THE EVOLUTION AND DYNAMICS OF STOCKS ON THE JOHANNESBURG SECURITIES EXCHANGE AND THEIR IMPLICATIONS FOR EQUITY INVESTMENT MANAGEMENT

Artwell Shingirai Chimanga

A thesis presented in fulfilment of a Doctoral of Philosophy

in the Graduate School of Business

University of Cape Town

December 2013

Supervisor: Professor N Biekpe

"I liken her (stock market) to one of these violent rivers which, when they become enraged, flood the plains, ruin the trees and the buildings, life earth from this part, drop in another; each person flees before them, everyone yield to their impetus without being able to hinder them in regard. And although they (stock markets) are like this, it is not as if men, when times are quiet, could not provide for them dikes and dams so that when they rise later, either they go by a canal or their impetus is neither so wanton nor so damaging."

Niccolò Machiavelli, *Italian Philosopher* (1532:55), Extract from his book "The Prince".

Acknowledgements

Sincere thanks to all those who lent their time and support to the production of this thesis. My sincere gratitude is extended to Prof Biekpe, my supervisor, for his guidance, patience, and limitless enthusiasm throughout my research journey from the evolution of ideas on to the write up of this thesis. I am also deeply indebted to Associate Prof Chinyoka from the Applied Mathematics department for his assistance with the Matlab programming. I am also grateful to my wife, family and friends for all the phenomenal support throughout my studies. I would also like to thank Dr Patient Rambe for proofreading the draft thesis and providing some informative comments. However, I am entirely responsible for the views, arguments and perspectives advanced in this piece of work.

Plagiarism Declaration

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of a university or other institute of higher learning, except where due acknowledgment has been made in the text.

Signed by candidate

Signature: Signature Removed Date: October 2013

TABLE OF CONTENTS

LIST OF TABLES

List of figures

THE EVOLUTION AND DYNAMICS OF STOCKS ON THE JSE AND THEIR IMPLICATIONS ON EQUITY INVESTMENT MANAGEMENT

ABSTRACT

This thesis explores the dynamics of the Johannesburg Stock Exchange returns to understand how they impact stock prices. The introductory chapter renders a brief overview of financial markets in general and the Johannesburg Securities Exchange (JSE) in particular. The second chapter employs the fractal analysis technique, a method for estimating the Hurst exponent, to examine the JSE indices. The results suggest that the JSE is fractal in nature, implying a long-term predictability property. The results also indicate a logical system of variation of the Hurst exponent by firm size, market characteristics and sector grouping. The third chapter investigates the economic and political events that affect different market sectors and how they are implicated in the structural dynamics of the JSE. It provides some insights into the degree of sensitivity of different market sectors to positive and negative news. The findings demonstrate transient episodes of nonlinearity that can be attributed to economic events and the state of the market. Chapter 4 looks at the evolution of risk measurement and the distribution of returns on the JSE. There is evidence of fat tails and that the Student t-distribution is a better fit for the JSE returns than the Normal distribution. The Gaussian based Value-at-Risk model also proved to be an ineffective risk measurement tool under high market volatility. In Chapter 5 simulations are used to investigate how different agent interactions affect market dynamics. The results show that it is possible for traders to switch between trading strategies and this evolutionary switching of strategies is dependent on the state of the market. Chapter 6 shows the extent to which endogeneity affects price formation. To explore this relationship, the Poisson Hawkes model, which combines exogenous influences with self-excited dynamics, is employed. Evidence suggests that the level of endogeneity has been increasing rapidly over the past decade. This implies that there is an increasing influence of internal dynamics on price formation. The findings also

demonstrate that market crashes are caused by endogenous dynamics and exogenous shocks merely act as catalysts. Chapter 7 presents the hybrid adaptive intelligent model for financial time series prediction. Given evidence of non-linearity, heterogeneous agents and the fractal nature of the JSE market, neural networks, fuzzy logic and fractal theory are combined, to obtain a hybrid adaptive intelligent model. The proposed system outperformed traditional models.

CHAPTER 1

"Can someone truly tell me what's happening in global financial markets? Where to start and how to proceed…or is it an illusion with all floating monetary measures in an interwoven-world?"

Ranjit Goswami, Wondering Man, Business News, February 16, 2007

Introduction

Global financial markets are increasingly becoming volatile and complex as investment managers seek ways to maximize investment returns and minimize risk (Chimanga, 2007) and (Damodaran, 2007). This increasing complexity and volatility coupled with the recent wave of financial crises in several markets has sparked off a debate about the nature and characteristics of stock markets. Recent studies have shown that global market dynamics are evolving faster than existing theory can explain, see (Baca et al., 2010; Chiarella et al., 2012 and Markwat, 2009). Literature further suggests that the contagion effect in financial markets is becoming more pronounced due to the rapid global economic integration, thus further complicating stock market dynamics, see (Khalsa, 2008; Longstaff, 2010 and Horta, 2008).

Soros (2008) points out that almost all researches have attributed the worldwide market crash to greedy bankers, slack regulation and credulous investors, to name a few. However, he believes that there is also a less talked about and apparent cause and that is our inadequate understanding of how markets dynamics work, how and why prices move and how risk evolves. Given the paucity of research into the latter, the current research contributes to a broader understanding of these issues by exploring different market dynamics that affect stock prices. The study draws attention to market dynamics amid continuing uncertainty over the role of investors, economic and other fundamental factors in shaping the stock market dynamics.

This research addresses three main objectives: 1. To document the JSE market structure and dynamics to explain why the current market structures and dynamics exist. 2. To demonstrate that the existence of these dynamics and the market structures imply the existence of opportunities for investors to exploit and obtain abnormal returns. 3. To develop a model that can forecast these market behaviours with a view to exploit them for profit.

1.2 A brief background of stock markets

A stock market is a public place for the trading of company stocks at a price agreed by two counterparts. According to Mantegna and Stanley (1999), stock markets exemplify adaptive complex systems consisting of a large number of interacting agents, self-organizing into non-equilibrium steady states. The World Federation of Exchanges (WFE, 2011) reports that the size of the world stock market is estimated at about US$45.4 trillion, of which United States (US) stock markets alone account for 36.3% of the world market capitalization. Table 1-1 illustrates the three major regions as typically reported in most financial publications and their percentage contributions to the world stock market capitalization.

Table 1-1: Contribution of different regions to world market capitalization

Market	**% 2011 Contribution to World Market Capitalization**
United States	36.3%
Europe & Australasia	44.0%
Emerging	19.7%

Source: The World Bank World Markets Stats

Furthermore Figure 1-1 shows the growth in the world market capitalizations since 1990. As is evident from the graph, world stock markets are booming and phenomenal growth has been recorded in emerging stock markets. Emerging markets stocks rose from 3% of world stock markets capitalization in 1993 to almost 20% in 2011.

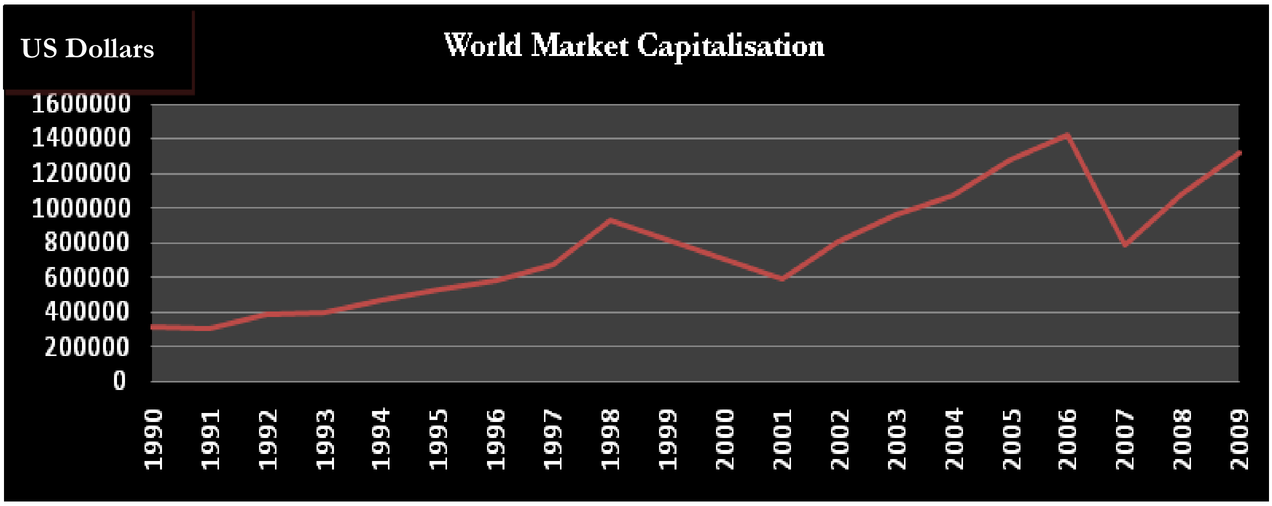


Figure 1-1: Growth in world markets capitalization

1.2.1 Market participants

Less than 50 years ago, buyers and sellers were mostly individual investors, such as rich families with strong historical ties to a particular corporation (Cesari et al, 2011). However, markets have gradually become more complex and institutions have assumed the role of market participants, see (Gabaix et al, 2006; and Muslumov et al, 2005). The increasing number of large institutional investors has been accompanied by some positive developments in market operations like decreases in the fixed and excessive broker fees through the breaking up of solid up-front costs (Edmister, 1982).

1.3 A review of the South African stock market

The JSE is the 14th largest equities exchange in the world, with a total market capitalization of R 6.9 trillion ($828bn) (JSE, 2012). The exchange trades shares for a wide variety of industries, with the largest fraction of market capitalization coming from the mining industry (Chimanga & Kotze, 2009). About 32% of the firms on the JSE are international and the rest are domestic firms. In spite of its characterisation as an emerging market, the JSE constitutes a large number of institutional investors and demonstrates diversified ownership, in contrast to other African markets (Bloomberg, 2006). Information about the behaviour of certain key variables released by the Reserve bank and Statistics South Africa (STATSA) is widely viewed as influential to price determination on the JSE, (Hancocks, 2010 and Barr et al, 2002). According to Samouilhan (2006), another factor that is important to the JSE is the movement of the international stock markets.

The JSE boasts of approximately 125 years of operation as a market for the trading of financial instruments. During this time, the JSE has evolved from a traditional floor-based stock trading market to a modern stock exchange providing electronic trading, clearing and settlement in equities, derivatives and other associated financial products (JSE, 2012). A committee of stockbrokers with full voting rights directs the JSE and makes decisions concerning how it is run.

1.3.1 JSE market concentration

A publication by the Competition Authorities (2009) shows that the Competition Act has played a crucial role in decreasing the high levels of concentration in the South African economy inherited from apartheid in 1994. This concentration was evidenced by the multi-national corporations' domination of the SA market during the apartheid era. The competition authorities point out that at independence in 1994, the Anglo American stock constituted about 44% of the market capitalisation of the JSE with the top four firms accounting for 77%. By 2011, the JSE had significantly transformed in terms of market concentration. BHP Billiton (now the largest company by market capitalisation) makes up 8% of the market capitalisation and the top four firms combined, account for a mere 17.4% of the JSE market capitalisation.

Jafta (2011) attributes the dilution of concentration on the JSE to the new South African competition policy and legislation and the nation's readmission to the world stage after the lifting of the sanctions Teoh et al. (1999), on the other hand, had attributed the dilution of concentration on the JSE to the liberalisation of the JSE stock market which led to the inclusion of international investors. However, market liberalisation has also resulted in South African companies, such as Anglo American, being able to invest in international markets instead of diversifying into non-related market sectors in a restricted South African market.

With regard to concentration amongst institutional investors, the top eight investment managers make up over half of the JSE market capitalisation represented by the Shareholder Weighted Index (SWIX)[1]. This investor structure is not normally characterised by high levels of trading activity, particularly in the small to mid-cap stocks, (Mala et al, 2006). This is because these portfolio managers are too big to buy or sell smaller caps without affecting prices. Gobodo (2007) argues that such investor behaviour often results in a skewed liquidity structure, with the average All Share Index Top 40 (ALSI 40) company trading about 65% of its market cap in a year. On the other hand, the average small and mid-cap company trades only about 32% of its market cap in any 12 month period (Charivanda, 2009).

1.3.2 JSE market liquidity

A significant benefit of deregulation of the JSE in 1994 was the increased liquidity. Total trade as a percentage of JSE market capitalisation is now 30%, more than four times its level before deregulation. Post deregulation, the JSE experienced a remarkable increase in participation by foreigners, which has been positive for the performance of the stock market. This is notwithstanding the marginal gains in liquidity as the increased number of new players coincided with some of the largest companies moving their primary listings to foreign exchanges. Consequently, the majority of the trades in some dual listed companies such as SAB Miller, Anglo-American and Old Mutual, now takes place offshore (Treasury, 2011). This lost trade represents about 10% of the total trade that takes place on the JSE in a year (Gobodo, 2007).

---

[1]SWIX is an index for South African investment managers invested on the JSE. It excludes the portion of the company held by strategic and foreign holders.

Casavalone (1996) identifies seven drivers of market illiquidity on the JSE, which are namely exchange controls, South African savings and tax structures, pyramids, dominance of blue chip shares relative to other shares and their effect on share prices, transaction cost and off market trading, manual systems and a lack of market makers and trading restrictions. Of these factors, exchange controls have been the biggest hindrance to total markets efficiency (Flatters et al., 2008). This is because strict exchange controls restrict domestic investors to the local market as they cannot easily move their capital to other markets, while deterring foreign investors from participating on the JSE. The factors identified by Casavalone (1996), have led to the widespread adoption of buy and hold strategies by investors and ultimately market illiquidity. In recognition of the need to relax exchange controls, the South African Reserve bank and the Ministry of Finance have instituted the requisite relaxation on a phased basis.

1.4 Thesis outline

The thesis comprises eight chapters. The second chapter examines the dynamics or structure of the JSE returns. The third chapter explicates the JSE structural dynamics to provide a comprehensive account of their existence. The fourth chapter looks at risk measurement and the distribution of stock market returns on the JSE. The fifth chapter investigates how different agent interactions affect market dynamics. The sixth chapter renders evidence of reflexivity and the extent to which it affects price formation and market dynamics. The seventh chapter devises a forecasting technique based on adaptive intelligent models to predict stock market returns. The eighth chapter summaries and concludes the research.

CHAPTER 2

THE FRACTAL NATURE OF THE JOHANNESBURG STOCK EXCHANGE

″If market moves are arbitrary (as the random walk proponents suggest), then internal components would rarely 'make sense' mathematically, and then only by statistically insignificant fluke occurrences.″

Robert Prechter, *Elliott Wave Theorist*: Elliott Wave Website, April 1977

2.1 Introduction

The wave of financial crises in the past decade has shown that the Efficient Market Hypothesis (EMH) is not as flawless as originally portrayed in the finance literature. The past century witnessed at least ten financial crises, which should never have happened in such a short timeframe, considering the EMH theory (Taleb, 2007a). Mandelbrot (2004) argues that the problems with the EMH stems from the demanding assumptions and over-simplification of the various interactions and dynamics of the market. The main assumption of the hypothesis is that price changes follow a random walk process, making predictions of future market movements impossible.

The purpose of this chapter is to analyse the JSE stock price movements using the fractal analysis framework. Peters (1994) introduced Fractal market analysis as a pioneering approach to stock market analysis. The technique uses quantum theories to study and characterise the inherent predictability of financial markets, (Nichols, 2009). The premise in this study is that the JSE stock prices exhibit fractal statistical patterns, also known as “long term memory”. The study hypothesises that different kinds of price series exhibit different degrees of memory.

The findings suggest that the JSE return series is fractal in nature. The overall All share index exhibited evidence of long-term predictability. The results also show a logical variation of the Hurst exponent by sector indices and characteristics of the markets sampled. The Hurst exponent measures long term memory in time series. It relates to the autocorrelations of the time series, and the rate at which these decrease as the lag between pairs of values increases. Resources, Non-Cyclical Services and Financials show the lowest average Hurst exponent values implying anti-persistence in the return series. These results contradict the EMH and suggest that some of the JSE returns series are predictable.

