start from 1 July 2007 to 31 August 2009. The remaining period starting from 1 September 2009 onwards is the period after the global financial crisis. The CSSD and CSAD was calculated for the three periods so as to test if there was evidence of herding behaviour as aligned to the three objectives of this study. Section 4.7.1 and section 4.7.2 below provide a detailed explanation of the CSSD and CSAD measures.

4.7.2 Herding during normal periods- pre and post global financial crisis

Christie and Huang (1995) derived the first dispersion model of by estimating the cross-sectional standard deviation (CCSD) of returns. This is based on daily data and it supports the estimates of rational asset pricing models and suggested that herding is not an important factor in asset returns determination. Christie and Huang (1995) used CSSD as a measure of the average proximity of individual asset returns to the realized market average to test herding behaviour. In addition, Chang et al.. (2000) used CSAD in a non-linear regression specification to examine the relation between the level of equity return dispersions and the overall market return. According to these methodologies the existence of herding behaviour would cause INDI₂₅, FINI₁₅ and RESI₁₀ returns not to diverge much from the overall market return. This is based on the belief that investors suppress their own views and make investment decisions based on the collective actions of the market.

During stress periods where herding behaviour is evident, investors suppress their own beliefs and follow the market consensus and this would mostly occur during periods of market volatility. This effect of herding behaviour was explored by examining whether the dispersions were significantly lower than average during periods of market stress. During periods of

extreme market movements, rational asset pricing models expects that large changes in the market return translates into an increase in dispersion since individual assets differ their sensitivity to the market return (Christie & Huang 1995; Chang et al.. 2000). In other words, dispersion in factor sensitivities will repel away INDI₂₅, FINI₁₅ and RESI₁₀ returns from the market represented by the JSE ALSI. Thus, herding behaviour and rational asset pricing models offer conflicting predictions for the behaviour of dispersions during periods of market stress (Christie & Huang, 1995). Research by Tan et al. (2010) and Angela, Miruna and Andreea (2015) shows evidence that dispersions increase significantly during periods of large absolute price changes and these results are consistent with the predictions of rational asset.

In order to evaluate the existence of herding within the INDI₂₅, FINI₁₅ and RESI₁₀ indices, the level of dispersion will be calculated for indices portfolios and the effects of herding on market volatility. Herding behaviour can be explained by the relationship between share price movements with the market, illustrated by beta. Beta illustrates systematic risk which is both unpredictable and impossible to completely avoid. Systematic risk is also known as market risk and it affects the whole market and not only a particular industry or stock (Savor & Wilson, 2016).

To quantify the dispersions of individual returns from market return, this research used CSSD which is the difference between an INDI₂₅, FINI₁₅ and RESI₁₀ share's return and the market return. The dispersion of equity returns, CSSD, is measured by the following expression:

$$(CSSD) = \sqrt{\sum_{n=1}^n \left(\frac{R_i - R}{N-1} \right)^2} \quad (1)$$

where \bar{r} and \bar{r} is the cross-sectional average of the n returns in the portfolio and R_i is the observed return of INDI₂₅, FINI₁₅ and RESI₁₀. This measure incorporates key attributes of herding behaviour by quantifying the degree to which asset returns tend to rise and fall in comparison with the portfolio return. Dispersions are expected to be low when herd behaviour is present and when dispersions are high then it implies that herding behaviour will be absent. Damodaran (2012).

4.7.3 Herding during periods of market stress-during the global financial crisis

During periods of market stress, the differential predictions of herding behaviour and rational asset pricing models are most distinct because the sensitivity of individual securities differ to the market return. The rational asset pricing models predicts that during periods of market stress the levels of dispersion are induced whereas the herding of individual returns around the market translates into a reduced level of dispersion (Christie & Huang, 1995; Chang et al., 2000).

In order to test the presence of herd behaviour on the JSE tradable indices during periods of market uncertainty, this research used Christie and Huang (1995)'s of the formulae below.

$$\text{CSSD} = \partial + \beta^L D^L + \beta^X D^X + e_t \quad (2)$$

Where

$D^L = 1$ if the market return on day t lies in the extreme lower tail of the return distribution $D^L = 0$ otherwise, and $D^X = 1$ if the market return on day t lies in the extreme upper tail of the return distribution $D^X = 0$ otherwise. The ∂ coefficient denotes the average dispersion of the INDI₂₅, FINI₁₅ and RESI₁₀ excluding the regions covered by the two dummy variables. Rational asset pricing models predict significantly positive coefficients for β^L and β^X , and negative estimates of β^L and β^X would be consistent with the presence of herd behaviour

This research will use 99% and 95% confidence intervals in distributions to define extreme market price movements as done by Christie and Huang (1995).

The second return dispersion methodology employed in this paper is suggested by Chang et al. (2000) and uses the cross-sectional absolute deviation of returns (CSAD) as a measure of return dispersion. According to Chang et al. (2000) CSAD shows that rational asset pricing models also predict that there is linear relation between the equity return dispersions and the market return. The relation is non-linearly when investors follow aggregate market behaviour during periods of large average price. CSAD is expressed as

$$\text{CSAD} = \frac{1}{N} = \sum_{i=1}^n |\beta_i - \beta_m| (R_m - r_f)_{i,t} \quad (3)$$

Where β_m be the systematic risk of an equally-weighted market portfolio, r_f is the return on INDI₂₅, FINI₁₅ and RESI₁₀ with the zero-beta portfolio, β_i is the time-invariant systematic risk measure of the security i ranges $1 \dots n$ and $t \ 1 \dots t$

In order to capture any possible non-linear relation between security return dispersions and the market return Chang et al.. (2000) proposed an alternate test of herding and used an additional regression parameter. To measure the possibility that the degree of herding may be asymmetric in the up-versus the down-market, the following formulae was used

$$CSAD^{UP}/t = a + \gamma_1^{UP} R^{UP} + \gamma_2^{UP} (R^{UP})^2 + E^t \quad (4)$$

$$CSAD^{DOWN}/t = a + \gamma_1^{DOWN} R^{DOWN} + \gamma_2^{DOWN} (R^{DOWN})^2 + E^t \quad (5)$$

Where CSAD is the average absolute value of the deviation of each stock relative to the return of the INDI₂₅, FINI₁₅ and RESI₁₀ equally weighted market portfolio, R in period t , and R^{DOWN} and R^{UP} is the absolute value of an equally-weighted realized return of INDI₂₅, FINI₁₅ and RESI₁₀ on day t when the market is up (down). Both variables were computed on a daily basis. When herding behaviour is present during periods of large price movements then there would be a less proportional increase or decrease in the CSAD measure.

4.8 Conclusion

Consistent with the objectives of this study which is to establish whether the JSE tradable sector index (INDI₂₅, FINI₁₅, RESI₁₀) was influenced by herding behaviour before, during and after the global financial crisis this chapter explained the methodological designs and methods employed in order to evaluate herding behaviour. This research adopted the measures by Christie and Huang (1995) and Chang et al. (2000). Following on the past studies that have done this research saw that the two conventional methodologies provides a critical analysis of

herding behaviour. The next Chapter will discuss the findings of this study to determine whether herding behaviour is present on the JSE tradable sector index during the period of study.



Chapter Five – Results and Analysis

5.1 Introduction

This chapter presents the data analysis and empirical findings on the presence of herding behaviour using the JSE tradable indices which include the industrials index (INDI₂₅), the financials index (FINI₁₅) and lastly the resources index (RESI₁₀). Primarily this research had

three main questions to answer which was if herding exists on the JSE tradable indices before, during and after the global financial crisis looking at the period from January 2007 to December 2017.