The rest of the chapter is organized as follows. Section 2 reviews the literature on the development of modern finance theory and renders a brief description of the Fractal Market Analysis technique. Section 3 describes the data and data manipulation. Section 4 presents the methodology, and Section 5 describes the results, followed by the conclusions of the study in Section 6.

2.2 Literature Review

For his PhD dissertation, Bachelier (1900) researched the movements of prices of the underlying assets and concluded that the price movements are random and each price movement is independent of previous movements. Bachelier's work led to the formulation of the EMH that now dominates modern finance theory and most empirical work. The EMH implies the absence of a detectable and predictable structure in the market (Greenblatt, 1998). It postulates that prices are driven by the unanticipated arrival of news about fundamentals (Curtler et al, 1989, Kortian, 1995). In other words, EMH models consider price fluctuations to be a consequence of exogenous/outside influences.

Mandelbrot (1963a and b), on the other hand, demonstrated that cotton prices and consequently stock returns exhibit a biased random process, or fractional Brownian motion, as opposed to a pure random process that is postulated by the EMH. For Peters (1989), a biased random process means that there is a long-term dependence, or memory, between observations. In other words, the events of one period influence all the periods that follow.

Mandelbrot (2004) argues that investment practitioners still insist on using the EMH and its rigid assumptions not because they make financial models work but because "they make the mathematics easy". Furthermore, Peters (1999) contends that such formulation take the models far from reality. Evidence, from the recent spate of financial crisis, has also shown that current financial model assumptions are not adequate and have become inadequate for explaining the complexity of financial markets (Velásquez, 2010).

Greene and Fielitz (1977) made the first immerse contribution towards understanding the fractal nature of financial markets. Using the rescaled-range (R/S) method, they found evidence of long memory in daily equity returns. Recent contributions on the Indian stock market (Chitrakalarani et al, 2012), the G7 stock markets (Kasman et al, 2007), and on Chinese and Japanese stock markets (Lin, 2011), demonstrate that market returns have fractal properties. Peters' (1989) study applied the modified (R/S) to bond returns over the period from January 1950 through June 1988, and revealed that they follow a biased random walk. Similar studies (Richards, 2000; Mulligan, 2000 and Schmitt et al, 1999) also confirm fractal properties in the foreign-currency rates.

Musongole (2002) conducted the only notable study on the empirical description of the movement of the JSE overall index using fuzzy techniques. The study reported that the JSE overall index could be characterized as persistent. However, this study only examined the overall Johannesburg Stock Exchange index and not the different sub-sectors.

The current study explores the movements of different market characteristics such as firm size, geographical location and sector grouping to understand the effect they have on the JSE price formation.

2.2.1 Fractal market analysis

The construct "fractal" is derived from the Latin adjective *fractus* while the related Latin verb *frangere* means to break or to create irregular fragments (Mandelbrot, 1967).

Fractal patterns are not only found in price changes of securities but also in the distribution of galaxies throughout space, in the outline of shorelines and in the pretty designs generated by computer programs (Stamps, 2002 and Taylor et al, 2001).

Fractal market analysis explores and describes the patterns hidden within seemingly random financial markets, and calculates the probability of future events (Nichols, 2012). Nichols (2012) elaborates that ascertaining these fractal patterns and projections is critical to identifying specific critical balance points where the potential energy may evolve in one direction or another. If the location of points were to be identified ahead of time, the trajectory of stock prices and markets could be empirically ascertained or predicted. Fractal Market Analysis also tackles head-on "anomalies" that cannot be explained by traditional capital market theories and asset-pricing models such as recurring events that include market stampede, bubbles and crashes (Mandelbrot 1963b, 2004).

Mistry (2008) argues that stock markets become unstable when fractal structures breaks up and this occurs when investors with a long-term view stop participating in the market altogether or become short-term investors. Investment forecasts are shortened when investors feel that long-term fundamental information is no longer reliable or important. Periods of economic or political turmoil, including uncertainties in the long-term outlook, possibly accounts for most of these events (Cutler et al, 1989).

2.3 Data and data manipulation

Daily closing stock market composite indices of twenty-seven sub-sectors and firm sizes (i.e. small cap, mid cap and large caps) of shares listed on the JSE from 2000 to 2010 were extracted from the McGregor BFA and DataStream platforms. The data series are transformed into a series of continuously compounded percentage returns as follows:

$R_t = 100In(P_t/P_{t-1})$	**Equation 2-1**

where P_t and P_{t-1} are the closing prices of an index on day *t* and day *t-1*, respectively. The logarithmic returns are more appropriate for the analysis than percent price changes because the range in R/S analysis is the cumulative deviation from the average return, and the logarithmic return sum to the cumulative return.

2.4 The Hurst process and R/S analysis

Many researchers are interested in the results of the existence of long-term memory properties which, not only serves as negative evidence of weak-form EMH, but is also closely related to the predictability of stock prices. The Hurst exponent has been widely used as a method to measure long–term memory properties, see (Goodhart and O'Hara, 1997, Geweke et al, 1983 and Peng et al, 1994). This measurement quantifies the degree of persistence of similar price change patterns, and is closely related to weak-form EMH. Also, there are studies that have proposed that the Hurst exponent could be used as an efficiency measurement of stock markets.

Harold Edwin Hurst (1951) developed the R/S Analysis in the early 20th century, whilst working on the Nile River Dam project. Hurst designed a method to study natural phenomena such as the flow of the Nile River (Mitra, 2011). The method served to demonstrate that the process was not random, but patterned. He defined a constant, *K*, which measures the bias of the fractional Brownian motion. Mandelbrot (1968) defined this pattern as fractal. He changed the constant from *K* to *H* in honour of Hurst. The Hurst exponent varies between 0 and 1.

According to the original theory, H=0.5 would imply an independent process i.e. each movement on the time series is independent of previous movements. R/S analysis is non-parametric, so there is no requirement for the shape of the underlying distribution. A Hurst exponent (H) that lies in this range $0.5<H\leq1.00$ implies a

persistent time series characterized by long memory effects. Theoretically, what happens today influences the future.

In terms of chaotic dynamics, there is sensitive dependence on initial conditions. This long memory occurs regardless of time scale (self-similarity). There is no time scale, the key characteristic of fractal time series. An H that lies in the range $0 \leq H < 0.50$ signifies anti-persistence. An anti-persistent system covers less distance than a random one. For the system to cover less distance, it must reverse itself more frequently than a random process. A theorist with a standard statistics background would equate this behavior to a mean-reverting process.

The presence of long-memory components in asset returns has important implications for the paradigms used in modern financial economics. For example, optimal consumption /savings and portfolio decisions may become extremely sensitive to the investment horizon if stock returns were long-range dependent. Problems also arise in the pricing of derivative securities with martingale methods, since the class of continuous time stochastic process most commonly employed is inconsistent with long term memory, see (Farmer et al (2005), Andersen and Bollerslev (1997) and Maheswaran and Sims(1992)) for examples. Traditional tests of the capital asset pricing model and the arbitrage pricing theory are no longer valid since the usual forms of statistical inference do not apply to time series exhibiting such persistence.

2.4.1 Rescaled Range (R/S) analysis method: step by step

1) R/S analysis is a simple but highly data intensive process. It follows these sequential steps: The study will analyse AR (1) [Autoregressive (1)] residuals of logarithmic returns for the JSE stock market returns. Using the AR (1) residuals helps to eliminate or at least minimize linear dependency commonly referred to as pre-whitening/detrending. First, a series of logarithmic returns (S_t) is regressed as the dependent variable against (S_{t-1}), the independent variable to obtain the

intercept, *a*, and the slopes, *b*. The AR(1) residual of (S_{t-1}) subtracts out the dependence of (S_t) on (S_{t-1});

$M_t = S_t - (a + b * S_{t-1})$	**Equation 2-2**

where M_t = the AR (1) residual of *S* at time *t*. The AR (1) residual method does not eliminate all linear dependencies. However, Brock et al (1987) argues that it eliminates enough dependence to reduce the effect to insignificant levels, even if the AR process is level 2 or 3.

2) After the pre-whitening process, the R/S analysis is conducted. The analysis starts with a time series of length *M*. This is then converted into a time series of length *N=M-1* of the logarithmic ratios of the residuals:

$N_t = \log(M_{(t+1)}/M_t)$, *t=1,2,3……..(M-1)*	**Equation 2-3**

3) The period is divided into *A* contiguous sub-periods of length *n*, such that *A*n=N*. Each sub-period is labeled I_a, with *a=1, 2, 3. . . n*. For each I_a of length *n*, the average value of the logarithmic residual ratios is defined as:

$e_a = \left(\frac{1}{n}\right) * \sum_{k=1}^{N} N_{k,a}$	**Equation 2-4**

where e_a =average value of the N_t contained in sub-period I_a of length n.

4) The time series of accumulated departures $(X_{k,a})$ from the mean value for each sub-period I_a is defined as:

$X_{k,a} = \sum_{i=1}^{k} (N_{i,a} - e_a), k = 1, 2,3 \dots \dots, n$	**Equation 2-5**

5) The range is defined as the maximum minus the minimum value of $(X_{k,a})$ within each sub-period I_a:

$R_{I_a} = \max(X_{k,a}) - \min(X_{k,a}), where\ 1 \le k \le n$	**Equation 2-6**

6) The sample standard deviation calculated for each sub-period I_a:

$$S_{I_a} = \sqrt{(\frac{1}{n}) * \sum_{k=1}^{n} (N_{k,a} - e_a)^2}$$	**Equation 2-7**

7) Each range R_{I_a} is now normalized by dividing by the S_{I_a} corresponding to it. Therefore, the rescaled range for each I_a sub-period is equal to R_{I_a} / S_{I_a}. From step 3 above, *A* contiguous sub-periods of length *n* exist. Therefore, the average R/S value for length *n* is defined as:

$$(R/S)_n = (1/A) * \sum_{a=1}^{A} (R_{I_a} / S_{I_a})$$	**Equation 2-8**

8) The length *n* is increased to the next higher value and *(M-1)/n* is an integer value. Values of *n* include the beginning and ending points of the time series, and steps 2 through 7 are repeated until *n=(M-1)/2* are used. We now perform an ordinary least squares regression of log (*n*) as the independent variable and $\log(R/S)_n$ as the dependent variable. The intercept is the estimate for log(*c*), the constant. The slope of the equation is the estimate of the Hurst exponent, *H*.

2.4.2 Validation of the R/S analysis results- Bootstrap Resampling Technique

Research is always confronted with one major question when analyzing any process: that is whether or not results did not happen by random chance? Perhaps there were not enough data, or there may even be a question as to whether R/S analysis works at all. This research suggests a technique developed by Scheinkman and LeBaron (1986) to validate the R/S analysis results. The technique involves checking whether there exists a true structure in the periods with Hurst exponent greater than 0.5. For each sample, the series is scrambled and the Hurst exponent calculated. The scrambled series has the same distribution as the original sample except that the sequence is random. If there is some structure in the time series, after scrambling, the structure will be destroyed and the calculated Hurst exponent should be close to that of a random series (H=0.5).

2.5 Hurst exponent results

In this section, the Hurst exponent results for different groups of indices are presented. First, the ALSI is compared with a sample of International indices to see if they have the same characteristics. Secondly, different firm size indices are compared. Lastly, different JSE/FTSE industrial sector indices are compared.

2.5.1 ALSI vs. International stock indices

In this section, the ALSI is compared to international stock market indices. The results in Table 2-1 show that the JSE is fractal in nature, judging from the Hurst exponent results. The JSE has a Hurst exponent of 0.6101, which corresponds with the results for most of the sampled international markets with the exception of the Nikkei and the NASDAQ, with Hurst exponents of 0.437 and 0.470 respectively, suggesting that these markets are anti-persistent. Evidence from these results seems to suggest that the long-memory property of stock markets might be linked to the level of development and location within which each stock market operates.

Table 2-1: International indices results

International Indices	Classification Code	Hurst exponent
ALSI	J203	0.6101
NASDAQ	COMPX	0.470
Taiwan Weighted	TWI	0.519
Hang Seng	HSIX	0.659
Thailand Set	SET.IN	0.650
Nikkei 225	N225	0.437

Table 2-2 presents the average Hurst exponents for developed markets and emerging markets, which are 0.543 and 0.645 respectively, suggesting that, on average, there is more long-term predictability in emerging markets compared to developed economies. The weaker long memory property for developed stock markets can be possibly be attributed to the fact that they are relatively more informationally efficient than emerging markets. For developed markets, prices tend to reflect publicly available information and any new information is arbitraged away more than is the case for emerging markets. On the contrary, emerging markets are characterized by thin trading caused by various institutional rigidities that perpetuate informational inefficiency and asymmetry, see (Al-Khazali (2002) and Oprean (2012)).

Table 2-2: Emerging vs. Developed markets

Market Classification	Number of Countries Sampled	Average Hurst	Standard Deviation
Emerging Markets	15	0.645	0.0113352
Developed Markets	17	0.543	0.0024157

2.5.2 Firm size Hurst results

The study also examines whether firm size influences the long-term predictability on the JSE. The results in Table 2-3 demonstrate that while all the firm sizes exhibit a long-term structure, the small cap group shows stronger predictability. The results can be explained by the fact that many investors on the JSE restrict their holdings to the largest and most widely researched companies resulting in smaller companies, such as those outside the top 40 and mid-caps, being neglected by most investors despite being attractive in terms of growth, see (Mkhize and Mbanga, 2006). Small caps are also a target of momentum investors seeking stocks that have experienced recent acceleration in earnings or upward price movement, see (Rappaport, 2005). The theory behind momentum investing is that stocks that have done well in the recent past will continue to do so, see (Reilly, 2002 and Berger et al, 2008).

Table 2-3: Firm size results

Index styles	**Classification Code**	**Hurst exponent**
Top 40	J200	0.562

Mid-Caps	J201	0.583
Small Caps	J202	0.723

2.5.3 FTSE/JSE industrial sectors

This section examines the JSE classified by sub-sector and reports the Hurst exponent results. The FTSE/JSE classification system categorises listed firms into sub-sectors that closely describe the nature of their business. The results show that the Hurst exponents of the 27 different sectors under study range from 0.343 to 0.704 (see Table 2-4). The study findings suggest that there is a logical system of variation of H by economic and sector grouping. Resources, Non-Cyclical Services and Financials sub-sectors show the lowest average H values. These sub-sectors have average H values that are less than 0.5, meaning they are anti-persistent, hence mean-reverting. These series would be choppier, or more volatile, than a random series, because they consist of frequent reversals (mean reversion). The Oil and gas sector has a Hurst exponent greater than 0.5 which is not in line with the rest of the subsectors under Resources. Also worth noting from the results is the Transport sector which recorded the largest Hurst exponent of 0.704, meaning that it has the strongest persistence compared to the other sub-sectors under study. This implies that fluctuations in the market have a relatively small impact on the transport industry compared to the other sectors. The information technology sector also exhibited an average Hurst exponent greater than 0.5 meaning that price formation is persistent in nature.

2.6 Validation of the Hurst results (Bootstrap Resampling Technique)

To validate the results the bootstrap resampling technique was used. The stock returns time series were scrambled in Matlab a 1000 times and the average Hurst exponent was calculated. The results are shown in Table 2-5. There is evidence to support the existence of a profound structural difference for the time series under study. All the original series have H estimates significantly different from 0.5, whereas those of the scrambled series are in the range of 0.499 and 0.510, which are approximately equal to the random walk value of 0.5. This drop in the value of H suggests that the scrambling processes destroyed the long memory process in the original time series. These results prove Mandelbrot's assertion that the R/S analysis is robust with respect to the distribution of the underlying series.

Table 2-1: FTSE/JSE Global sector classification analysis

Industrial Sectors	Classification Code	Hurst exponent
Resources		
Oil and Gas	J500	0.629
Gold	J150	0.424
Platinum	J153	0.386
Coal	J042	0.431
Non-cyclical consumer Goods		
Beverages	J353	0.544
Health Care	J540	0.638
Food Producers	J357	0.558
Pharmaceuticals & Biotech	J457	0.615
Non-Cyclical Services		
Food and Drugs	J063	0.356
Mobile	J678	0.417
Fixed line communications	J673	0.343
Basic industries		
Forestry and paper	J173	0.634
Chemicals	J011	0.529
Construction and materials	J235	0.474
Steel and other metals	J018	0.607
Cyclical services		
Leisure	J053	0.519
Media	J054	0.458
General retailers	J052	0.583
Support services	J058	0.597
Transport	J059	0.704
Financials		
Real estate	J086	0.386
Venture capital	J231	0.466
Banks	J081	0.484
Non- life Insurance	J083	0.401
Life Insurance	J084	0.613
Information technology		
technology hardware	J093	0.630
Software	J097	0.679

Table 2-2: The average Hurst exponent on 1000 scrambling runs

Index	Mean Hurst exponent after scrambling	Standard deviation
All share	0.5125	0.0109288
Top 40	0.5124	0.01035
Mid-Caps	0.5001	0.0071544
Small Caps	0.5042	0.0109402
Oil and Gas	0.5019	0.0023629
Gold	0.5048	0.0012945
Platinum	0.5049	0.0051644
Coal	0.5116	0.0023072
Beverages	0.5070	0.0103466
Health Care	0.5018	0.022787
Food Producers	0.5008	0.011374
Pharmaceuticals & Biotech	0.5037	0.0014466
Food and Drugs	0.5124	0.0088332
Mobile	0.5096	0.0045409
Fixed line communications	0.5075	0.0133173
Forestry and paper	0.5009	0.0036254
Construction and materials	0.5078	0.0020435
Steel and other metals	0.5054	0.005941
Leisure	0.5093	0.0058996
Media	0.5064	0.0073805
General retailers	0.5085	0.0060949
Support services	0.5030	0.0062746
Transport	0.5069	0.0133106
Real estate	0.5077	0.0003269
Venture capital	0.5025	0.0017414
Banks	0.5010	0.0035961
Non-life Insurance	0.5112	0.0172539
Life Insurance	0.5125	0.013032
technology hardware	0.5092	0.0112057
Software	0.5057	0.0093794
Nasdaq	0.5096	0.0129222
S& P 500	0.5023	0.0062301
Taiwan	0.4997	0.0028304
Hang Seng	0.5082	0.0032122
Thailand	0.5011	0.0036705
Nikkei	0.5056	0.0024157
Emerging Markets	0.5053	0.0030213

2.7 Practical implications

The results presented in this study have important implications for equity price forecasting on the JSE. The findings in this chapter suggest that stock market behaviour can be more logically explained through precise and realistic modelling. By combining the Hurst exponent results and neural networks, we can improve stock market returns forecasting. This can be particularly useful in neural nets where models can target time series with higher predictability i.e. H>0.5.

2.8 Conclusion

This chapter demonstrated that the JSE ALSI is fractal in nature and rendered a conceptual introduction to the Fractal Market Analysis to investors on the JSE. This concept demonstrates more precision and is more convincing in its description of the characteristics of stock prices. These results imply long-term predictability for the ALSI. The results also showed a logical variation of the Hurst exponent by sector grouping and classification of the markets sampled. Resources, Non-Cyclical Services and Financials showed the lowest average H values. These sub-sectors showed average Hurst exponent values that are less than 0.5 meaning they are anti-persistent hence mean-reverting. Emerging markets showed more long-term predictability than developed markets.

The above results can be extended to portfolio optimization in investment analysis. The biggest challenge with portfolio optimization is dealing with the noise in the expected returns, see (Black and Letterman (1992)). By combining the Hurst exponent results and neural networks, portfolio optimization can be improved. This can be done by only incorporating stock with higher predictability i.e. H>0.5 into the portfolio.

A later chapter will explore whether or not these findings can be extended to cover increasing efficiency, in risk management and portfolio attribution. Given the results from this chapter, Chapter 7 will explore the possibility of combining the Hurst exponents within a certain range to create a more efficient stock portfolio that is characterized by higher risk-adjusted ratios.

CHAPTER 3

EXPLANATION OF THE JSE STRUCTURAL DYNAMICS

"The potential implications for understanding behavior are that even over a low frequency range, price activity can be characterized by intermittent bursts of activity involving a relatively narrow range of frequencies, separated by relative quiescent periods…."

Ramsey and Zhang, *Mathematical Economists*, (1997)

3.1 Introduction

The previous chapter demonstrated that fractals describe the behaviour of the JSE robustly. However, they do not explain the existence of this behaviour. Consequently, this chapter seeks to examine the fractal statistics observed in Chapter 2 using chaos theory to postulate why the fractal behaviour exists. The chaos theory examines complex nonlinear dynamic systems (Levy, 2007) with a view to understand stock price formation. Some economists argue that non-linear dynamics provide a natural way of visualising the important connections between the fine points of trading and the macro-dynamics of stock markets, see (Scheinkman et al., 1989; LeBaron, 1994).

The chapter investigates the economic and political events that affect different sectors and explain the appearance of non-linear windows on the JSE. Nawrocki (1996), postulates that macro-economic and political announcements are essential in generating serial dependence in financial markets. The goal of this research is to broaden our understanding of the JSE and to position investors to make profits given the inefficiencies and imperfections in market information flows. The effectiveness of the technique suggested in this Chapter is connected to a few market characteristics that are likely to influence the investors' choices on stock market dynamics.

To detect major economic and political events that contribute to the non-linear dependencies on the JSE, the Hinich and Patterson's (1995) windowing' approach is utilized. This study hypothesizes that certain sectors react with greater sensitivity to certain macro-economic and political news than other sectors. Conclusions are also drawn concerning the degree of sensitivity of the market to positive and negative news.

The study successfully extracted some of the economic indicators that are responsible for the significant non-linear market movements on the JSE. It is shown that some economic indicators become significant during a crisis period and do not have any significant effect on price movement during tranquil periods. One important finding that emerged from the sub-period analysis is that the highest number of significant non-linearities occurs during the crisis period for the Resources sector. The analysis finds mixed sensitivity reactions to different news announcements by different sectors. These results help explain the fractal structure described in Chapter 2.

The chapter is organized as follows. The next section reviews other studies conducted on non-linear dynamics and price sensitivity. The third section discusses the data and data manipulation. The fourth section presents the methodology and the fifth section reports the findings. The sixth section concludes the study.

3.2 Non-linear dynamics in financial markets

Non-linear dynamics has its origins in the much celebrated "three body problem" and the endeavors, at the turn of the century, by a great theoretical physicist, Henri Poincare, to calculate the movement of a planet around the sun when under the influence of nearby planets. Barrow-Green (1996) and Brock (1986) define a dynamic system as being linear if it can be completely described by its local and global properties. Non-linear dynamics do not have this property of equivalence between local and global dynamics and thus are considerably more difficult to analyze (Pesaran and Potter, 1992). Non-linear systems have impulse response functions that are history and shock dependent, unlike their linear counterpart (Lee and Pesaran, 1995). Mathematically, a dynamical system (θ, x) is non-linear if the map θ is not affine. A non-linear dynamical system is one in which a transformation $f: x \rightarrow f(x)$ and an affine map $\lambda: f(x) \rightarrow f(y)$ do not exist such that:

$(f \bullet \theta)(x) = \lambda\big(f(x)\big) \quad for\ all\ x \epsilon X$	**Equation 3-1**

This implies that the resultant transformation f may be disproportionate to the input x or y , (Kalman, 1963). This concept has now been extended to explaining economic and financial markets dynamics, see Hsieh (1991). There is overwhelming empirical evidence of non-linear structure in stock market returns since the late 1980s, both from developed and emerging markets, (Romero-Meza et al, 2006; and Lim, 2008).

A research conducted by Mangani (2004) on the JSE found that a structural non-linear dynamic model could be used to describe the JSE return generating process. However, this study did not take into consideration the fact that non-linear dependence might not be consistent throughout the sample period. Hinich and Patterson's (1995) study on developed stock markets data showed that the behavior of the non-linear dependence structures is at best episodic in nature. The study revealed that stock markets data are characterized by extended periods of pure noise, only interspaced by episodes of significant non-linear periods. Similar follow-up studies include those conducted on developed countries' foreign exchange rates (Brooks and Hinich, 1998), Asian foreign exchange rates (Gilmore, 2001), Latin American stock markets (Romero-Meza *et al*., 2005) and on Asian stock market data (Lim, 2008). These studies also came up with the same conclusion.

3.2.1 Events that cause market non-linearity

The past fifty years of finance research has produced a remarkable amount of papers examining the effect of news announcements on financial markets; see (Andrew (1995) and Chen et al (2001)). Although many of these researchers examined the influence of firm-specific announcements, others investigate the notion that stock markets react to macro-economic news (Birz and Lott, 2011; and Christiansen et al., 2005). Some American statistics, particularly real activity statistics, have been shown to have the ability to move market prices especially commodities stocks (Ghura, 1990). Fair (2002) identified sixty-nine economic and political events, for the US stock markets, that led to large stock price changes.

The most significant studies on factors that affect movements on the JSE are those of Barr and Kantor (2002), Hancocks (2010), Moolaman and Du Toit (2005). Barr and Kantor (2002) developed a model to capture the impact of several macro-economic factors. Moolaman and Du Toit (2005) used the co-integration and error correction techniques to map the relationship between the JSE stock process and various economic factors. The results showed that the short-term fluctuations were caused by economic factors such as interest rates, risk premium, the exchange rate, and foreign stock markets among other variables. Hancocks (2010)'s study explored the influence of South African macroeconomic variables on the performance of the JSE. The findings suggest that money supply, inflation, long and short- run interest rates, and the exchange rate had significant influence on stock market prices.

Unfortunately, none of these studies interrogated how these macro-economic events affect JSE indices and how they evolve over time. This study draws on these issues by taking an opposite approach. Instead of the usual event studies approach, it relies on the data to decide endogenously the events that generate nonlinear market behavior. This approach has the advantage of not subjectively hypothesizing about an event first and then measuring the resulting market reaction.

3.2.2 Price sensitivity asymmetry on stock market data

Studies have been conducted on developed markets' price sensitivity, but none on the JSE. Andersen et al. (2005) showed that US markets react differently to macro-economic news depending on the state of the economy, with bad news having no significant impact during a boom and negative impact during a market downturn. According Soroka (2006), there is a growing body of research suggesting that responses to positive and negative information are asymmetric, that negative information has a much greater impact on individuals' attitudes than positive information. Soroka's paper explores these asymmetries, and the responsiveness to positive and negative economic shifts, and finds strong evidence of asymmetries on the U.K. markets.

Cenesizoglu (2006) analyses the return reaction asymmetries of portfolios with different characteristics to the same macroeconomic news. The study finds that returns on a portfolio of firms with high market capitalization and low book-to-market ratio react stronger to macroeconomic news than returns on a portfolio of firms with low market capitalization and high book-to-market ratio. Roache and Rossi (2010) studied the effects of US and Asian economic news on commodity prices and found that commodities have been relatively insensitive to macro-economic news compared to other financial assets and major exchange rates. Unfortunately, all the literature above focuses more on international markets and the reaction of the aggregate stock market rather than the reaction of individual sectors. The differential reaction across sectors with different characteristics remains to be explored. The current research will test the effect of macro-economic news on price sensitivity asymmetry on the JSE sectors.

3.3 Event detection technique

This study employs a technique proposed by Hinich and Patterson (1995), which is a reverse of the usual event studies that relies on the data to decide endogenously the events that generate nonlinear market behaviour. This test makes use of the Hinich Bi-correlation test to detect periods of significant temporal dependencies within a data series, by splitting the data sample into smaller sub-samples. Once the strong temporal dependencies sub-samples are identified, they are matched up with the economic and political events from both international and the local market provided by the Forex Capital markets and Standard Bank economic research departments. The matching up procedure endeavours to show that the nonlinear periods match up to at least one important macro-economic or political event. In order to identify the event that generates the non-linear dependencies, the daily changes in the time series behaviour are observed.

3.3.2 The Hinich- Bicorrelation Test

The Hinich-Bicorrelation test requires the removal of serial linear dependence from the data before performing the test. This is achieved by fitting an autoregressive model to each time series. This will ensure that the remaining serial dependence can only be attributed to the non-linear return generating process. A decision should be made on the length of the window. Lim (2007) argues that there is no unique value for the window length. According to Brooks and Hinich (1998), the length of the window should be adequately long enough to be statistically tested and small enough to identify the arrival and disappearance of temporal dependencies. In this research, the window length of 35 observations as suggested in the Brooks and Hinich (1998) study is adopted. $\{y(t)\}$ is used to denote the sampled data process, where t is the time unit. The null hypothesis for each window is that $y(t)$ is a stationary white noise process that has zero bicorrelation. The alternative hypothesis is that the process generated within the window has a non-zero bicorrelation.

$C_{yyy}(r,s) = E[y(t)y(t+r)y(t+s)]$ in the set 0<r<s<L	**Equation 3-2**

where L is the number of lags in the window and r and s are return series at t and t+1 respectively. The Hinich Bicorrelation statistics and its distribution are given by:

$H = \sum_{s=2}^{L}\sum_{r=1}^{s-1} G^2(r,s) \sim X^2(L-1)(\frac{L}{2})$	**Equation 3-3**

where $G(r,s) = (a-s)^{\frac{1}{2}} C_{zzz}(r,s)$, and $C_{zzz}(r,s) = (a-s)^{-1} \sum_{t=1}^{a-s} Z(t)Z(t+r)Z(t+s)$

where $Z(t)$ are the standardized observations, obtained by subtracting the sample mean of the window and dividing by its standard deviation. The lag L is specified as $L = a^n$ with $0 < n < 0.5$. Because of the small sample size in the non-overlapping windows, bootstrapping is introduced with 10,000 replications. This improvement satisfies the threshold for the H statistic that has a test size of 5%.

3.3.3 Evidence of price sensitivity asymmetry

This section explores whether the JSE sector indices' sensitivity to news announcements is symmetrical. The study explores possible factors that might condition the reaction of different sector indices to announcements. For this purpose, the regression models 3-4 and 3-5 are used.

$\Delta p_t = \alpha + \sum_{k=0}^{2} \beta_k Z_{t-k} + \sum_{l=1}^{2} \gamma_1 \Delta p_{t-1} + \varepsilon_t$	**Equation 3-4**

where the change in the future price Δp_t is the dependent variable, Z_t represents the news arrival including $K-1$ lags, and L lags of the stock return are the exogenous variables, and ε is the error term. The composite indicator is used for conditioning the price response[2]. On a day without an announcement, the composite will have a value of zero. On a day with just one announcement, the composite's value will be one. On

[2] The composite is the aggregation of the standardized scores for each announcement.

a day with more than one announcement, the surprise will be the summation of the individual standardized scores.

For the positive-negative news model, we define positive news as any announcement surprise that should lead to an increase in the price of the sector index. The classification of positive or negative news depends on the sector being analyzed. For example, unexpected higher inflation is not necessarily positive news for the cyclical services sector but can be classified as positive news for the Resources sector, since this would naturally lead to an increase in commodity prices see (Hancocks, 2010). The mean equation of the GARCH model is written as:

$\Delta p_t = \alpha + \sum_{k=0}^{K} \beta_k^+ Z_{t-k}^+ + \sum_{k=0}^{K} \beta_k^- Z_{t-k}^- + \sum_{l=1}^{L} \gamma_1 \Delta p_{t-1} + \varepsilon_t$	**Equation 3-5**

where $Z^+(Z^-)$ and $\beta^+(\beta^-)$ are the composite surprise variable and coefficient for positive (negative) news, respectively see (Roache and Rossi, 2010).