According to Reinhart and Rogoff (2008) the South African economy experienced the effects of the global financial crisis between 1 July 2007 and 31 August 2009. In this regard, this research was split into three categories, namely before the 2007-2009 global financial crises, during the global financial crises and after the global financial crises. With that in mind, the pre-crisis period is considered to be from the 1 January 2007 to 30 June 2007, during the crisis period which is specified above and lastly after the crisis period from 1 September 2009 to 31 December 2017.

5.2 Restatement of research objectives

In order to guide this study, the following research objectives are stated (see subsection 1.6):

1. To establish whether the JSE tradable sector index (RESI₁₀, INDI₂₅, FINI₁₅) had evidence of herding behaviour before the global financial crisis
2. To establish whether the JSE tradable sector index (RESI₁₀, INDI₂₅, FINI₁₅) had evidence of herding behaviour during the global financial crisis
3. To establish whether the JSE tradable sector index (RESI₁₀, INDI₂₅, FINI₁₅) had evidence of herding behaviour after the global financial crisis

5.3 Results

This section presents the tables and graphs of the findings of this research on whether evidence of herding behaviour existed before the global financial crisis, during the global financial crisis and after the global financial crisis or not.

5.3.1 Descriptive statistics

A total of 50 stocks were considered comprising of 25 largest industrial stocks by market capitalization, 15 largest financial stock by market capitalization and lastly 10 largest resources stocks by market capitalization. Daily closing prices for RESI₁₀, INDI₂₅, FINI₁₅ and JSE ALSI from January 2007 to December 2017 were used (in total 2751 days were observed). Although

not every stock was present for the total period as noted earlier, in an effort to avoid the impact of survivorship bias, the delisted stocks will be examined until their last trading date. In order to investigate the existence of herding within the indices, the level of dispersion was calculated for all the indices. The indices considered were RESI₁₀, INDI₂₅, FINI₁₅ and JSE ALSI.

Since the study period was divided into three categories, starting with the period from 1 January 2007 to 30 June 2007 (in total 124 days were observed) which was before the global financial crises, then the period from 1 July 2007 to 31 August 2009 (in total 293 days were observed) which was the period during the global financial crisis and lastly from 1 September 2009 to 31 December 2017 (in total 2334 days were observed) which was the period after the global financial crises, results are presented as such from Tables 5.1 to 5.4.

The first step was to calculate the mean, standard deviation, average return dispersion and standard deviation dispersion for RESI₁₀, INDI₂₅, FINI₁₅ and JSE ALSI using Microsoft Excel. This was done to provide general performance of the indices before, during and after the global financial crisis.

5.3.2 Descriptive statistics before the global financial crisis

This section provides the results of estimates for mean, average dispersion, mean and standard deviation of the tradable indices before the global financial crisis. Table 5.1 provides the estimates of the mean, standard deviation, average return dispersion and standard deviation dispersion for RESI₁₀, INDI₂₅, FINI₁₅ and JSE ALSI before the global financial crisis.

Index	Mean	Average return dispersion	Standard deviation	Standard deviation of dispersion	Covariance
FINI ₁₅	0,16%	0,340%	0,01989	0,0140%	0,43
RESI ₁₀	0,13%	0,934%	0,01475	0,0025%	0,11

INDI25	0,11%	0,515%	0,01879	0,0018%	0,17
JSE ALSI	0,10%	0,410%	0,01312	0,0011%	0,13

Table 5.1: Average daily returns and standard deviations before the global financial crises

The results provided in table 5.1 of the four indices from the beginning of January 2007 up to end June 2007 (in total 124 days were observed). These results provide the general performance of the four indices (RESI10, INDI25, FINI15 and JSE ALSI). The RESI10 index yielded daily returns of 0.13 percent with a standard deviation of 0.01475 and a covariance of 0.11, the INDI25 index had an average daily return of 0.11 percent while its standard deviation was 0.01879 and covariance of 0.17. Lastly, the FINI15 index had the least performance amongst the other indexes (RESI10, INDI25, FINI15 and JSE ALSI) with an average daily return of 0.16 percent, covariance of 0.43 and a standard deviation of 0.01989. The JSE ALSI as benchmark of the market had an average return of 0.10 percent with a standard deviation of 0.01312 and covariance of 0.13.

From these results it can be deduced that looking at the mean and standard deviation of the RESI10, INDI25, FINI15 and JSE ALSI indices, the JSE tradable sector indices (RESI10, INDI25, FINI15) performed better than the market (JSE ALSI) before the global financial crisis. Also looking at standard deviation, the FINI15 index had the highest standard deviation. If an investor had invested in the FINI15 index as an individual security, a great loss could have been incurred. This was as a result of the high risk that was associated with this index before the global financial crisis as shown by a high covariance of 0.43.

5.3.3 Descriptive statistics during the global financial crisis

This section provides the results of estimates for mean, average dispersion, mean and standard deviation of the tradable indices during the global financial crisis.

Table 5.2 below provides the estimates of the mean, standard deviation, average return dispersion and standard deviation dispersion for RESI₁₀, INDI₂₅, FINI₁₅ and JSE ALSI during the global financial crisis.

Index	Mean	Average return dispersion	Standard deviation	Standard deviation of dispersion	Covariance
FINI ₁₅	-0,0127%	0,0470%	0,0118	0,0124%	-0,09
RESI ₁₀	0,1572%	0,0530%	0,0147	0,0025%	0,12
INDI ₂₅	0,0528%	0,0511%	0,0081	0,0018%	0,01
JSE ALSI	0,1027%	0,0183%	0,0121	0,1200%	0,02

Table 5.2: Average daily returns and standard deviations during the global financial crises

Table 5.2 above shows findings from the beginning of July 2007 up to end August 2009 (in total 293 days were observed). The RESI₁₀ index yielded daily returns of 0.1572 percent with a standard deviation of 0.0118 and covariance of 0.12. Also RESI₁₀ index recorded an average return dispersion of 0,053 percent and standard deviation of dispersion of 0.0025 percent. Secondly, the INDI₂₅ index recorded an average daily return of 0.0528 percent while its standard deviation was 0.0081 with an average return dispersion of 0.0511, covariance of 0.01 percent and a standard deviation of dispersion of 0.0018 percent. Finally, the FINI₁₅ index had the lowest mean with a daily return of (0.0127) percent, a standard deviation of 0.0118, an average return of dispersion of 0.047 percent, a covariance of -0.09 and a standard deviation of dispersion of 0.0124 percent. The market as represented by the JSE ALSI had an average return of 0.1027 percent with a standard deviation of 0.0121 an average return of dispersion of 0.0183 percent and a standard deviation of dispersion of 0.1200 percent.

Using the findings recorded in table 5.2, the FINI₁₅ index had the least performance during the global financial crisis against the other indices. Also, results show that during the global financial crises period only RESI₁₀ index outperformed the market.

5.3.4 Descriptive statistics after the global financial crisis

This section provides the results of estimates for mean, average dispersion, mean and standard deviation of the tradable indices after the global financial crisis.

Table 5.3 provides the estimates of the mean, standard deviation, average return dispersion and standard deviation dispersion for RESI₁₀, INDI₂₅, FINI₁₅ and JSE ALSI after the global financial crisis.