3.4 Data Samples and Description

The data used in this chapter includes all the JSE sector indices for the period July 2004 to June 2010. This duration is significant because it captures the period during which major market microstructure changes have taken place. The sample is divided into two sub-periods, namely the pre-crisis period (June 2004-June 2007) and the crisis period (August 2007-June 2010). In total, eleven series of returns are examined. The different sector series are transformed into series of continuously compounded percentage returns as follows:

$R_t = 100In(P_t/P_{t-1})$	**Equation 3-6**

where P_t and P_{t-1} are the closing prices of the index on day *t* and day *t-1*, respectively. According to Peters (1991), percentage change may not be the appropriate series for nonlinear dynamic series analysis, since the series of interest are the sums of the cumulative returns. The macroeconomic news data set includes the scheduled releases of macroeconomic indicators published in the Forex Capital Markets and Standard

Bank (SA) Economic Calendars. South African and International political events of significance were extracted from the World-Monitor (2012).

3.5 Detecting periods of transient nonlinear dependence

The Hinich Bicorrelation statistic for each time window is computed in Matlab. The Matlab program transforms the Hinich Bicorrelation obtained from equation 3-2 into a percentile using the cumulative distribution function of the test statistic. It is impossible to show the entire computed Hinich Bicorrelation statistics for each rolling time window, hence we report the results through graphical illustration, as shown in Figure 3-1 and 3-2. The values near 1 in the plots indicate strong evidence of nonlinearity for a particular window.

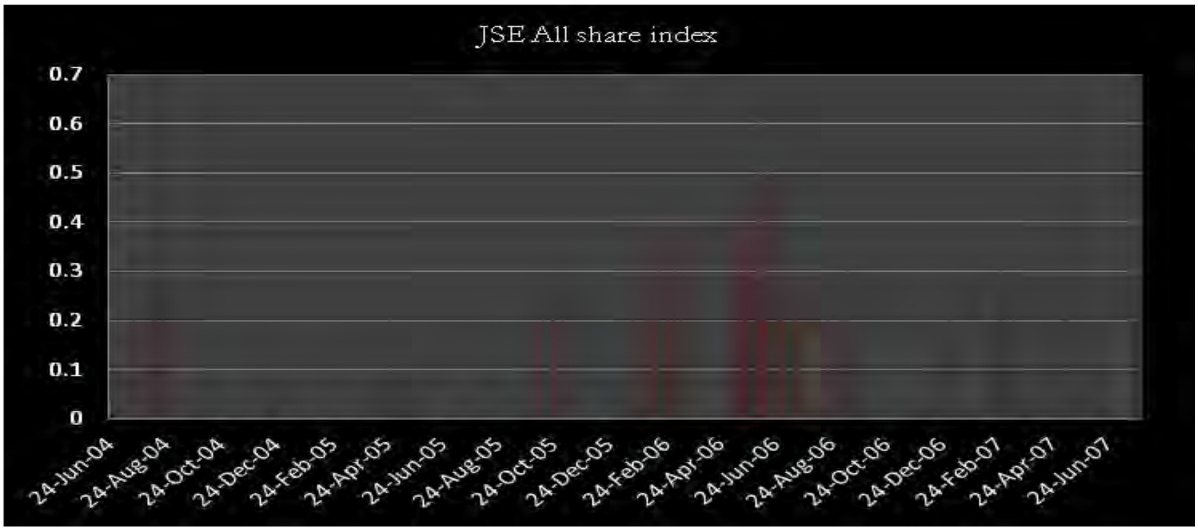


Figure 3-1: ALSI significant episodes pre-crisis period

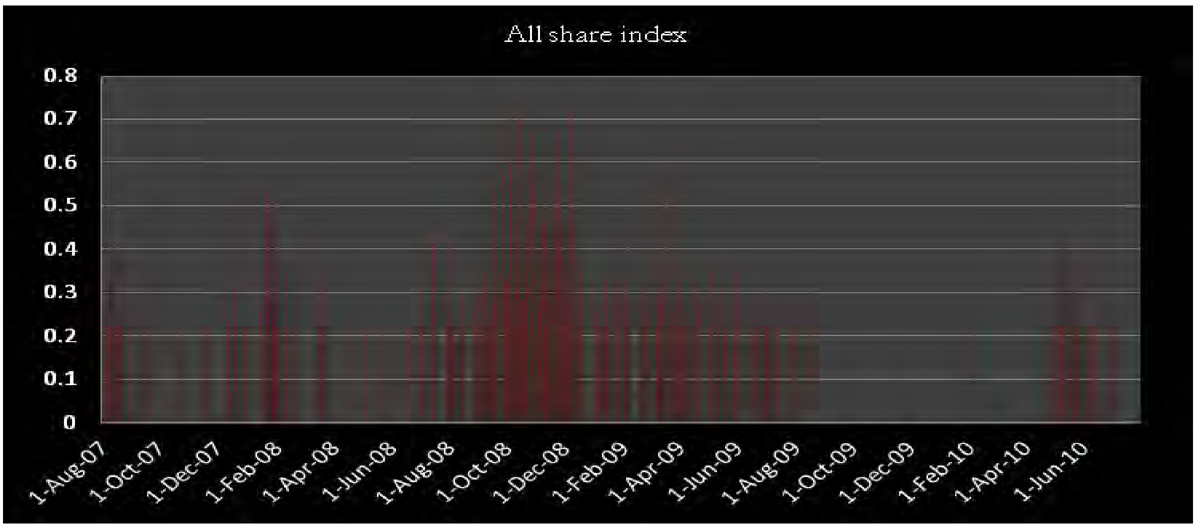


Figure 3-2: ALSI significant episodes during crisis period

The results in Figure 3-1 and 3-2 reveal evidence of transient nonlinear dependencies for both the pre-crisis and crisis periods. The All share index returns series seems to be characterized by few brief episodes of highly significant non-linearity followed by longer stretches of relatively quiet behavior. The results are not surprising as there has been growing evidence in literature reporting the short bursts of nonlinear dependence in international stock and foreign exchange market data see (Brooks et al, 2000; and Hinich and Patterson, 1995).

Table 3.1 and 3.2 provide the percentages of the significant Hinich Bicorrelation statistics for the different JSE sectors pre-crisis and during the crisis. One important finding that emerged from the sub-period analysis is that the highest number of non-linearities occurred during the crisis period for all economic sectors especially for platinum and gold subsectors. This result implies that investors see precious metals as good hedges against inflation. The financial sector's results also compare very well with other sectors during the financial crisis. One would have expected a higher number of significant windows during the crisis because of the 2007 global credit crunch for the financial sector. The JSE's financial sector might have been protected from the large price movements experienced by the rest of the world during the global credit crunch because of their non-exposure to the US toxic assets. The Reserve Bank has maintained that the turmoil in global financial markets that started in 2007 only affected South Africa indirectly, as local banks had almost no direct exposure to US subprime mortgages, see (Reserve Bank of SA Report, 2008). The variation of the non-linear dependence also matches with fractal dynamics results given in Table 2-4 in Chapter 2. This result implies that the fractal nature of the JSE is a function of non-linear dynamics.

Table 3-1: Pre-crisis period: July 2004-2007

Sectors	Total number of rolling time windows	Total number of significant H windows	Percentage of significant H windows
Resources			
Oil and Gas	23	1	4.3%
Gold	23	2	8.7%
Platinum	23	2	8.7%
Coal	23	2	8.7%
Non-cyclical Consumer Goods			
Beverages	23	1	4.3%
Health Care	23	1	4.3%
Food Producers	23	1	4.3%
Pharmaceuticals	23	1	4.3%
Non-Cyclical Services			
Food and Drugs	23	2	8.7%
Mobile	23	2	8.7%
Fixed line communications	23	2	8.7%
Basic Industries			
Forestry and paper	23	1	4.3%
Chemicals	23	1	4.3%
Construction	23	2	8.7%
Steel and other metals	23	1	4.3%
Cyclical Services			
Leisure	23	2	8.7%
Media	23	1	4.3%
General retailers	23	1	4.3%
Support services	23	1	4.3%
Transport	23	2	8.7%
Financials			
Real estate	23	2	8.7%
Venture capital	23	1	4.3%
Banks	23	1	4.3%
Life Insurance	23	1	4.3%
IT			
technology hardware	23	1	4.3%
Software	23	1	4.3%

Table 3-2: Crisis period: August 2007-July 2010

Sectors	Total number of rolling time windows	Total number of significant H windows	Percentage of significant H windows
Resources			
Oil and Gas	22	3	13.6%
Gold	22	8	36.4%
Platinum	22	7	31.8%
Coal	22	4	18.1%
Non-cyclical consumer Goods			
Beverages	22	4	18.1%
Health Care	22	4	18.1%
Food Producers	22	5	22.7%
Pharmaceuticals	22	3	13.6%
Non-Cyclical Services			
Food and Drugs	22	5	22.7%
Mobile	22	4	18.1%
Fixed line communications	22	4	18.1%
Basic Industries			
Forestry and paper	22	3	13.6%
Chemicals	22	3	13.6%
Construction	22	5	22.7%
Metals	22	4	18.1%
Cyclical Services			
Leisure	22	4	18.1%
Media	22	3	13.6%
General retailers	22	3	13.6%
Support services	22	3	13.6%
Transport	22	3	13.6%
Financials			
Real estate	22	5	22.7%
Venture capital	22	4	18.1%
Banks	22	4	18.1%
Life Insurance	22	4	18.1%
IT			
technology hardware	22	3	13.6%
Software	22	3	13.6%

Figure 3-3 shows the nonlinear surface for the ALSI stock market returns produced by a locally-weighted regression technique. On the whole, the results from Hinich

Bicorrelation statistic test and the locally-weighted regression techniques are consistent in suggesting that nonlinearity does exist in the contemporaneous JSE ALSI stock prices.

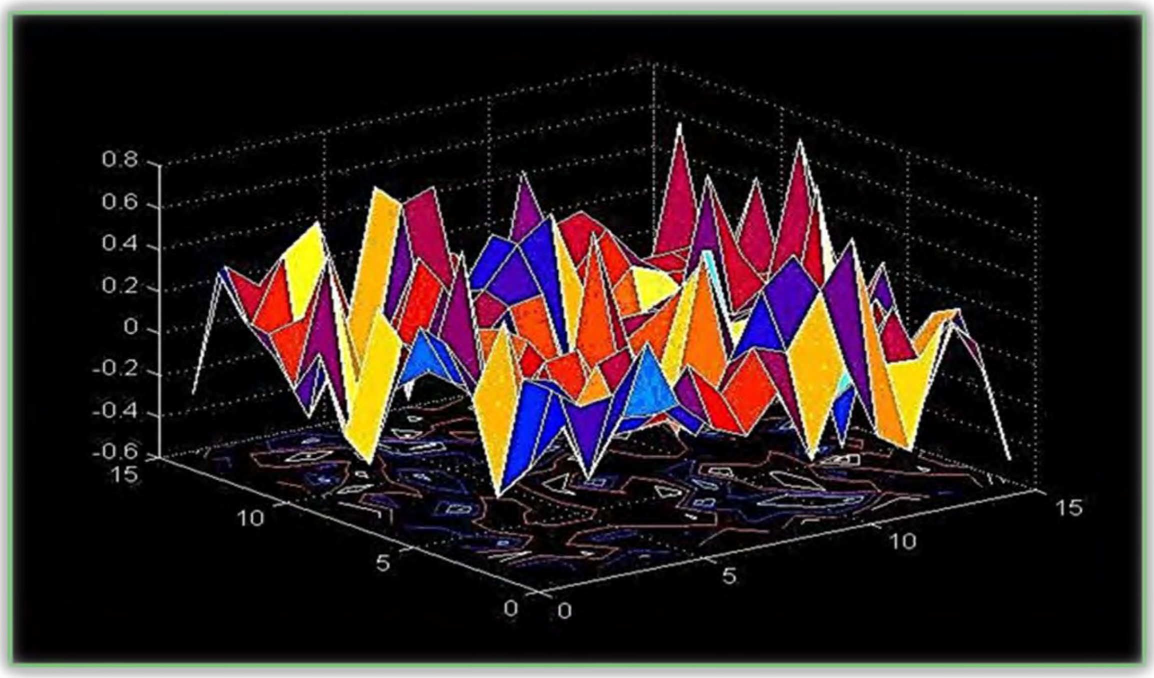


Figure 3-3: Non-linear surface of the JSE returns

3.5.1 Events responsible for the nonlinear dependencies

Different economic sector indices, pre-crisis and during the crisis are analyzed to identify the major events that are responsible for the transient burst of significant *H* windows in this section. The information presented in this section can be integrated into existing research to come up with more accurate models for the JSE and other emerging markets. Table 3-3 shows the economic indicators that are important under different market conditions.

Table 3-3: Significant macro-economic announcements

Period	**Significant Economic/Political Announcements**
Pre-Crisis period	South African retail Sales
	South Africa PPI/CPI figures
	Chinese Industrial Production
Crisis period	U.S. Retail Sales
	South Africa Vehicle sales
	South Africa Retail Sales
	U.S. Employment situation
	U.S. Federal Open Market Committee Statement
	U.S. PPI/CPI figures
	Chinese Industrial Production

The results seem to indicate that some economic indicators become significant during a crisis period and do not have any significant effect on price movements during tranquil periods, see table 3-3. The study finds that economic data from the US like retail sales and the employment situation only become important in crisis periods. This result can be explained by the fact that during a recession or crisis, analysts depend on the world's largest economy, the US, for direction because it often provide clues that an economy recovery is imminent (Baumohl, 2005).

Another interesting observation is that local inflation figures influence significant price movements during the pre-crisis period but not during the crisis period. This means that during a crisis investors consider higher inflation figures to be normal and will not react to it. The results also indicate that the Chinese production figures are important in both pre-crisis and crisis periods. This result indicates the impact of the Chinese economy on the South African economy, which is heavily dependent on natural resources. Natural resources account for 60% of South African exports (STATSA, 2011).

The findings also showed that no major political events observed in the period studied significantly affected the JSE market. Another interesting observation is the absence of significant economic and political news from Europe, which is one of South Africa's major trading partners. South Africa trade with Europe accounts for 27% of all South African trade receipts, (DG Trade Statistics, 2011). Finally, we also note that there are many large price movements that are not associated with any economic/political events. These can be attributed to the self-reinforcing effect of market sentiment. This has been discussed in more detail in Chapter 6.

3.6 Evidence of price sensitivity asymmetry

In this section, the state-dependence hypothesis that postulates that price reactions are asymmetric to different news announcements is tested. The results in Table 3-4 show that positive news is more important in some sectors of the JSE, while negative news is more important in others. In some sectors, the type of news does not have any significant bearing on the sensitivity of the index. The results indicate statistically significant sensitivity asymmetry in the resources sector. Most notable in this group is the impact of bad news on the gold index. The coefficient on the bad news aggregate is statistically significant and much higher than that on good news when compared to the other resources and sectors. This result can be explained by the fact that most investors see gold as a safe haven when the prospects of a bad economic outcome increases, Clapperton (2010). The other resource that exhibit significant bad news asymmetric sensitivity is platinum, which highlights its growing popularity in recent years as a safe investment haven like gold, Sari et al (2010). As for the metals and oil and gas sectors, there is a positive reaction to good news, underscoring their typically pro-cyclical characteristics, but there is little sensitivity to bad news.

Results from the rest of the sectors show significant sensitivity asymmetries, which favour good news, except for the financial sector, which is symmetric for both types of news. Besides the pro-cyclical characteristics explanation for these sectors, this behaviour could also be partly attributed to the market trading regimes that drive short-term market movements. For example, noise traders are more likely to engage in trend-chasing behavior in up markets and anchoring behavior in down markets, (Altı et al (2012) and Andersen et al (2005)). A comparison of the news impact on the cyclical services sector to those that also exhibit positive sensitivity to good news, shows that the cyclical services sector's coefficient on good news aggregate is much higher than when compared to non-cyclical consumer goods. Some of these results are contrary to previous studies done on developed markets, which showed that bad news have a bigger impact than good news; see (Li and Parker, 2005; Andersen et. al., 2002). The variation in sensitivity to news seems to be in line with the variation in Hurst exponents described in Section 2.5.3 of Chapter 2.