Index	Mean	Average return dispersion	Standard deviation	Standard deviation of dispersion	Covariance
FINI ₁₅	0,0793%	0,0250%	0,0117	0,014%	0,147
RESI ₁₀	0,0033%	0,0750%	0,0158	0,0001%	0,048
INDI ₂₅	0,0717%	0,0860%	0,0997	0,018%	0,139
JSE ALSI	0,040%	0,0920%	0,0093	0,020%	0.0232

Table 5.3: Average daily returns and standard deviations post the global financial crises

Looking at table 5.3 the performance of the FINI₁₅ index during the post global financial crises period (1 September 2009 to 31 December 2017) was 0.0793 percent for the mean, with a standard deviation of 0.0117, an average return dispersion of 0,025 percent, a covariance of 0.147 and an average return dispersion of 0.025 percent. The RESI₁₀ index had a mean of 0.0033 percent, a standard deviation of 0,0158, an average return dispersion of 0,075 percent, a covariance of 0.048 and a standard deviation of dispersion of 0,0001 percent. In addition, the INDI₂₅ index recorded a mean of 0.0717 percent, a standard deviation of 0.00997, a standard deviation of dispersion of 0,018 percent, a covariance of 0.139 and an average return of 0,086 percent. Lastly the JSE ALSI index recorded a mean of 0,040 percent, a standard deviation of 0.0093, a standard deviation of dispersion of 0,020 percent, a covariance of 0.0232 and an average return of 0,092 percent.

Looking at the findings recorded in table 5.2 and table 5.3 FINI₁₅ index, the mean improved during the post global financial crises period from -0.0127 percent to 0,0793 percent implying that investors in this index earned better returns after the global financial crisis. On the contrary, the RESI₁₀ index performance in terms of return declined from 0.1572 percent to 0.0033 percent. The INDI₂₅ index still maintained the lowest level of risk with a standard deviation of 0.00997. In this regard, after the global financial crises both the FINI₁₅ index and the INDI₂₅ index performed above the JSE ALSI which had a return of 0.040 percent and 0.0093.

5.3.5 Descriptive statistics for the entire study period

This section provides the results of estimates for mean, average dispersion, mean and standard deviation of the tradable indices for the entire period of study.

Table 5.4 provides the estimates of the mean, standard deviation, average return dispersion and standard deviation dispersion for RESI₁₀, INDI₂₅, FINI₁₅ and JSE ALSI for the entire period of study January 2007 to December 2017.

Index	Mean	Standard deviation	Covariance
FINI ₁₅	0,035%	0,0145	0,414
RESI ₁₀	0,011%	0,0195	0,178
INDI ₂₅	0,060%	0,0113	0,188
JSE ALSI	0,040%	0,0122	0,305

Table 5.4: Average daily returns and standard deviations for the 11year period of study

For the whole period from 1 January 2007 to 31 December 2017 (which is in total 2751 days were observed). The INDI₂₅ index had the of return of 0.060 percent with a standard deviation of 0.0113 and a covariance of 0.188. The FINI₁₅ index had a mean of 0,035 percent with a standard deviation of 0.0145 and a covariance of 0.414. The RESI₁₀ index had a mean of 0.011 percent and a covariance of 0.178 with a standard deviation of 0.0195 and finally the JSE ALSI index had a mean of 0,04 percent with a covariance of 0.305 and a standard deviation of 0.0122.

Overall, the INDI₂₅ index had the highest performance while maintaining a lowest level of risk. The FINI₁₅ index performed moderately and the RESI₁₀ index was the riskiest amongst all the indices. The next section discusses the CSSD measure results of the three indices against the JSE ALSI index as a benchmark for the four periods as shown from Figure 5.5 to 5.8 below.

5.4.1 Herding behaviour on the JSE tradable indices

The Cross Sectional Standard Deviation (CSSD) measures the dispersion which is the spread between the market and in this case an indices return. As such CSSD is the dispersion between the JSE ALSI returns and RESI₁₀, INDI₂₅ and FINI₁₅ independently. Herding behaviour is absent when the dispersion between the JSE ALSI and the indices (RESI₁₀, INDI₂₅ and FINI₁₅) is negative Christie and Huang (1995).

In this study, the methodologies of Christie and Huang (1995) and Chang et al. (2000) were followed. Two sets upper and lower of dummy variables were formed (D^L and D^X) to describe the difference in behaviour of investors which was allied with the periods of market volatility and normal periods. The limits used on these studies are 5 percent and 1 percent criteria to limit the dummy variables to 5 percent and 1 percent of the upper tail and lower tail of the distribution of market return Christie and Huang (1995). Tables 5.5 to 5.8 below shows the CSSD estimates indices at 95 percent and 99 percent confidence intervals.

5.4.2 CSSD before the global financial crisis

This section provides the results of estimates for CSSD of the JSE tradable indices before the global financial crisis.

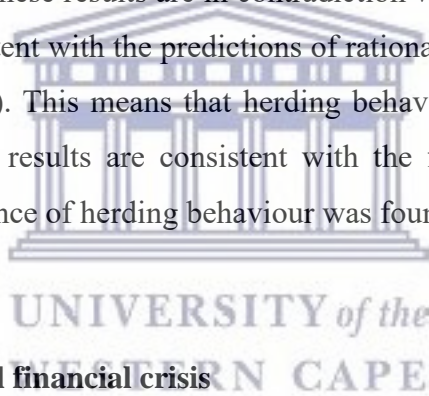
Table 5.5 provides the estimates of β_L and β_u for RESI₁₀, INDI₂₅, FINI₁₅ and JSE ALSI indices at 99 percent and 95 percent confidence interval for the period before the global financial crisis.

Using ALSI	95% Confidence			99% Confidence		
	a	β_L	Bu	A	β_L	Bu

FINI₁₅	0,0018	-0,00261	-0,0028736	0,00072899	0	0
INDI₂₅	0,0003	-0,00031	-0,0003339	0,00080746	0	0
RESI₁₀	0,0061	-0,00018	-0,0090880	0,00096173	0	0

Table 5.5: CSSD for the period before the global financial crises

From table 5.5, at 95 percent confidence interval the estimates of β_L for FINI₁₅, INDI₂₅ and RESI₁₀ are -0.002613, -0.000315 and -0.000189 respectively. At 99 percent confidence interval the estimates of β_L are all zero. Conversely, at 95 percent confidence interval estimates of β_u are -0.00287368 for FINI₁₅, -0.00033395 for INDI₂₅ and -0.00908805 for RESI₁₀. At 99 percent confidence interval all estimates of β_u are zero. Since all coefficients of β_u and β_L are negative at 95 percent confidence interval and zero at 99 percent confidence interval it implies that herding behaviour is absent. These results are in contradiction with the predictions of herding behaviour but however consistent with the predictions of rational asset pricing as documented by Christie and Huang (1995). This means that herding behaviour is not present before the global financial crisis. These results are consistent with the findings Prosad, Kapoor and Sengupta (2012) that no evidence of herding behaviour was found on the Indian Stock Market over the period 2006 to 2011.



5.4.3 CSSD during the global financial crisis

This section provides the results of estimates for CSSD of the JSE tradable indices during the global financial crisis.

Table 5.6 provides the estimates of β_L and β_u for RESI₁₀, INDI₂₅, FINI₁₅ and JSE ALSI indices at 99 percent and 95 percent confidence interval for the period during the global financial crisis.

Using ALSI	95% Confidence			99% Confidence		
	a	β_L	β_u	A	β_L	Bu

FINI15	0,0738	0,02613	0,0287368	0,0172899	0	0
INDI25	0,0623	0,07505	0,0043339	0,0070746	0	0
RESI10	0,0574	0,01905	0,0028005	0,0009173	0	0

Table 5.6: CSSD for the period during the global financial crises

Table 5.6 above shows that the estimates of β_L and β_U all have positive coefficients ranging from the lowest value of 0,01905 under β_L for the RESI10 index to the highest of 0,07505 for the INDI25 index. However, the results are insignificant under the 99 percent confidence interval. The CSSD has been increasing implying that herding behaviour is present. The reason for the increase could be either investors that may be following herding behaviour towards the market portfolio or a group of investment experts. During periods of high market volatility (as mentioned in chapter three, periods of market volatility are defined as market periods characterized by unstable security values), investors emotions tend to increase and the fear of missing out on good investments. With that in mind, this can lead investors to follow herding behaviour is search of a form of reassurance Seetharam and Britten (2013).

Agudo et al. (2008) also documented results that are consistent with the findings of this research during the global financial crisis, that during periods of market uncertainty, investors become more emotional and as a result investors are expected to deviate from rational behaviour. During that period, if dispersions of return were low relative to the average return, it is an indication of herding behaviour. Rational asset pricing models such as the CAPM expect that during periods of market stress, dispersion would increase. Individual assets will vary in their sensitivity to the market. Hence during periods of market uncertainty, returns would be highly dispersed due to attempts to diversify. Thus, herding behaviour offers contrasting predictions to that of rational asset pricing models (Agudo et al., 2008).

5.4.4 CSSD after the global financial crisis

This section provides the results of estimates for CSSD of the JSE tradable indices after the global financial crisis.

Table 5.7 provides the estimates of β_L and β_u for RESI₁₀, INDI₂₅, FINI₁₅ and JSE ALSI indices at 99 percent and 95 percent confidence interval for the period after the global financial crisis.

Using ALSI	95% Confidence			99% Confidence		
	a	β_L	β_u	A	β_L	Bu
FINI ₁₅	0,018	-0,00261	-0,0028736	0,0027599	0	0
INDI ₂₅	0,013	-0,00758	-0,0085008	0,0017746	0	0
RESI ₁₀	0,009	-0,00433	-0,0053176	0,0017322	0	0

Table 5.7: CSSD for the period after the global financial crises

Table 5.7 above shows the estimates of β_L as -0.002613 for INDI₂₅, -0,00758 for FINI₁₅, -0,00433 for RESI₁₀ at 95 percent confidence interval and zero for all indices at 99 percent interval. Also the estimates for β_u are -0.0028736 for FINI₁₅, -0,0085008 for INDI₂₅ and -0,0053176 for RESI₁₀ and conversely zero at 99 percent confidence interval. The estimates for both β_L and β_u have negative coefficients implying that herding behaviour was absent after the global financial crisis period.

Similar findings were documented by Ababio and Mwamba (2017) that herding behaviour was absent during normal market phases (as mentioned in chapter three, normal periods are defined as market periods characterized by steady security values). Ababio and Mwamba, (2017) study focused on the period from January 2010 to September 2015 which is covered by the research under the after global financial crisis category. It should be noted that herding behaviour appears to be asymmetric and this may be due to loss in investor confidence markets during periods of market stress.

5.4.5 CSSD for the entire period of study

This section provides the results of estimates for CSSD of the JSE tradable indices for the entire period of study.

Table 5.8 provides the estimates of β_L and β_u for RESI₁₀, INDI₂₅, FINI₁₅ and JSE ALSI indices at 99 percent and 95 percent confidence interval for the entire study period.

Using ALSI	95% Confidence			99% Confidence		
	α	B1	β_u	A	β_L	β_u
FINI ₁₅	0,028	0,0002613	0,000287368	0,019972899	0	0
INDI ₂₅	0,003	0,0003941	0,000433395	0,007780746	0	0
RESI ₁₀	0,041	0,0007189	0,000790588	0,04296173	0	0

Table 5.8: CSSD for the 11-year period of study

Table 5.8 is a summary of the findings for the whole period of study. These results shows that β_L have positive estimates of 0.0002613, 0.0003941 and 0.0007189 for FINI₁₅, INDI₂₅ and RESI₁₀ respectively at 95 percent confidence interval. β_u also had positive estimates of 0,000287368, 0,000433395, 0,000790588 at 95 percent confidence interval. At 99 percent confidence interval both β_L and β_u have zero value for the whole period of study. With that in mind, this means that overall herding behaviour was present on the JSE tradable indices, however it was seen to be dominant during periods of high market volatility, in this case during the global financial crisis.

The overall findings are similar to what was documented by Angela, Miruna and Andreea (2015) in their article that examined the existence of herding behaviour during the period January 2008 to December 2010 on the Central and South Eastern Europe: Czech Republic, Poland, Hungary, Romania and Bulgaria stock markets using the LSV model proposed by

Lakonishok et al. (1992) and the PCM model (Portfolio Change Measure) proposed by Wermers (1995).

It is essential to note that during periods categorized as normal phase's investors actions can be described by the modern finance theory. In other words, investors would follow their own beliefs however, during periods described with high market volatility investors emotions tend to increase (Seetharam & Britten, 2013). As a form of reassurance investors then follow investment decisions of their peers. Conversely, Lao and Singh (2011) documented results that suggested that herding behaviour existed in both the periods of high market volatility and when there is low market volatility. According to Lao and Singh (2011) the level of herding depends on market conditions. In the Indian stock market, the study recorded herding behaviour to be more common during up-swings rather than in low swings.

By knowing that herding behaviour is predominant during periods of markets stress, reviewing the market trends can assist investors and potential investors to make an educated and risk evaluated decision. That is whether the desired stock or company is stable, growing and has an improving future irrespective of the market stress. Therefore, following herding behaviour can minimize investors in investing in unprofitable stocks (Seetharam & Britten, 2013).

To further validate the findings above, this study also compares graphically the JSE ALSI daily return with RESI₁₀, INDI₂₅ and FINI₁₅ returns independently from January 2007 to December 2017 as depicted from Figure 5.1 to Figure 5.3.

The figure 5.1 shows a comparison of the returns of RESI₁₀ and the JSE ALSI indexes.