Table 3-1: JSE sector sensitivity to macroeconomic announcements[3]

	Aggregate without +/- news regressor			Aggregate +/- news regressor			
Sectors	Aggregate news t	Aggregate news t–1	Aggregate news t–2	Positive news t	Positive news t–1	Negative news t	Negative news t–1
Resources							
Oil and Gas	0.09	0.04	-0.02	0.16**	0.04	-0.01	0.01
Gold	-0.08***	- 0.03	0.03	0.06	-0.03	-0.39***	-0.05
Platinum	–0.07***	–0.02	0.02	0.03	0	-0.23***	0.05
Metals & minerals	-0.01	0.02	-0.02	0.12**	-0.09	-0.18	0.11
Non-Cyclical Consumer Goods							
Beverages	0.08	-0.03	0.03	0.01*	0.02	-0.12	0.03
Health Care	0.04**	0	-0.06	0.04**	-0.04	0.07	-0.06
Food Producers	0.1	0.02	0.02	0.01**	-0.02	0.002	0.08
Pharmaceuticals	0.08	0.05	0.01	0.04*	0.08	-0.04	0.07
Non-Cyclical Services							
Food and Drugs	0.12*	0.02	0.04	0.12***	0.02	0.11	-0.04
Mobile	0	0.03**	-0.03	0.03*	0.07	0.03	0.02
Fixed line coms	0.02	-0.06	0.02	0.07*	0.04	0.07	-0.07
Basic industries							
Forestry and paper	0.05	0.02**	0.01	0.02*	0.06	0	0.01
Chemicals	0.01	0	0.06	-0.04**	0.00	-0.06	0.05
Construction	0.02	0.04	-0.001	0.16**	-0.01	0.05	0.06
Steel	0.12	0.03	-0.04	0.16**	0.04	-0.12	0.04
Cyclical services							
Leisure	0.06	0.004	-0.01	0.18***	0.02	-0.03	0.05
Media	0.01	0.025	-0.02	0.16***	-0.04	0.01	0.09
General retailers	0.08	0.04	-0.03	0.13*	0.04	-0.05	0.06
Support services	0.03	0.04	0.06	0.08***	0.08	0.045	-0.04
Transport	0.05	-0.05	0.06	0.05***	0.06	0	0.08
Financials							
Banks & Insurance	0.06***	0	-0.03	0.06	-0 .05	0.06***	0.06***
Information tech							
Technology hardware	0.02	0.05	-0.07	0.02*	0.05	-0.06	0.07
Software	0.04	0	-0.04	-0.01*	0.04	-0.02	0.05

[3] Significance at the 90 %, 95% and 99% levels denoted by *, **, and *** respectively.

3.7 Practical implications of results

Having identified the macro-economic events that are responsible for some of the non-linear dynamics on the JSE, it is now possible to carry out micro forecasting by carefully following the events identified and predicting when possible major market movements are going to occur. The results will also be useful to stock exchanges and Central banks seeking to preserve orderly markets. Portfolio managers holding these assets in their portfolios should also have an interest in knowing how they respond to macroeconomic news which will help them build diversified portfolios.

3.8 Conclusion

This study investigated the impact of different economic and political events on different sectors and provided evidence of price sensitivity asymmetry on the JSE. Hinich and Patterson's (1995) technique was adopted to identify the economic and political events. The technique is a reverse of the usual event studies that relies on the data to determine endogenously the events that trigger nonlinear market behaviour. The study also employs regression analysis to test the state-dependence hypothesis that postulates that price reactions are asymmetric to different news announcements.

The results reveal overwhelming evidence in support of episodic nonlinear serial dependence in all the JSE sectors analysed. Major economic events that contributed to short bursts of non-linear behaviour were identified and they include international and local factors. No evidence of significant political events in the period studied was reported. The results also suggest that a very large proportion of shocks cannot be attributed to macro-economic news meaning that some of the movements are associated with endogenous factors. The results also show that different economic indicators are important under different market conditions. For example, some economic indicators become important only during the crisis period and do not have any effect during tranquil periods. The results also show that price reactions are asymmetric to different news announcements. The most notable result is that of the gold index, which is impacted more by bad news when compared to the other resources.

Given the prevalence of these episodic transient features across the JSE industrial sectors, there is need for researchers and investment practitioners to take into account these salient features in their model construction. Future research should also consider extending the results of this study to individual firms to examine the adjustment of stock prices to firm-specific events, which will provide deeper insight into issues on corporate actions.

CHAPTER 4

RETURN DISTRIBUTION AND RISK MEASUREMENT ON THE JSE

'The problem is that measures of uncertainty using the bell curve simply disregard the possibility of sharp jumps or discontinuities and, therefore, have no meaning or consequence. Using them is like focusing on the grass and missing the (gigantic) trees."

Benoit Mandelbrot and Nassim Taleb, *Mathematicians*, (2006)

4.1 Introduction

The distribution of stock market returns has serious implications on risk management and modeling, see (Andersen et al., 2001). The exact nature of the JSE stock market return distribution has not been widely debated even though it is of great consequence to equity management; see Andersen et al (2001) and Stein et al (1991). This research contributes to this debate through an in-depth analysis of the JSE returns to identify the distribution of stock returns, evidence of volatility clustering and how they affect risk measurement.

Mandelbrot (1963a, b) was the first mathematician to provide evidence that stock market returns are not Gaussian distributed, but exhibit fat tails. Follow-up studies supporting these results include Cont et al. (1997), Rachev (2003), and Mantegna and Stanley (2000). Mandelbrot (1963a) argues that extreme market movements are far too frequent in financial data series for the normal distribution to hold. He argues for a stable Paretian model, which has the property of infinite variance which caters for fat tails in the return distribution. As far as the JSE stock prices are concerned, there is limited literature on their statistical properties, Mangani (2007) and Chen et al (2003). Mangani (2007) evaluated the distributional and time series features of JSE stock prices and found that the assumptions of normality and linearity are inappropriate. He reported that the JSE return distributions are highly leptokurtic and generally display excess skewness. Chen et al (2003) explored the distribution of the long-run JSE returns limited on an upgrade or downgrade market index.

The current study is important for several reasons. Given that the measure of return distribution can be used for better risk estimation, the study also provides information on tail probabilities. Return distribution is connected to various risk measures such as expected loss and the Value at Risk (VaR) model, (see LeBaron and Yamamoto, 2008). The distribution structure of stock returns is also important if one is in the business of avoiding or profiting from risk. A financial institution, for example, might be required by its regulators to estimate the value of its market assets daily. Such a financial institution can better estimate the potential losses and set aside a certain amount of capital to cushion against its losses if it can predict future return clustering. The approach used is also complementary to traditional tests employed in the study of financial contagion, see (Benedetti et al, 2013).

The main findings in this study are as follows. First, there is evidence of volatility clustering and a long-term memory structure in the returns. The stock returns also exhibit positive skewness indicating a high probability of observing positive returns. Second, fat tails and the Student-t distribution were found to fit the JSE stock returns well. This result is surprising as we expected the Cauchy distribution to give a better performance because of the recent spate of financial crises. Finally, there is evidence to suggest that the Gaussian/normal distribution-based VaR measure fails dismally as a risk management measure during periods of high stock volatility.

The research is organized as follows: The next section focuses on fat tails, their distributions, and volatility clustering. The third section discusses the data and descriptive statistics used in the analysis of this research. The fourth reports on the results of volatility clustering, distribution and risk analysis. The fifth section concludes the study.

4.2 Fat tails and Scaling of the distribution of price fluctuations

A fat tail is a property of some probability distributions exhibiting exceptionally large kurtosis particularly relative to the normal, thin-tailed distribution, (Bahat et al 2005). Financial economists consider fat tails undesirable because of the extra risk they imply (Morera, 2008) and (Taleb, 2007a). The presence of fat tails means that there is a high probability of large returns deviations. According to Mitzenmacher (2003), fat tail distributions have power law decay. More specifically, the distribution of a random variable is said to have a fat tail if

$f_x(x) \sim x^{-(1+\propto)}$ as, $x \to \infty$, $\propto > 0$	**Equation 4-1**

where $f_x(x)$ is the probability density function. Most researchers use the term "fat tail" only in cases of infinite variance i.e. when $0 < \propto < 2$, see (Nolan, 2009) and (Fernández et al, 1998). According to Peters (1991), the most common explanation of the fat tails is that information shows up in infrequent clumps, rather than in a smooth and continuous fashion. However, Peters (1994) contends that it is the market reaction to clumps of information that causes the fat tails.

Cont's (2005) alternative explanation of the causes of fat tails is that the reaction to the information itself could be the reason why clumps occur and not the information arriving in clumps. He postulates that if investors do not take into account new information until trends start forming, and then react, in a cumulative fashion, to all the information previously overlooked, fat tails could as well occur. It would mean that people react to information in a nonlinear way. The reaction of investors in this fashion implies that the present is influenced by the past, a clear violation of the efficient market hypothesis (EMH), (Lo, 2008). According to Reilly et al (2002), the EMH suggests that information is reacted to in a cause and effect manner.

The normal distribution is popular in finance generally because the factors influencing stock prices are mathematically tractable under the normality assumption and the central limit theorem provides for such a distribution. However, world markets are typically not mathematically well behaved, (Blanchard, 1979). LeBaron (2006) found that fat tails in market return distributions also have some behavioural origins. For example, investor sentiments have been shown to cause some large market moves, see (Filimonov and Sornette, 2011).

4.3 Volatility Clustering

Volatility clustering is another well-known stylized fact in financial markets, see (Mantegna et al, 2000) and (Lux et al, 2000). Volatility clustering manifests itself as periods of tranquillity interrupted by periods of turbulence, (Kirchler and Huber, 2007). If one examines the empirical JSE All share returns series shown in Figure 4-1, it is easy to observe that large prices fluctuations are often followed by other large price movements while small fluctuations are more likely to be followed by small fluctuations, implying long memory.

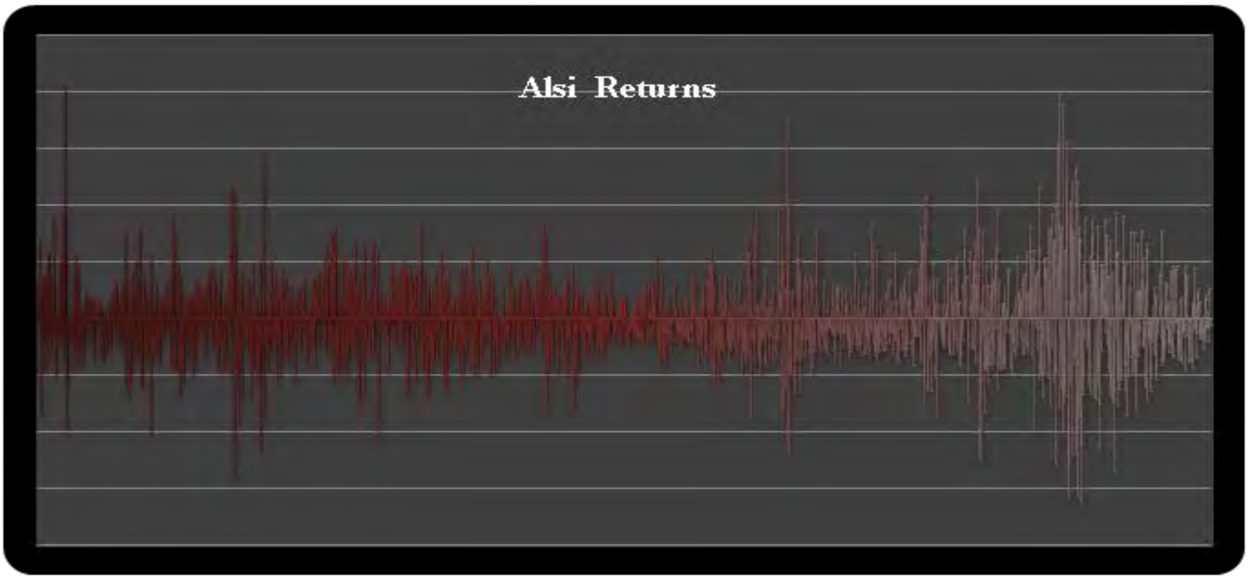


Figure 4-1: All share returns from January 2000-2010

According to Brock et al (1996), **i**nvestor heterogeneity could be the best justification for volatility clustering experienced on financial markets. Andersen et al. (2005) argues that the memory in financial time series can be explained by the aggregation of different time series with different persistence levels and arrival of information. LeBaron (2006) also examined the effects of the diversity in time horizons on price dynamics. He found that the presence of heterogeneity in horizons may lead to an increase in return unpredictability. Yamamoto's (2006, 2010), social engineering experiment found that for volatility clustering to exist there has to be social learning, that is, the herd behaviour has to prevail. This is because in an economy with social learning, expectations are likely to converge at some point and likely to lead to the volatility clustering of the returns for some periods and a lack of it in other periods (Yamamoto, 2006).

4.4 Data and descriptive statistics

The descriptive statistics given in Table 4-1 were calculated from daily, weekly and monthly stock returns of the All Share Index (ALSI) defined as;

$R_t = log_e(P_t/P_{t-1})$	**Equation 4-2**

where R_t is the return at time t; P_t and P_{t-1} are the ALSI levels at time t and $t-1$ respectively.

Table 4-1: Returns descriptive statistics

	Minimum	**Maximum**	**Mean**		**Std. Deviation**	**Skewness**		**Kurtosis**	
	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error	Statistic	Std. Error
Daily	-6.605	8.216	0.037	0.027	1.371	0.289	0.049	3.395	0.098
Weekly	-0.097	0.095	0.002	0.001	0.024	0.434	0.106	3.860	0.212
Monthly	-0.113	0.220	0.011	0.004	0.047	1.426	0.221	4.081	0.438

The results in Table 4-1 show that all the time series frequencies exhibit high kurtosis, indicating fat-tailed distributions. The level of kurtosis seems to increase with sampling frequency. Higher kurtosis means that more of the variance results from infrequent extreme deviations, as opposed to frequent modestly sized deviations, (SAS Elementary Statistics, 2011). All the three stock returns series presented display positive mean returns, with positively skewed distributions. Positive skewness indicates that the distribution has a long right tail, which suggests high probability of observing large positive returns, (Xiong and Idzorek, 2011).

Table 4-2: Jarque-Bera normality test results

Frequency	Jarque-Bera Statistics	P- value	Normally Distributed
Monthly returns	206.23575	1.65E-45	FALSE
Weekly returns	32.76916	7.66E-08	FALSE
Daily returns	233.05406	2.47E-51	FALSE

The Jarque-Bera statistical test results in Table 4-2 clearly indicate that the return frequencies under study do not conform to the popular normality assumption. The results also contradict the standard assumption in the mean-variance framework, and indeed many other holistic asset allocation frameworks, returns are independent from period to period and normally distributed (J.P Morgan Asset Management, 2009).

4.5 Quantitative Analysis of Volatility Clustering

In order to determine the presence of volatility clustering on the JSE returns series, an autocorrelation analysis of squared returns is performed. In the presence of volatility clustering, the squared return series should be highly auto-correlated, see (Watanabe, 2001). Given the measurements at time $X_1, X_2, \dots \dots \dots . X_N$, the lag k autocorrelation function is defined as

$r_k = \sum_{i=1}^{N-k} (X_i - \bar{X})(X_{i+k} - \bar{X}) / \sum_{I=1}^{N} (X_i - \bar{X})^2$	**Equation 4-3**

Autocorrelation is the interdependence or relationship between two values of the same variable at different times. When the autocorrelation is used to detect volatility clustering, it is usually only the first (Lag 1) autocorrelation that is of interest. The Box-Ljung test used to test for volatility in this study is given by equation 4-4:

$Q(N) = (T+2)T[\frac{\rho^2(1)}{(T-1)} + \frac{\rho^2(2)}{(T-2)} + \cdots \ldots \ldots .. + \frac{\rho^2(N)}{(T-N)}]$	**Equation 4-4**

where ρ_i denotes the sample correlation at lag i, and T denotes the sample size. Under the null hypothesis of independently and identically distributed observations, Q(N) has an asymptotic Chi-squared distribution with N degrees of freedom.