Graphical Depiction of RESI₁₀ vs JSE ALSI Daily Returns

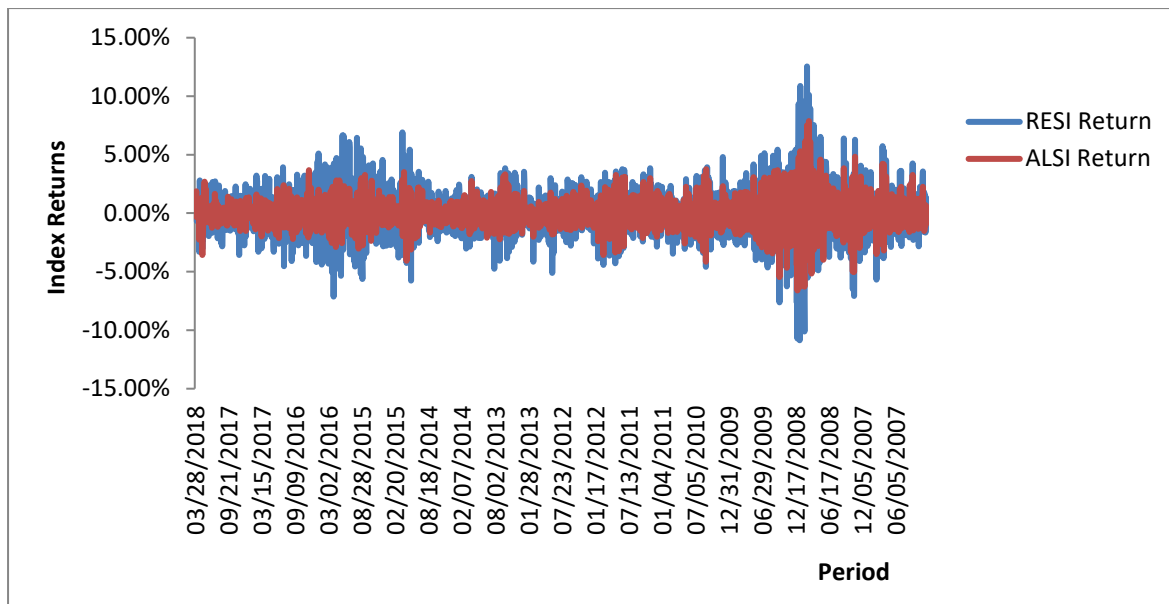


Figure 5.1: Comparative returns for the 2007 to 2017 period

Source: researcher’s own compilation, JSE stock data obtained from Bloomberg

The graph 5.1 compares the daily return for RESI₁₀ and JSE ALSI indexes from January 2007 to December 2007. The graph shows that the RESI₁₀ returns for the entire period of study have been mostly outperforming the JSE ALSI index returns. The dispersions between the two indexes is not very substantial. The graph clearly shows that the dispersions are high during the period between 2008 and 2009 which was during the global financial crisis. This analysis is the same as what was documented above on table 5.6 that herding behaviour was present during the global financial crisis.

The figure 5.2 shows a comparison of the returns of INDI₂₅ and the JSE ALSI indexes.

Graphical Depiction of INDI25 vs ALSI Daily Returns

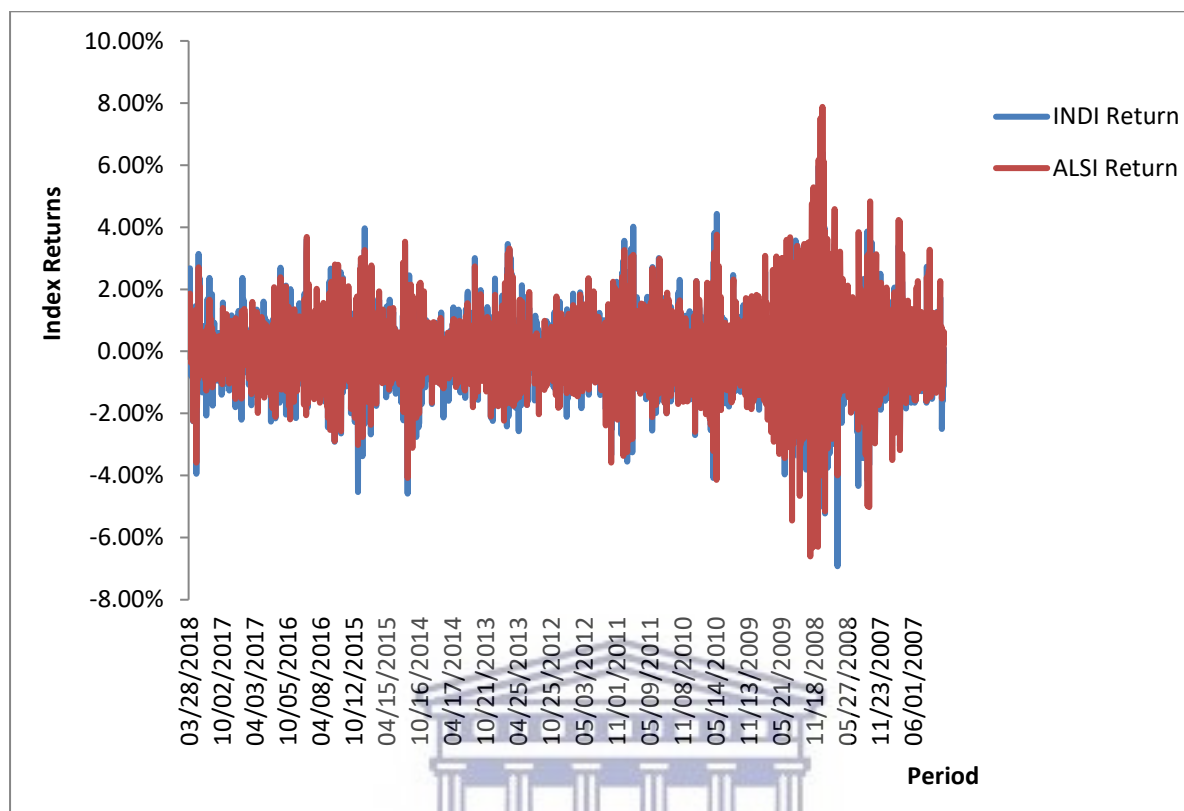


Figure 5.2: Comparative returns for the 2007 to 2017 period

Source: researcher’s own compilation, JSE stock data obtained from Bloomberg

The graph 5.2 is a comparison between the JSE ALSI and the INDI25 indexes returns from January 2007 to December 2017. The graph depicts that for most periods during the period of study the JSE ALSI returns are above that of INDI25 index, and also the dispersion between the two is not very momentous. From the graph above herding behaviour is seen during the year 2008, however it is not very substantial. The same as the observation made above on the graph that compares RESI10 and JSE ALSI that the graphs provides same findings as recorded on table 5.6 that herding behaviour was present during the global financial crisis.

The figure 5.3 shows a comparison of the returns of FINI15 and the JSE ALSI indexes.

Graphical Depiction of FINI15 vs ALSI Daily Returns

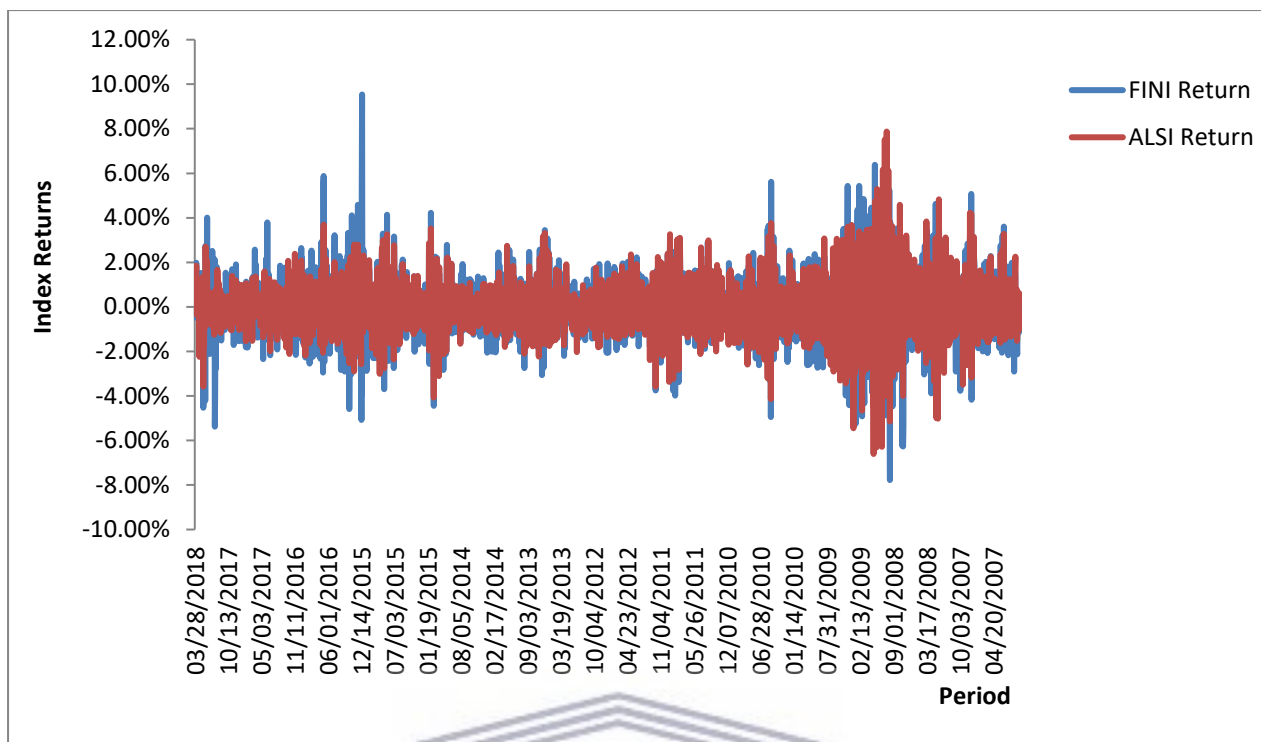


Figure 5.2: Comparative returns for the 2007 to 2017 period

Source: researcher's own compilation, JSE stock data obtained from Bloomberg

The graph 5.3 compares the FINI₁₅ returns to the ALSI returns from January 2007 to December 2017. The graph shows that FINI₁₅ index returns have been above JSE ALSI index returns from 2014 to 2018 consistently. On the contrary, during the period 2007 to 2013 the JSE ALSI index returns were above that of the FINI₁₅ index. Again, this observation is in agreement with the findings documented on table 5.6 that herding behaviour was present during the global financial crisis on the FINI₁₅ index.

The graph comparisons from graph 5.1 to graph 5.3 provided further support to the findings of the CSSD measure shown in tables 5.5 to 5.8. With that in mind, herding behaviour was visible during the global financial crisis i.e during period of high market volatility. These discoveries are consistent with what was recorded by (Angela, Miruna & Andreea, 2015; Sarpong & Sibanda, 2014; Lao & Singh 2011; Ababio & Mwamba, 2017).

5.4.6 Herding behaviour on the JSE indices during the global financial crisis period using CSAD

This section of the research applies the cross-sectional absolute deviation of returns (CSAD) measure of herding behaviour proposed by Chang et al.. (2000). The research results were presented as in three categories, starting with the period from 1 January 2007 to 30 June 2007 which was before the global financial crises, then the period from 1 July 2007 to 31 August 2009 which was the period during the global financial crisis and lastly from 1 September 2009 to 31 December 2017. As stated earlier CSAD measures if investors are more likely to follow herding behaviour during periods of large price movements focusing on the belief that there is a nonlinear relation between the indices (RESI₁₀ FINI₁₅ and INDI₂₅) return dispersions and the ALSI return. When herding behaviour is present the coefficient of CSAD would be negative.

5.4.7 CSAD before the global financial crisis

This section provides the results of estimates for CSAD of the JSE tradable indices before the global financial crisis.

Table 5.9 provides the estimates of CSAD for RESI₁₀, INDI₂₅ and FINI₁₅ indices for the period before the global financial crisis.

Index	Period	CSAD
FINI ₁₅	01/01/2007 30/06/2007	0,0047325
RESI ₁₀	01/01/2007 30/06/2007	0,0024127
INDI ₂₅	01/01/2007 30/06/2007	0,0013752

Table 5.9: CSAD for the period before the global financial crises

The results in Table 5.9 report the findings of the CSAD for RESI₁₀, INDI₂₅, FINI₁₅ during the pre global financial crises period dates. The data availability for the pre global crises period range from January 2007 to June 2007 (in total 124 days were observed). The CSAD ranges from a high of 0.0047325 for the FINI₁₅ index to a low of 0.0013752 for the INDI₂₅ index. The

RESI₁₀ index reported a CSAD value of 0.0024127. These results imply that there is no evidence of herding behaviour on the JSE Limited tradable indices (RESI₁₀, INDI₂₅ and FINI₁₅) before the global financial crisis. These findings are consistent to what was documented in the same period by this research using the CSSD measure.

5.7.8 CSAD during the global financial crisis

This section provides the results of estimates for CSAD of the JSE tradable indices during the global financial crisis.

Table 5.10 provides the estimates of CSAD for RESI₁₀, INDI₂₅ and FINI₁₅ indices for the period during the global financial crisis.

Index	Period	CSAD
FINI ₁₅	01/07/2007 31/08/2009	-0,0199505
RESI ₁₀	01/07/2007 31/08/2009	-0,0224127
INDI ₂₅	01/07/2007 31/08/2009	-0,0137752

Table 5.10: CSAD for the during the global financial crises

Table 5.10 shows results for the CSAD on RESI₁₀, INDI₂₅ and FINI₁₅ indices during the global financial crisis. The period during the global financial crisis was from 1 September 2009 to 31 December 2017 (in total 2334 days were observed). The results show that INDI₂₅ index recorded the highest CSAD value of -0.0137752, FINI₁₅ index recorded a CSAD value of -0.0199505 and lastly RESI₁₀ index recorded the lowest CSAD of -0,0224127. In these results in mind, there is evidence of herding behaviour during the global financial crisis. Again, these results are in agreement with what was recorded by this research using the CSSD herding measure.

Looking at the findings by both the CSAD and CSSD measure, this research recorded that herding behaviour was present during periods of market volatility (as mentioned earlier,

periods of market volatility are defined as market periods where security value fluctuates dramatically). These results are consistent with the finding recorded by Tan et al. (2008) that herding behaviour was found in the Shanghai market when there was high market volatility and when markets were rising. Angela, Miruna and Andreea (2015) recorded similar findings that showed evidence of herding behaviour amongst investors on the Czech Republic, Hungary, Romania and Bulgaria stock markets.

5.4.9 CSAD after the global financial crisis

This section provides the results of estimates for CSSD of the JSE tradable indices after the global financial crisis. Table 5.11 provides the estimates of CSAD for RESI₁₀, INDI₂₅ and FINI₁₅ for the period after the global financial crisis.

Index	Period	CSAD
FINI ₁₅	01/09/2009 31/12/2017	0,0059895
RESI ₁₀	01/09/2009 31/12/2017	0,0012437
INDI ₂₅	01/09/2009 31/12/2017	0,0023562

Table 5.11: CSAD for the after the global financial crises

Table 5.11 depicts the estimates of CSAD for the RESI₁₀, INDI₂₅ and FINI₁₅ indices after the global financial crisis period. The post global financial crisis period was from 1 September 2009 to 31 December 2017 (in total 2334 days were observed). The table above shows that the RESI index recorded the lowest CSAD value of 0.0012437, the INDI₂₅ index had a CSAD value of 0,0023562 and FINI₁₅ index recorded the highest CSAD value of 0,0059895. This suggests that there was no evidence of herding behaviour on JSE tradable sector indices (RESI₁₀, INDI₂₅ and FINI₁₅) after the global financial crisis. These results provide a further support to the findings above using the CSSD measure.