Table 4-3: Basic characteristics of the stock return indices at different frequencies

Frequency	**Function**	**Autocorrelation**	**Std. Error**	**Box-Ljung Statistic**	
				Value	Sig.
Daily	$\rho(1)$	0.073	0.010	56.888	0.000
	$\varrho^2(1)$	0.084	0.020	20.825	0.000
Weekly	$\rho(1)$	0.427	0.020	441.804	0.000
	$\varrho^2(1)$	0.029	0.043	1.835	0.176
Monthly	$\rho(1)$	0.305	0.034	80.237	0.000
	$\varrho^2(1)$	0.091	0.090	0.858	0.354

The results in Table 4-3 show that there is no evidence of significant volatility clustering in the weekly and monthly data. This result is confirmed by the Ljung–Box statistic, which shows p-values that are greater than 0.05 for the monthly and weekly returns. This means that there is no evidence of clustering of economic shocks, or conditional heteroscedasticity, in the weekly and monthly data. Volatility clustering is only evident in the daily data where the estimated autocorrelation coefficients for the squared return series denoted by $\varrho^2(1)$ are significantly different from zero, using heteroscedasticity-consistent standard errors. From previous research, evidence of volatility clustering suggest that the price formation process is a function of heterogeneous beliefs across traders, see (Connolly et al., 2000; Brock et al, 1996).

4.6 Distribution Analysis

This section explores a distribution that best fit the JSE stock market returns. It compares the overall fit of the Cauchy, Gaussian, and Student's t distributions, all of which are subclasses of the family of stable Paretian distributions. The above distributions were chosen because they constitute the few stable distributions with closed formulas for densities and distribution functions (Mandelbrot, 1964).

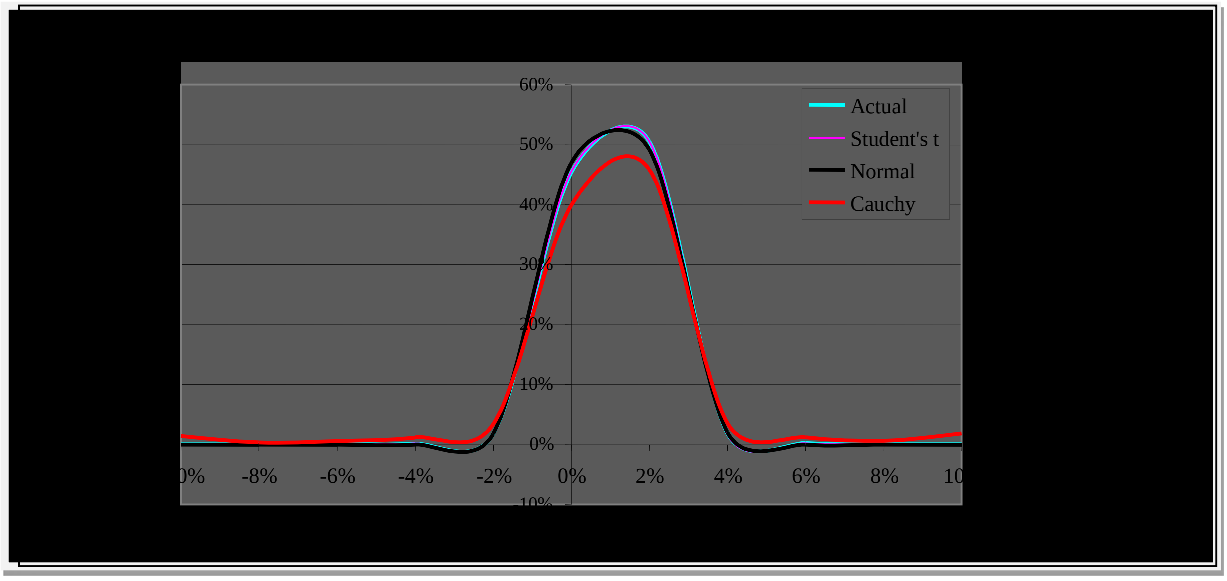


Figure 4-2: Frequency distribution of daily stock returns

The above frequency distribution curves of total daily stock returns does not match the shape of the actual stock returns. The Cauchy distribution has fewer observations centered on the mean compared to the other curves including the one for the actual returns. Most of the return observations appear to be distributed in the tails. Both the student's t and normal distributions seem to capture very well the returns close to the mean but not the proportions distributed in the tails. This customary frequency distribution graph is somewhat misleading with regard to the tails observations, which is why the actual frequencies in Table 4-4 are emphasized.

The table allocates 2499 trading day stock returns since January 1, 2000 to January 2010 in various daily stock returns bins ranging from -20% or worse to + 20% or higher. As shown in Table 4-4, the fit between the actual data series and the Student's t distribution is commendable. This is confirmed by the high Chi Square p-value of 0.84. The Normal distribution fit is not as good as the student's t distribution as it misses 21 of the worse returns and 40 of the best returns. Surprisingly, the Cauchy distribution fit is also poor as its tails are excessively fat. The Cauchy results are surprising because with the recent spate of financial crisis, a large number of extreme events were expected hence fatter tails in the actual returns. The levy distribution had the worst fitting as it completely missed out all the worst returns and over-estimated the positive returns.

Table 4-4: Overall fit of the distributions

Daily Returns (Bins)	Actual returns	Student t	Normal	Cauchy	Levy
≤-20%	0	0	0	45	0
-18%	0	0	0	12	0
-16%	0	0	0	2	0
-14%	0	0	0	4	0
-12%	0	0	0	9	0
-10%	0	1	0	19	0
-8%	1	1	0	31	0
-6%	3	4	0	62	0
-4%	15	18	2	82	0
-2%	116	115	112	198	0
0%	1188	1194	1249	997	1193
2%	1034	1037	974	602	524
4%	122	117	180	241	349
6%	14	8	2	69	195
8%	5	3	0	43	90
10%	1	1	0	23	45
12%	0	0	0	14	37
14%	0	0	0	10	19
16%	0	0	0	6	8
18%	0	0	0	8	9
≥20%	0	0	0	22	30
Total	2499	2499	2499	2499	2499
Chi-square p-value	**-**	0.84	0.022	0	0

4.6.2 Assessing Risk frequency

For risk analysis, the frequencies of returns less than zero are examined. Negative returns are the biggest cause of distress to portfolio managers as this means they are losing money, (Liu, 2004). Table 4-5 shows the number of days in each return bucket on a cumulative basis. Thus, in the actual data series, there were 135 days with a negative return of –2% or lower. Table 4-5 shows that the Cauchy distribution resulted in 122 days (out of 2499) with a negative monthly return of -8% or worse compared to only 1 day in the actual data. Thus, the Cauchy distribution overstated this risk frequency of -8% or worse by 122 times as shown in Table 4-5.

Table 4-5: Cumulative frequency distribution of negative returns

Daily Returns (Bins)	Actual returns	Student t	Normal Distribution	Cauchy Distribution	Levy Distribution
-10%	0	1	0	91	0
-8%	1	2	0	122	0
-6%	4	6	0	184	0
-4%	19	24	2	266	0
-2%	135	139	121	464	0

Table 4-6: Risk frequency multiples

Daily Returns (Bins)	Actual returns	Student t	Normal Distribution	Cauchy Distribution	Levy Distribution
-10%	1	1	0	91	0
-8%	1	2	0	122	0
-6%	1	1.5	0	46	0
-4%	1	1.3	0.1	14	0
-2%	1	1	0.9	3.4	0

As shown by the risk frequency multiples in Table 4-6, the Student's t distribution captures the left tail risk at all levels extremely well. At every return cut-off points, the number of days captured by this distribution is very close to the actual data (resulting in multiples close to 1). The Normal distribution completely misses out the entire left tail as the -4% return threshold is already over 4 standard deviations away (multiple of 0.1≈0). For the Cauchy distribution, it is the opposite problem. The tails are excessively fat and it overstates the risk frequency at every cut-off point by a factor ranging from 3.4 times to 122 times the actual risk frequency.

4.6.3 An analysis of risk severity

Risk severity in this study measures how badly the distributions perform under adverse market conditions, see (Bocker et al, 2005) and (Harlow, 1991). A risk-manager who wants to measure the market risk of a given portfolio is mainly concerned with the potential losses likely to be caused by an adverse market movement over a given period, (Colquitt, 1999) and (Jorion, 2007). Here emphasis is placed on the returns from the left-tail consisting of the 30 worst daily returns to assess the risk severity of the different distributions. The return distributions are compared to actual returns.

Table 4-7 shows the ranking of the 30 worst daily returns. It is clear from Table 4-7 that the Student's t distribution matches the actual data very well. The Normal distribution misses out all 21 values as its very worst value (-3.999%) is still higher than the actual data's 18th worst value of -4.206%. On the other hand, the Cauchy and the Levy distribution values are much worse when compared to the actual data. In fact, the Levy distribution completely misses out the entire left tail.

Table 4-8 shows the risk severity multiples for the worst returns. The risk severity multiples are calculated by dividing the distribution returns by the actual returns. The results show that the Cauchy distribution overstates the worst return by a multiple of 319.3 times. Meanwhile, the Normal and Levy distributions understate this return by 0.61 and -0.03 respectively. While the Levy distribution misses out this 30 worst observation left-tail risk, the normal distribution misses out on 19 of the worst observations and the Cauchy distribution overstates it by a factor range of 18 to 319 times. The Student's t distribution however almost gets it just about right through the entire range, although it understates the risk from the 26th worst return onwards.

The results above imply that the student-t distribution does a good job in describing the JSE returns and using this distribution in risk measurement will provide more accurate results. Future chapters will discuss how this can be used in stock returns modelling.

Table 4-7: Ranking of the worst 30 returns

Ranking worst returns	Date	Actual	Student t	Normal	Cauchy	Levy
1	05-Dec-08	-6.61%	-10.37%	-4.00%	-2109%	0.21%
2	24-Nov-08	-6.31%	-8.76%	-4.00%	-1826%	0.31%
3	28-Oct-08	-6.29%	-6.65%	-4.00%	-967%	0.32%
4	21-Sep-01	-5.72%	-6.53%	-3.99%	-763%	0.36%
5	18-Mar-09	-5.45%	-6.37%	-4.00%	-671%	0.40%
6	18-Sep-08	-5.15%	-6.18%	-3.99%	-563%	0.40%
7	29-Oct-08	-5.11%	-4.93%	-3.98%	-465%	0.42%
8	23-Jan-08	-5.02%	-4.89%	-3.98%	-354%	0.41%
9	31-Jan-08	-4.99%	-4.79%	-3.96%	-276%	0.42%
10	07-Nov-08	-4.86%	-4.56%	-3.96%	-255%	0.44%
11	21-Nov-08	-4.83%	-4.47%	-3.96%	-198%	0.45%
12	14-Jun-06	-4.80%	-4.40%	-3.96%	-168%	0.46%
13	13-Dec-01	-4.73%	-4.39%	-3.95%	-145%	0.46%
14	08-Jun-06	-4.71%	-4.38%	-3.96%	-136%	0.56%
15	05-Feb-09	-4.66%	-4.38%	-3.95%	-128%	0.58%
16	09-Dec-08	-4.46%	-4.27%	-3.95%	-112%	0.58%
17	13-Dec-02	-4.44%	-4.24%	-3.95%	-107%	0.59%
18	03-Jan-01	-4.21%	-4.19%	-3.94%	-95%	0.59%
19	16-Jul-08	-4.00%	-4.00%	-3.94%	-90%	0.61%
20	10-Oct-08	-3.99%	-3.98%	-3.93%	-88%	0.62%
21	17-Apr-00	-3.96%	-3.96%	-3.93%	-85%	0.64%
22	03-Oct-01	-3.91%	-3.89%	-3.93%	-81%	0.65%
23	26-Nov-08	-3.88%	-3.79%	-3.93%	-79%	0.67%
24	16-Feb-06	-3.73%	-3.68%	-3.93%	-78%	0.69%
25	22-May-06	-3.69%	-3.63%	-3.92%	-76%	0.69%
26	19-Dec-01	-3.51%	-3.37%	-3.92%	-73%	0.70%
27	18-Sep-07	-3.50%	-2.89%	-3.92%	-72%	0.70%
28	03-Dec-08	-3.47%	-2.60%	-3.92%	-68%	0.71%
29	30-Apr-09	-3.44%	-2.46%	-3.91%	-65%	0.74%
30	18-May-04	-3.40%	-2.37%	-3.81%	-62%	0.75%

Table 4-8: Risk severity multiples

Ranking worst returns	Date	Student t	Normal	Levy	Cauchy
1	05-Dec-08	1.57	0.61	-0.03	319.33
2	24-Nov-08	1.39	0.63	-0.05	289.44
3	28-Oct-08	1.06	0.64	-0.05	153.8
4	21-Sep-01	1.14	0.7	-0.06	133.44
5	18-Mar-09	1.17	0.73	-0.07	123.29
6	18-Sep-08	1.2	0.77	-0.08	109.28
7	29-Oct-08	0.96	0.78	-0.08	91.07
8	23-Jan-08	0.97	0.79	-0.08	70.66
9	31-Jan-08	0.96	0.79	-0.08	55.37
10	07-Nov-08	0.94	0.82	-0.09	52.47
11	21-Nov-08	0.92	0.82	-0.09	41.14
12	14-Jun-06	0.92	0.82	-0.1	34.97
13	13-Dec-01	0.93	0.84	-0.1	30.77
14	08-Jun-06	0.93	0.84	-0.12	29.05
15	05-Feb-09	0.94	0.85	-0.12	27.54
16	09-Dec-08	0.96	0.89	-0.13	25.26
17	13-Dec-02	0.95	0.89	-0.13	24.14
18	03-Jan-01	1.00	0.94	-0.14	22.53
19	16-Jul-08	1.00	0.99	-0.15	22.57
20	10-Oct-08	1.00	0.99	-0.16	21.92
21	17-Apr-00	1.00	0.99	-0.16	21.38
22	03-Oct-01	1.00	1.01	-0.17	20.71
23	26-Nov-08	0.98	1.01	-0.17	20.42
24	16-Feb-06	0.99	1.05	-0.18	20.83
25	22-May-06	0.98	1.06	-0.19	20.56
26	19-Dec-01	0.96	1.12	-0.2	20.83
27	18-Sep-07	0.83	1.12	-0.2	20.45
28	03-Dec-08	0.75	1.13	-0.21	19.7
29	30-Apr-09	0.71	1.14	-0.21	18.73
30	18-May-04	0.70	1.12	-0.22	18.23

4.6.4 Effectiveness of the Gaussian based Value at Risk (VaR) model.

One of the most important tasks of financial institutions is evaluating and controlling exposure to risk. A commonly used measure for estimation of market risk is the Value at Risk (VaR) model. Jorion (2007) defines VaR as the maximum loss over a target horizon such that there is a low pre-specified probability that the actual loss will be larger. The focus of this section is to test the validity of the Gaussian-based VaR as a risk management tool. Most practitioners use the Gaussian distribution VaR because they believe that it is a lot more transparent than other distributions.

Table 4-9 shows how often the VAR model would have failed to capture extreme market movements for the JSE All share index since 1950. We compare the results with the MSCI Barra Developed Markets index (DMI). As shown in Table 4-9, the VAR model would have failed to work in 18 different years a total of 47 times and 66 times for the MSCI Barra Developed Markets index. Surprisingly the VaR model worked more times compared to the world index in the mid-1980s when sanctions were imposed on South Africa. Teoh's (1999) study demonstrates that sanctions imposed by the international community on South Africa had little effect on the financial markets. If anything, this actually insulated the South African stock market from the international market shocks..