The findings recorded for the post global financial crisis period using both the CSSD and CSAD measure could have been as a result of loss aversion argument which states that

investors have tendencies to prefer avoiding losses than to acquiring equivalent gains (discussed in detail in section 2.4.2). For the reason that individual investor returns tend to diverge from the market during periods of positive market returns, while during periods of negative market returns they tend to converge Kahneman and Tversky (2013). In this case after the global financial markets investors started to diverge from the market.

5.4.10 CSAD for the entire period of study

This section provides the results of estimates for CSSD of the JSE tradable indices for the entire period of study. Table 5.12 provides the estimates of CSAD for RESI₁₀, INDI₂₅ and FINI₁₅ for the entire period of study.

Index	Period	CSAD
FINI ₁₅	01/01/2007 31/12/2017	-0,0000598955
RESI ₁₀	01/01/2007 31/12/2017	0,0000224127
INDI ₂₅	01/01/2007 31/12/2017	0,0000137752

Table 5.12: CSAD for the 11-year study period

Table 5.12 shows results of the CSAD measures for RESI₁₀, INDI₂₅ and FINI₁₅ during the whole period of study. The period of study of this research was from January 2007 to December 2017 (in total 2751 days were observed). The table above depicts that the CSAD is -0.0000598955 for FINI₁₅ and positive for the RESI₁₀ and INDI₂₅ indices as 0.0000224127 and 0.0000137752. These results imply that there was no evidence of herding behaviour on the RESI₁₀ and INDI₂₅ indexes during the entire period of study. On the hand, there was evidence of herding behaviour during the entire period of study for the FINI₁₅ index. Ababio and Mwamba, (2017) also recorded similar findings that there was evidence of herding behaviour during the period from January 2010 to September 2015.

Looking at the tables 5.9 to 5.12 results shows that herding behaviour was present during the period of global financial crisis on the JSE tradable indices. These results are consistent with

the findings of Walter and Webber (2006) that the CSAD tend to increase rather than decrease during market environments characterized by extreme price movements. Chang et al.. (2000) argues that this is inconsistent with the operational definition of herding behaviour which requires a decrease in dispersion levels, implying that investors are following aggregate market behaviour, disregarding their own investment strategies (Seetharam & Britten, 2013)

Overall, using the CSAD measure, this research found the same findings using the CSSD measure. It is essential to note that the JSE all-share index fell from a high of 35 542 on the 23rd of May 2008 to a low of 18 066 on 21 November 2008 and it recovered to 27 895 on the 5th of January 2010 (Statistics SA, 2016). In summary, it is possible that the volatility and uncertainty caused investors to follow one another in order to come together to the market consensus opinion in order to avoid losses findings (Prosad, Kapoor & Sengupta (2012). This may have resulted in greater herding behaviour during the financial crisis period than the non-crisis period. It is important to note that South Africa has a large international investor presence (46 percent of the free-float on the All Share Index), which may have resulted in a more efficient market and a less noticeable difference in herding behaviour between the before and after the global financial crisis periods JSE (2017).

5.5 Conclusion

As mentioned in the introductory section, this chapter aimed to provide an answer to the three main questions which was if there was evidence of herding behaviour on the JSE limited tradable indices which include RESI₁₀, INDI₂₅ and FINI₁₅ before, during and after the global financial crisis looking at the period from January 2007 to December 2017. In this regard, this research used the herding behaviour measures formulated by Christie and Huang (1995) and Chang et al.. (2000) to examine if evidence of herding behaviour existed on the JSE tradable indices. This research overall found herding behaviour to be present on the indices RESI₁₀, INDI₂₅ and FINI₁₅ indices during periods of market volatility, in this case during the global financial crisis (periods of market volatility are defined as market periods characterized by unstable security values). Conversely no herding behaviour was documented during normal periods (normal periods are defined as market periods where security's value does not fluctuate

dramatically). These findings were also documented by was recorded by Angela, Miruna and Andreea (2015) on the study that was done on Czech Republic, Poland, Hungary, Romania and Bulgaria using the CSAD measure, Sarpong and Sibanda (2014) on the study done on the JSE focusing on mutual funds using the LSV measure. Conversely, Ababio and Mwamba (2017) study on the JSE found herding behaviour present on the banking sector (financials). Seemingly, the conclusion that herding behaviour is more profound in emerging markets does not relate to the JSE Limited tradable indices.



Chapter Six – Conclusion

6.1 Introduction

In this concluding chapter, this study summarises the research findings and the contributions of the study. Principally, this research effort sought to establish whether the (Christie & Huang 1995), Chang et al. (2000) measures on herding behaviour could be applied in the SA financial market. This was done by using the JSE tradable sector index which include the industrials index (INDI₂₅), the financials index (FINI₁₅) and lastly the resources index (RESI₁₀). There were three main objectives underpinning this study which was to establish whether the JSE tradable sector index (RESI₁₀, INDI₂₅, FINI₁₅) had evidence of herding behaviour before the global financial crisis, during the global financial crisis and after the global financial crisis (see section 1.6). This research overall found herding behaviour to be present on the indices RESI₁₀, INDI₂₅ and FINI₁₅ indices during periods of market volatility, in this case during the global financial crisis (periods of market volatility are defined as market periods characterized by unstable security values). Conversely no herding behaviour was documented during normal periods (normal periods are defined as market periods where security's value does not fluctuate dramatically). The rest of the chapter is organised as follows: section 6.2 presents a summary of empirical findings and section 6.3 presents the significance of this research and section 6.4 provides a summary of recommendations for future research.

6.2 Summary of findings

An examination to observe if evidence of herding behaviour was present on the JSE tradable sector indices was carried out. This was guided with the main objectives of establishing whether there was proof of herding behaviour on the JSE tradable sector index (INDI₂₅, FINI₁₅, RESI₁₀) before the global financial crisis, during the global financial crisis and after the global financial crisis. The study period starting from 1 January 2007 to 30 June 2007 was classified as the pre global financial crises, then the period from 1 July 2007 to 31 August 2009 was categorized as during the global financial crisis and lastly from 1 September 2009 to 31 December 2017 was classified as the post global financial crises.

The study adopted the measures of herding behaviour by Christie and Huang (1995), Chang et al. (2000) as the base models. The CSSD and CSAD measures were applied to the tradable sector index, utilising the three main JSE tradable indices namely the industrials index (INDI₂₅) which constitutes of 25 largest industrial stocks, the financials index (FINI₁₅) which comprises of 15 largest financial stock and lastly the resources index (RESI₁₀) which represents 10 largest resources stocks.

After calculating the CSSD and the CSAD for each period, using Microsoft Excel no herding behaviour was recorded by both measures before the global financial crisis. During the global financial crisis herding behaviour was found to be present on all the indices using both the CSSD and the CSAD measures. This could have been caused by investors following investments that were deemed to be good in order to avoid the fear of missing out on good returns. Lastly, during the post global financial crisis herding behaviour was found to be present on the FINI index which was consistent with the findings recorded by Ababio and Mwamba (2017) that herding behaviour present on the banking sector (financials). Conversely, no herding was recorded on the RESI and INDI indexes post global financial crisis. Overall, this research found that investors followed herding behaviour during periods of market volatility and on the other hand no herding behaviour was documented during normal periods.

6.3 Significance of this research outcome to investors

Herding behaviour is known to influence the investors buy and sell decisions, thus it has implications on investor trading, financing choices, managerial investment, market prices and market regulation.

This research tested evidence of herding behaviour on the JSE tradable indices. Results of this research found evidence herding behaviour to be present on a relative scale only. In other words, herding behaviour was found present during periods of market volatility (periods of market volatility are defined as market periods characterized by unstable security values). The most noteworthy ones being the 2007 to 2009 global financial crisis. The study period of this research was from January 2007 to December 2017, this period covered the market volatilities

of the JSE. The different market phases indicated the presence of herding behaviour to be different depending on whether the market was volatile or not.

This present study deviated from the previous studies on the JSE by focusing on the JSE tradable sector indices (which are a sound representation of the whole JSE) and using the CSSD and CSAD measures to evaluate herding behaviour. The present study also studied the three defined different market volatility periods in South Africa which are before, during and after the global financial crisis period, to determine the presence of herding behaviour on the JSE. In this regard, the findings of each time frame assists investors to make more informed decisions.

In addition, investors and field practitioners can employ the research outcome of this study that herding behaviour is predominant during period of market volatility as this influences investors decisions. During periods of market volatility investors can follow investment decisions of investment gurus using the belief that they will earn returns more than the market. However, looking at the findings of this research and the study by Hwang and Salmon (2004), herding behaviour was prominent during the crisis. Therefore, if investors follow herding behaviour they could maximize profits just before and during periods of market volatility.

This research documented that macroeconomic information i.e. interest rates, exchange rates influences herding behaviour on the JSE tradable indices. Therefore, investors should take enough cognisance of the macroeconomics factors in the market in order to make profitable investment decisions. This research documented herding behaviour was present during the global financial crisis. The global financial crisis was caused by subprime interest rate in the United States and which had effects on the global economy, thus, macroeconomic factors influence the behaviour and investment decisions of investors.

By knowing that herding behaviour is predominant during periods of markets volatility, reviewing the market trends can assist investors and potential investors to make an educated and risk evaluated decision. That is whether the desired stock or company is stable, growing and has an improving future irrespective of the market stress. Therefore, following herding

behaviour can minimize investors in investing in unprofitable stocks Seetharam and Britten (2013).

No one wants to invest in stocks that will perform poorly. By following herding behaviour during periods of market volatility through taking the time to look at the company's stockholder reports and other publicly available information, financial future will not have to come as a surprise. When investors follow all financial information forecasting the financial future will be the product of a well-planned financial strategy. This will minimize risk found in investing in poorly performing stocks and companies (Sarpong & Sibanda, 2014).

One of the findings of this study that herding behaviour is predominantly present during periods of market volatility will contribute substantially towards forthcoming frameworks utilized by investment companies. This will reshape the manner in which investor behaviour and their risk profiles are created (Ababio & Mwamba, 2017).

In addition, the analysis in this study showed that the initial decision is to identify the market or economic trends before following herding behaviour in investments. Thereafter if the market is in a crisis following herding behaviour could imply either potential investment loss or profit (Ababio & Mwamba, 2017). In corroboration with previous studies in developed and developing economies, the theory of herding behaviour has been noted to be instrumental especially during periods of market volatility. This is because it assists investors to make profitable decisions.

In addition, this study is important for the fellow students and researchers who are interested in studying behavioural finance with emphasis on herding behaviour since it provides the basis on which researchers could begin working from. This research used data on the JSE tradable sector which includes the industrials index (INDI₂₅) which constitutes of 25 largest industrial stocks, the financials index (FINI₁₅) which comprises of 15 largest financial stock and lastly the resources index (RESI₁₀) which represents 10 largest resources stocks. With that in mind, future researchers could employ the same data taken from different periods to check if results recorded in this research would be the same.

Furthermore, results of this research have shown that pre and post global financial crisis herding behaviour was absent. Since herding behaviour implies that investors follow each other's investment decisions, then it is not a sound or profitable investment strategy. Thus, investors and field practitioners who follow herding behaviour tend to buy and sell assets frequently as they chase the latest investment trends (Bikhchandani & Sharma, 2000). These investors tend to buy and sell frequently which results investors to incur a substantial amount of transaction costs, ultimately reducing the potential profits (Bikhchandani & Sharma, 2000).

In addition, when the stock prices adjust to reflect available information herding behaviour will not arise as shown by the findings of the post global financial crisis period. The stock market is considered informationally efficient under these assumptions and that the stock price reflects all fundamentals and there is no mispricing (Fama & French, 1992). Investors may follow the behaviour of group of investors that are believed to have experience and expertise in the financial market with the belief that this group knows something more than others (Bikhchandani & Sharma, 2000). At some point every investor is tempted to follow the latest investment trends referred to as herding behaviour towards the latest investment information. This may have negative implications as some investments go wrong. So in conclusion investors must do a proper analysis of the market before making investment decisions and following herding behaviour as it is not always a profitable strategy.

Based on the findings this study, it became apparent that research in the field of behavioural finance with emphasis on herding behaviour among investors within a South African context is important. Looking at empirical research on the herding behaviour of investors, this study contributed to the body of knowledge in terms of providing a framework to assist investors' decision making. The model used in this research made provision for analyzing potential irrational investor behaviours that can be associated with the level of risk tolerance in South Africa.

6.4 Recommendations for future research

From the literature reviewed by the researcher, tests on herding behaviour have been studied on both developed and developing markets, inclusive of South Africa. In theory, the presence of herding behaviour proves to influence the effectiveness of financial markets. The question remains whether this is true in the SA finance industry.

The period before the global financial crisis spanned from 1 January to 30 June 2007, such a period was too short to observe the herding behaviour of investors. For better results the study period could have stretched from an earlier date so that all the periods could be sizeable enough to provide meaningful results and analyses. Accordingly, there is a need to expand the period before the global financial crisis in order to assess the presence of herding behaviour on the JSE tradable sector.

This study recommends that future research can be made using data sets of volume and volatility measures, as opposed to only returns, as used in this study. Also another recent measures of herding behaviour such as the quantile regression model can also be evaluated in order to check if the results will be consistent with the first measures of herding behaviour by Christie and Huang (1995) and Chang et al. (2000).

In addition, the CSSD and CSAD measures do not account for fundamental variables. In other words, these measures do not distinguish unintentional herding from intentional herding (Bikchandani & Sharma, 2001). In that regard, research can be carried out using other measures to try and just the forms of herding behaviour. Also a positive value for cross-sectional standard deviation of returns does not necessary imply evidence of herding behaviour but it may be also described by a decrease in uncertainty of market return (Demirer & Kutan, 2007).

In Africa the JSE is the biggest securities exchange and using the 2017 database of the Financial Service Board registered financial service providers, there are more than 30 000 investment advisors and practitioners in South Africa. Studies should be done in order to test if herding behaviour is practical on the JSE and its effectiveness in comparative to other stock markets of

the same stature as the JSE.

Also, further research could focus on investigating the essential characteristics of financial markets inclined to herding behaviour since results documented by both developed and developing countries are different. This research suggests testing the herding behaviour hypothesis on market, industry and sectoral levels from different economies and then compare results in both emerging and emerged markets using different herding behaviour measures.

Finally, further research must take into account political risk in the South African market for example the firing of Finance Ministers Nhlanhla Nene and Pravin Gordhan was a political risk which contributed to market volatility. This also led to the downgrade of SA investment ratings, and also some investments were wiped from the JSE. In this regard, this research discovered that the SA stock market has its own volatility caused by political risk factors other than the financial crisis.



Chapter Seven - Bibliography

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