The VaR measure for the JSE as shown in Table 4-9 failed to capture extreme risk, 13 times in 2008 alone. This figure, however, is far less than the number of times (20) the MSCI index VaR failed. The Subprime Crisis that caused one of the biggest financial meltdown since the Great depression of 1929 possibly explains these large numbers compared to other crises periods. The SA Reserve Bank has maintained that the turmoil in global financial markets that started in 2007 has only affected South Africa indirectly, as local banks had almost no direct exposure to US subprime mortgages, (Mboweni, 2008).

Essentially, a VAR model relying on the Normal distribution that works 99.75% of the time would have failed in 13 out of the past 60 years (22%) for the JSE Alsi and 20 out of 60 years (33%) for the MSCI index. These results render the Gaussian based VaR useless as a risk management measure in volatile periods. The fact that the failure of the VaR measures coincides with some international crisis implies that the VaR measure gives good results for data from low volatile periods, but for data from financial crises, it is not effective.

Table 4-9: Number of daily returns missed by Gaussian VaR

Cause of Crisis	Year	All Share Index	MSCI Developed Markets index
Korean War	1950	1	1
Eisenhower Heart Attack	1955	1	1
Cuban Missile Crisis	1962	1	1
Oil prices crisis	1973	1	2
	1974	1	3
Financial Crisis	1986	2	3
	1987	4	6
	1988	3	5
	1989	1	1
Gulf War	1990	2	1
The Mexican peso crisis	1994	0	1
Asian Financial Crisis	1997	2	3
Russian financial crisis	1998	2	2
Dot-com bubble	2000	1	1
September 11 attacks	2001	3	4
	2002	2	2
Subprime Crisis	2008	13	20
	2009	7	9
	Total	47	66

4.7 Implication of Study

The fact that JSE stock returns distribution has been shown to be fat tailed and skewed provides a bridge between the highly technical theory of statistical distributional analysis, stochastic processes, and econometrics of financial returns and real world risk management and investments. Asset managers can now manage they risk, by using return distributions that can better model their market risk exposure. This result is also useful to Central Banks trying measure banks risk exposures under the Basel 3 accord.

4.8 Conclusion

In this chapter, a detailed analysis of the JSE returns is given in a bid to describe how they are distributed. The exact nature of the JSE stock market returns distribution has not been widely debated even though it is of great consequence to equity management. The main findings in this study are as follows. First, evidence of volatility clustering and a long-term memory structure in the returns were found. The stock returns also exhibit positive skewness indicating a high probability of observing positive returns. Second, there was evidence that fat tails and the Student-t distribution served as a better fit for the JSE stock returns. This result is surprising as we expected the Cauchy distribution to give a better performance because of the recent spate of financial crises. Finally, the study's findings suggest that the Gaussian-based VaR measure failed dismally as a risk management tool during periods of high volatility. The results also show that the JSE was not seriously affected by major financial crises when compared to other major markets. This could mean that the JSE was insulated from the big international market shocks that are being experienced in other developed markets.

CHAPTER 5

THE CASE FOR HETEROGENEOUS AGENTS ON THE JSE

"One of the things that microeconomics teaches you is that individuals are not alike. There is heterogeneity, and probably the most important heterogeneity here is heterogeneity of expectations. If we didn't have heterogeneity, there would be no trade"

Ken Arrow, *Economist*, February 2004.

5.1 Introduction

Understanding the nature and the dynamics of agent interactions on different markets is important, not only for academics in various fields of finance and economics, but also for investment practitioners in asset management. Literature has shown that the current global financial crisis resulted from systemic mistakes of economic agents and their model assumptions, see (Soros, 2008; Colander et al., 2008; Ramanauskas, 2008). This study argues that the assumption of rationality in financial markets leads to theories which are inconsistent with or inadequate for explaining observed market phenomena on the JSE.

The primary objective of this research is to construct a stock market system that resembles the real-life JSE trading. This system consists of heterogeneous market players that serve to provide an understanding of how their diverse characteristics influence the overall market outcomes and dynamics. The study also endeavours to show that the asset pricing model assumptions, that market agents are homogenous, underestimates equity prices, see (David (2008) and Chen et al (2002)). The distinctive feature of the methodology is modelling the actions and the decision-making process of different market agents and the market structure.

Our hypothesis is that expectations of market participants tend to be distributed differently depending on the market and economic conditions and news, see

(Ottaviani, 2006 and Case, 1989). The hypothesis makes three postulations: 1) Information is not limited and market participants generally infer it differently. 2) Future price formations are a function of the structure of the economy and market expectations. 3) Aggregate market predictions will have a significant effect on the overall market.

The study was successful in building a model that mimics the JSE market. On calibrating the simulated model, it exhibited a number of behaviours normally associated with real JSE market data, such as fat tailed returns distribution and self-replicating price structure. The results also showed that traders sometimes switch their characteristics between trading strategies. This evolutionary switching of traders seems to depend on the state of the market. Analysing correlations of the market states and agent strategies, the study finds that the fraction of technical analysts is large in times of market crises or crashes and bubbles. Simulations also showed that the homogenous-belief assumption tends to underestimate the expected stock prices and this can have serious implications for asset pricing.

The chapter is organized as follows. Section 2 reviews the literature on the Efficient Market Hypothesis (EMH) and the rational representative agent assumption and other alternative paradigms. Section 3 gives a description of the methodology. Section 4 presents the simulation results, and Section 5 concludes the chapter.

5.2 Literature Review

Much of the traditional finance theory is based on the efficient market hypothesis (EMH) and the homogeneous rational representative agent paradigm, see (Ramanauskas 2008; Lo, 2005 and Zeckhauser et al., 1991). Undoubtedly, these paradigms have played a vital role in determining the widely conventional understanding of risk, determinants of asset prices and portfolio management principles, see (Damodaran, 2007 and Myers, 1984). However, according to Yalçın (2010) there is now an increasing need to acknowledge that the gap between this idealization and reality may now be too large for theory to understand correctly the functioning of stock markets. The current paradigm deviates greatly from the salient features of observed phenomena, such as fat tails and non-linearity observed in financial markets, see (Mehra and Prescott, 1985; Weil, 1989 and Mandelbrot, 1963a, b).

Sargent (1996) argues that under the homogenous rational expectations theory all the market agents' expectations are identical and utilizes all the available information. Consequently, it is assumed that the conclusions that are being predicted do not differ from the market equilibrium results (Muth, 1961). In other words, it assumes that the errors that market players make are not systematic and variations from perfect forecast are merely random. According to Palmer (1994), the financial forecasting is usually done under the assumption that the expected variable is the same as the predicted.

According to Chen et al (2002), proponents of the EMH hypothesis argue that perfect homogenous rationality is the emergent feature of financial markets. For instance, they claim that the existence of arbitrage traders, evolutionary competition and noise traders generally offset each other ensuring that securities prices always reflect fundamentals correctly (Ramanauskas, 2008). Wang (2001) also argues that the impact of technical and noise traders is negligible as poor performance drives non-rational investors out of the market. However, stock prices generate positive returns in the end in the majority of cases (Jegadeesh and Titman, 1993). Hence, it is not apparent why non-rational investors should become extinct as they may well enjoy positive returns for their less than rational investment strategies.

For Ramanauskas (2008), the case of a negligible impact of technical and noise traders can also be further challenged. He argues that it is the technical and noise traders, rather than fundamentalist traders, who are more likely to react to non-fundamental news and drive market prices in the predictable direction, thereby imposing the rules of the game. Furthermore, it is well known that fundamentalist traders, instead of acting as market stabilizers, may actually endeavor to benefit from the consequential predictable market movements. Frankel and Froot (1987) showed that investors often recognize a considerable price deviation from their perceived fundamentals although they may find it logical to follow the trend until it reaches some turning point.

Amilon (2008) argues that the problem with assuming homogenous players is that it fails to explain stock market bubbles, fat tails and clustered volatility in markets. According to Yue et al (2000), the divergence between the EMH and the empirical evidence has encouraged researchers to shift their focus to behavioral finance. Most of them have adopted Kahneman and Tversky's (1979)'s prospect theory to explain the behaviour of stock market agents. Daniel et al. (1998) examines noise traders in market under-reaction and over-reaction. Other literature (Barber and Odean, 2001; Odeon, 1998) looks at the issue of over-confidence and gender, to explain market outcomes. While researchers like Bloomfield and O'Hara (1999) conducted human lab experiments to study their impact on stock markets.

To deal with highly demanding assumptions of the homogeneous rational man hypothesis, Simon (1957) proposed the bounded rationality theory. The theory relies on the notion that in decision-making, the rationality of market players is limited by the information they have, the intellectual limits of their minds, and the limited amount of time they have to make their choices (Foss, 2001). An alternative interpretation of the bounded rationality theory is that, because market players do not have the capacity and means to reach the best solution, they only apply their rationality after significant simplification of the options availed to them, (Simon, 1979). Sargent (1993) argues that the model with market players assumed to be bounded rationally may still converge to the rational expectation equilibrium. Hence, sometimes these two market models may be impossible to distinguish on a macro-level. The theory also has the same weakness as the rational man hypothesis as it fails to explain stock market bubbles and crushes.

5.3 JSE market simulation

The simulation approach is used to model multiple agent behaviour that resembles real-life JSE traders. According to Axelrod and Tesfatsion (2006), simulations permit increased understanding of systems through controlled computational experiments. The reason for using simulations instead of actual experiments is that the economy is never in a steady state and experiments are hard to carry out and are very expensive see (Toth, 2008). The expected simulated market should be able to reproduce several market dynamics, including predictability, volatility clustering, and fat tails. The simulations will be based on explicit assumptions, which are more realistic than those of most analytical models. The assumptions and parameters of the exogenous processes are calibrated to match historical data and to make the simulation analysis a valuable inductive inference tool for the real JSE market dynamics. The system will consist of the following three state variables: 1) the amount of cash in the system 2) the number of stocks in the system and 3) price of the stock. In addition, initial conditions and the parameters of traders are fixed and there is no restriction on short selling of the stock.

5.3.1 Design of the artificial stock market

The JSE operates an order-driven, central order book trading system with opening, intra-day and closing auctions. This implies that the simulation model will only consist of two entities: the agents and the market maker. The agents in the market will be either informed or uninformed traders. We define a strategy of a market participant as a set of rules, governing that participant's behaviour in the market. We give the mathematical definitions of the different strategies below:

a) Technical Analyst

Technical Analysts follow trends and accentuate the direction of historical prices, see (Nevmyvaka, 2005 and Osler 2012). Their investment decision is based on a simple extrapolative rule of their expected investment value:

$u_{t+1}^{s} = p_t + \delta(p_t - v)$	**Equation 5-1**

where v is the fundamental value of the asset, p_t is the asset price at time t. u_{t+1}^{s} is the price generated by decision rule of agent s and δ is the coefficient that measures the speed of adaptation. The technicians thus believe that the value of a stock can be extrapolated from past deviations from the fundamental value. Excess demand of the technical analyst is given by

$D_t^{\beta} = \delta(u_{t+1}^{s} - p_t) = b(p_t - v),$	**Equation 5-2**

with $b = \delta\sigma$. The technician buys/sells when the price is above/below the perceived fundamental value. In contrast to fundamentalists, technicians do not take into account the estimate of the probability of investment opportunities in the near future.

b) Fundamentalist

Fundamentalists apply a contrarian approach by selling when the market price goes above a certain value and buying when it goes below it. According to Hommes (2006), fundamentalists base their decision on a sophisticated estimate of the long run investment value L in relation to the current price and on an estimate of the probability for capital gains and losses. The investors' decision depends on a combination of economic fundamentals and an educated guess about the probability that an investment opportunity may disappear in the near future, see (Hommes, 2006 and Damodaran 2005). The excess demand, D_t^{f}, by a fundamentalist as a function of the market price p_t is given by

$D_t^{f} = i(L - p_t)f(p_t)$ if $p \epsilon [min, Max],$	**Equation 5-3**

$\beta(p) = 0$ if $p < min$ or $p > Max,$	**Equation 5-4**

where L is the long-run investment value expected by the fundamentalist, i measures the relative strength of their investment demand, and β(p) is a bimodal probability density with peaks near the extreme values min and Max. The fundamentalist investor believes that, when p_t is close to the topping price Max, the probability of losing capital gains and experiencing capital losses is high, and if p_t is close to the bottoming price m, the probability of missing a capital gain by failing to buy is high.

c) Noise traders

Noise agents form their price expectations randomly based on the uniform distribution. Yue et al (2000) argues that the boundary of the distribution sets up the randomness range in the expectation. Noise traders incorrectly believe that they have superior information about the future price of the stock (DeLong, 2005). The demand for the stock is derived from the expected utility maximization of constant absolute risk aversion utility of tomorrow's wealth as:

$\omega_t = \frac{r+E_t(p_{t+1})-(1+r)p_t+\rho_t}{2\gamma(\sigma^2_{p_{t+1}}+\sigma^2_\epsilon)}$	**Equation 5-5**

where γ is the coefficient of absolute risk aversion, $E_t(p_{t+1})$ is the expected price at time $t+1$ conditional on the information up to time t. The value $\sigma^2_{p_{t+1}}$ is the expected one period variance of p_{t+1} and ρ_t is the misperception of the expected price for tomorrow by the noise traders. The misperception of noise traders is an exogenously given independent and identically distributed normal random variable with mean ρ^* and variance σ^2_ρ.

5.3.2 Price Formation

According to aggregate excess demand of the market agents, the market maker determines the price changes. A technical analyst buys/sells a predetermined amount t^c of stocks when he is optimistic/pessimistic. For technical Analysts, excess demand is given by:

$ED^c = (n^+ - n^-)t^c$	**Equation 5-6**

where $x = \frac{n^+ - n^-}{n^c}$, the opinion index representing the average opinion among the traders and $x \in [-1, +1]$, when $x = 0$ it means there is a balance between the number of optimists and pessimists. The equation $x = +1$ / $x = -1$ corresponds to the extreme case where all technical analysts are optimists/pessimists. Fundamentalists buy/sell when the asset price is below/above its fundamental value and their excess demand is

$ED^f = n^f \gamma (p^f - p)$	**Equation 5-7**

where $\gamma > 0$ measures the reaction speed of fundamentalists to price deviations from the fundamental value. The value n^f is the number of fundamentalists. The noise traders in the market are captured by a noise term μ , normally distributed with standard deviation σ_μ. Their excess demand is

$ED^m = -r_0 n \mu$	**Equation 5-8**

where μ represents the actual average 'mood' of the noise traders, n is the number of noise traders, $r_0 = \frac{\varepsilon_2 - 1}{\varepsilon_1} * \frac{1}{E[|\vartheta|]}$ is a constant of proportionality, ε_i represents a Poissonian transition rate and $E[|\vartheta|]$ is the mean of the random variable, see (Alfarano et al, 2006). A stochastic process for the market maker is used for price adjustment. It is assumed that the market maker changes the price to the next increment (or price decline) with a certain probability dependent on the combined market's excess demand.

5.4 Model Calibration

The development of the model revealed a number of behaviours normally associated with the actual JSE market data, such as the presence of fat tails and self-replicating structure. Statistical comparison of observed data from the JSE data and the simulated results are given in Table 5-1. The statistics of the simulated daily returns compare very well to the observed data from the JSE All Share Index (ALSI), meaning that our model was effective in replicating the JSE stock market.

Table 5-1: Statistics of ALSI and simulated time series

	Mean	Variance	Skewness	Kurtosis	Jar-Bera
JSE All Share	-0.037	1.979	0.289	3.395	233
Model	-0.046	1.634	0.432	3.467	484

5.4.1 Evolution of Agents and Market

This section contains numerical experiment results aimed at giving some insights into the agent dynamics of the JSE stock market. The study analyses the behavioural dynamics from a bottom-up approach by creating individual market players that contribute to the aggregate market behaviours. The approach adopted in the study observes the strategies described in Section 5.3.1 and investigates different what-if scenarios and allows them to evolve over time through individual learning or evolutionary selection. The results show that traders switch between the three trading strategies as shown by the changes in proportions of the characteristics of traders in Table 5-2.

Table 5-2: Relationships between markets and agents

Market States	Agent behaviour	Correlation
Market Equilibrium	Fundamentalist	0.87(**)
	Technician	0.55(**)
	Noise trader	0.68(**)
Stock Market Bubble	Fundamentalist	0.43(**)
	Technician	0.83(**)
	Noise trader	0.54(**)
Market Crash	Fundamentalist	0.42(**)
	Technician	0.68(**)
	Noise trader	0.76(**)

(**)Significant correlations at 5%.

This evolutionary switching of traders also seems to depend on the state of the market. An analysis of the correlations of the market states and agent strategies demonstrates that, the fraction of technical analysts of 0.68 and 0.83 are statistically significant in times of market crashes and bubble formations. The results also indicate that when the market is in a state of equilibrium, both the fundamentalist and noise traders dominate the market with correlations of 0.87 and 0.68 respectively. The most probable reason why the demand of technical traders is generally lower is because fundamental trading prevents strong changes in the price. The presence of noise traders possibly explains the mean-reverting characteristics of a market that is in equilibrium. In a stock market bubble, the technical analysts tend to dominate the market with a ratio of 0.83. Fundamentalists have the lowest ratio of 0.43 in a market bubble meaning that they sometimes behave like technical analysts and start following market trends when prices are going up or exit the market completely. When the market is crashing, noise traders and technical analysts dominate the market as shown by the high correlation figures of 0.76 and 0.68 respectively.

5.5 Asset Pricing under Heterogeneous beliefs

In this section, asset pricing under the heterogeneous belief assumptions is explored to understand the dynamics and behaviour of the JSE. The effect of heterogeneity on asset prices has important implications for the equity puzzle discussed by Mehra and Prescott (1985). They calibrated a representative consumer asset pricing model to specific features of the U.S. economy and then calculated the implied equity premium, which is the excess rate of return on equities relative to riskless bonds, see Brown (2011). This model underestimated the equity premium by 600 basis points. This dramatic failure of the consumer model to generate an equity premium with an empirically plausible magnitude is presented as strong evidence against the representative consumer model of asset pricing.

Mehra and Prescott conducted their analysis under the assumption of homogenous beliefs across consumers. However, I will show below that the introduction of heterogeneity of beliefs can substantially increase the equity premium. In Sections 5.5.1 and 5.5.2 the formulas for different parameters and the CAPM-like relationship under heterogeneous beliefs (HCAPM) are presented to render a nuanced analysis of the impact of heterogeneous agents on price formation.

5.5.1 Price Aggregation

The equilibrium price formula is the same as the traditional equilibrium price for a representative agent holding the consensus belief. If $p_{i,0}$ is the equilibrium price and investor I is the only investor in the market, then:

$p_{i,0} = \frac{1}{R_f}[\mathbb{E}_i(\tilde{x}) - \theta_i \Omega_i \bar{z}_i]$	**Equation 5-9**

Hence the market equilibrium price is a weighted average of each agent's equilibrium price under the agent's unique belief represented by equation 5-10.

$p_0 = \Theta\Omega_a[\frac{1}{I}\sum_{i=1}^{I} \theta_i^{-1}\, \Omega_i^{-1} p_{i,0}]$	**Equation 5-10**

where Θ is the harmonic mean of the absolute risk aversion of all investors. I is the number of investors. Ω_a is the investors' aggregate covariance matrix. The equity risk premium (ERP) is given by:

$ERP = \Theta\Omega_a z_m / I$	**Equation 5-11**

where z_m is aggregate market portfolio and ERP is equity risk premium. It is observed from equation 5-11 that the equity risk premium becomes smaller as the number of investors increases.

5.5.2 The CAPM under Heterogeneous Beliefs (HCAPM)

This section discusses a Capital Asset Pricing Model (CAPM) with heterogeneous investor beliefs. The CAPM-like Relationship under heterogeneous beliefs (HCAPM) is given by

$\mathbb{E}_a(\breve{x}_k) - R_f p_0 = \frac{\sigma(\breve{W}_m, \breve{x}_k)}{\sigma_m^2}[\mathbb{E}_a(\breve{W}_m) - R_f W_{m,o}]$	**Equation 5-12**

where $\sigma(\breve{W}_m, \breve{x}_k)$=$\sum_{j=1}^{K} z_{m,j}\, \sigma_{kj}$ is the payoff covariance of the risky asset K and the market portfolio. The CAPM-like return relation under heterogeneous beliefs is given by equation 5-13 given below:

$\mathbb{E}_a[\tilde{r}]$-$r_f 1 = \beta[\mathbb{E}_a(r_m) - r_f]$,	**Equation 5-13**

where $\beta_k = \frac{W_{m,0}}{p_{k,0}} \frac{\sigma(\breve{W}_m, \breve{x}_k)}{\sigma_m^2} = \frac{cov_a(\tilde{r}_m, \tilde{r}_k)}{\sigma_a^2(\tilde{r}_m)}$ is the market beta coefficient. The above regression is the risk-return relationship that one would empirically obtain from the

Security Market Line (SML) in the heterogeneous market. The assumption that all individual investors hold the same tangency portfolio does not apply here. In the homogeneous-beliefs case, we employ Sharpe's approach, which is one dimensional in that it assumes that the mean rate of return vector and the variance-covariance matrix, are known, and investors agree on the values of these parameters, see (Sharpe, 1964).

Table 5-3: R-squares of the regression models

Simulation	Heterogeneous-belief agent model	Homogeneous agents
1	0.7	0.132
2	0.893	0.249
3	0.895	0.273
4	0.718	0.264
5	0.664	0.29
6	0.879	0.166
7	0.803	0.076
8	0.652	0.152
9	0.675	0.128
10	0.776	0.236
Average	0.766	0.197

Table 5-3 shows the R-square values of 10 simulations for the heterogeneous and homogenous–belief regression models. The results indicate that heterogeneous-belief agent model with a statistically significant R-square of 0.766, which is better than the homogeneous model (R-square of 0.192). This result is not entirely conclusive in justifying heterogeneous belief agent models which is why in Table 5-4 we compare price formation under heterogeneous and homogenous agents.

Table 5-4: The stocks' equilibrium prices from ten simulations runs

Simulation No	Market Generated Prices	Heterogeneous market	Homogeneous market
1	6.82	8.32	6.52
2	10.1	10.6	7.8
3	2.24	2.14	1.16
4	0.83	1.83	0.23
5	6.78	5.28	3.47
6	9.96	11.46	9.66
7	11.94	10.86	9.12
8	4.9	9.4	3.6
9	6.86	8.36	6.48
10	10.83	9.73	7.98
Average	7.125	7.798	5.602

Table 5-5: Paired test of the homogenous and heterogeneous prices

	Std. Deviation	**Std. Error Mean**	**95% C.I of the Difference**	
			Lower	Upper
Homogenous market	1.301794	0.411663	-2.898247	-1.035753
Heterogeneous market	0.095242	0.030118	-0.187868	0.324132

The study further tests for the difference between market-generated prices and expected prices for both the homogeneous and heterogeneous belief model. The results in Table 5-5 demonstrate a significant difference between the market generated and homogeneous prices. On the other hand, there is no significant difference between the market-generated prices and the heterogeneous market prices. These findings imply that heterogeneity matters for asset pricing and the effect is very significant. This means that traditional asset pricing models can be greatly improved by considering heterogeneity.

5.6 Implications of study

These findings address some of the fundamental questions surrounding the role of different investment strategies and homogenous rationality in the market. Given that people receive different signals, it is important to study heterogeneity in information and investor sentiments to ensure more accurate market predictions. For example, it is discernible that a large number of technical analysts trade during crises and bubbles compared to other traders. This means analysts can now use signals from technical analysts to predict when financial disasters are going to occur. The information found on the impact of heterogeneous beliefs on the equilibrium prices can assist in the development of future asset pricing theories.

5.7 Conclusion

This research encompasses areas in economics and finance, human behaviour, and agent modelling. The study lays down the framework of the JSE market structure using the Advanced Modeler software and Matlab. The goal was to learn about the potential market performance in the presence of aggregation of individual behaviours. Understanding the nature and dynamics of agent interactions of different markets is critical to an understanding of the causes of stock market bubbles and crashes.

The study replicated complex behaviour that is experienced in actual markets. Furthermore, commonly observed stylized facts of financial time series such as fat tails in return distributions and volatility clustering, were reproduced. The unique feature of the approach is the explicit modelling of the behaviours and the decision-making process of individual market participants such as market makers and investors, interactions between them, and the market rules and infrastructure.

The model was able to demonstrate that interactions in different proportions between fundamentalist, noise and technical traders are responsible for generating equilibrium, bubbles and crashes states in financial markets. Using correlations of the market states and agent strategies, the fraction of technical analyst were large during times of crises, crashes, and bubbles. This means analysts can now use signals from technical analysts to predict impending financial crises. Study findings suggest that when the market is in equilibrium, the proportion of fundamental is large compared to other traders.

Simulations also showed that heterogeneous models do a better job of predicting market prices when compared to their homogenous counterparts. The results also show that the homogenous-belief assumption tends to underestimate the expected stock prices and this can have serious implications for asset pricing.

5.8 Appendix

5.8.1 Setting the parameters

This section, presents the choice of the different parameters used in the Adaptive Modeler Software for simulating the JSE market. In all the simulations, the parameters mentioned here keep the same value unless it is otherwise mentioned. The parameters for the model, trading system, genomes and evolution of the system are given in this section.

Parameters used for simulation

Table 5-6: Model parameters

Model	
Population size	100,000
Fixed brokerage fee	
Agent trading minimum position unit	20%
Forecast based on virtual market price	Yes
Group size(% of population)	2.5%
Market operating times	09:30-16:00
Number of decimal places to rounding quotes	2
Minimum price increments for price generated by model	0.01

Table 5-7: Trading system parameters

Trading system	
Allow short positions	Yes
Significant forecast range	0-10%
Generate cash signal when forecast is out of range	
Threshold	50%
Start capital	100000
Broker commission, spread and spillage	
Fixed broker fee	10
Variable broker fee	0%
Average fixed bid/ask spread	0.04
Average slippage (+) or price movement (-)	0%

Table 5-8: Evolution of system parameters

Evolution	
Breeding cycle frequency (bars)	1
Minimum breeding age(bars)	80
Initial selection: random select (% of agents of min breeding age & older)	100
Parent selection: best performing (% of agents of initial will breed)	5
Off- spring will replace worst performing agents of the initial selection	
Mutation probability (% per offspring)	10

Table 5-9: Genomes parameters

Genomes	
Maximum genome size	1000
Maximum genome depth	unlimited
Minimum initial genome depth	2
Maximum initial genome size	5
Create unique genome	Yes

CHAPTER 6

REFLEXIVITY ON THE JOHANNESBURG STOCK EXCHANGE

"How do we know when irrational exuberance has unduly escalated asset values? We should not underestimate or become complacent about the complexity of the interactions of asset markets and the economy."

Alan Greenspan, *(Former) Chairman of the U.S Federal Reserve*, 1996.

6.1 Introduction

This chapter seeks to find out the extent to which reflexivity (endogeneity) affect price formation on the Johannesburg Stock Exchange (JSE). According to Soros (1988), reflexivity refers to the self-reinforcing effect of market sentiments, whereby rising prices attract buyers whose actions drive prices higher until the process becomes unsustainable. The same process can operate in reverse order leading to a catastrophic collapse in prices. Literature has shown that in the last decade major market movements far exceeded the typical market reaction to macroeconomic news releases, meaning that extra movements could be attributed to the self-reinforcing effect of market sentiment, see (LeRoy 2008; Shiller 1981; Leroy and Porter 1981).

To address this issue, this study considers stock markets as paradigms of intricate human societies, in which external news impose exogenous influences on stock prices affecting investors whose interactions via complex social and economic systems lead to stock markets price formation. For this, the self-excited Poisson Hawkes model is used, which, according to Filimonov and Sornette (2011), combines exogenous influences with self-excited dynamics in natural and parsimonious ways using JSE All Share Index (ALSI) futures contracts traded on SAFEX from 2000 to 2010. This model measures the proportion of price movements that are due to endogenous influences, after removing the impact of exogenous factors, see (Lillo et al, 2012). The study also discusses how reflexivity accounts for market bubbles and crashes.

The results show that over the past decade, the JSE has been strongly driven by internal or endogenous dynamics. The research finds that the level of endogeneity has increased significantly from mid-2003 to mid-2009. In contrast, the impact of exogenous factors generally remains more constant with major increases occurring just before market crashes. These results imply that market crashes are essentially caused by endogenous factors and exogenous shocks merely act as catalysts.

The rest of the chapter is organized as follows. Section 2 reviews the literature on the history of the reflexivity concept. Section 3 gives a description of the data and data manipulation. Section 4 presents the methodology, and Section 5 describes the results, followed by the conclusions of the study in Section 6.

6.2 Literature Review

Economists have been aware of certain cyclical characteristics of economic evolution since the works of Smith (1776), Ricardo (1810) and many other. Two main theories have attempted, over the years, to explain the causes and characteristics of business cycles. The leading one today is known as real business cycle (RBC) theory and assumes that economic fluctuations arise from exogenous shocks and that the economic system is otherwise stable, see (Kydland and Prescott, 1988). The second one is the endogenous business cycle (ECB) theory, which proposes that economic fluctuations are due to intrinsic processes that endogenously destabilize the economic system, see (Samuelson, 1939; Chiarella et al, 2009) Both theories have their successes and shortcomings , but the RBC theory is the one that garners consensus in the current economic literature.

The efficient hypothesis (EMH) claims that market prices fully reflect all extant information. According to Samuelson (1965), large price movements should only occur because of significant economic or financial news. The closely related rational expectations theory made famous by Muth (1961) and Lucas (1972) holds that, in the absence of exogenous shocks, financial markets tends towards an equilibrium that accurately reflects the participants' expectations. Figure 6-1 illustrates the EMH relationship between exogenous news, participants and the price.

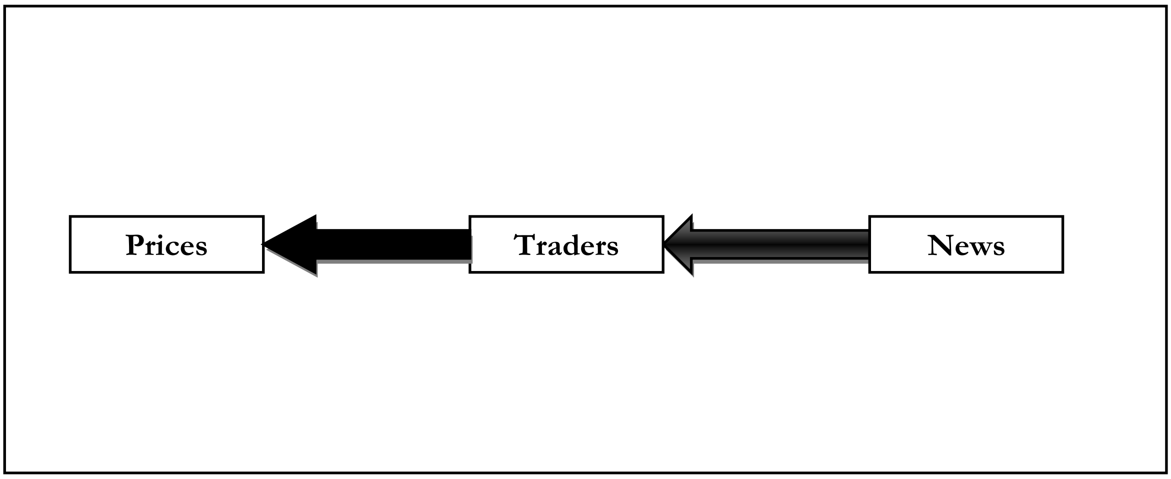
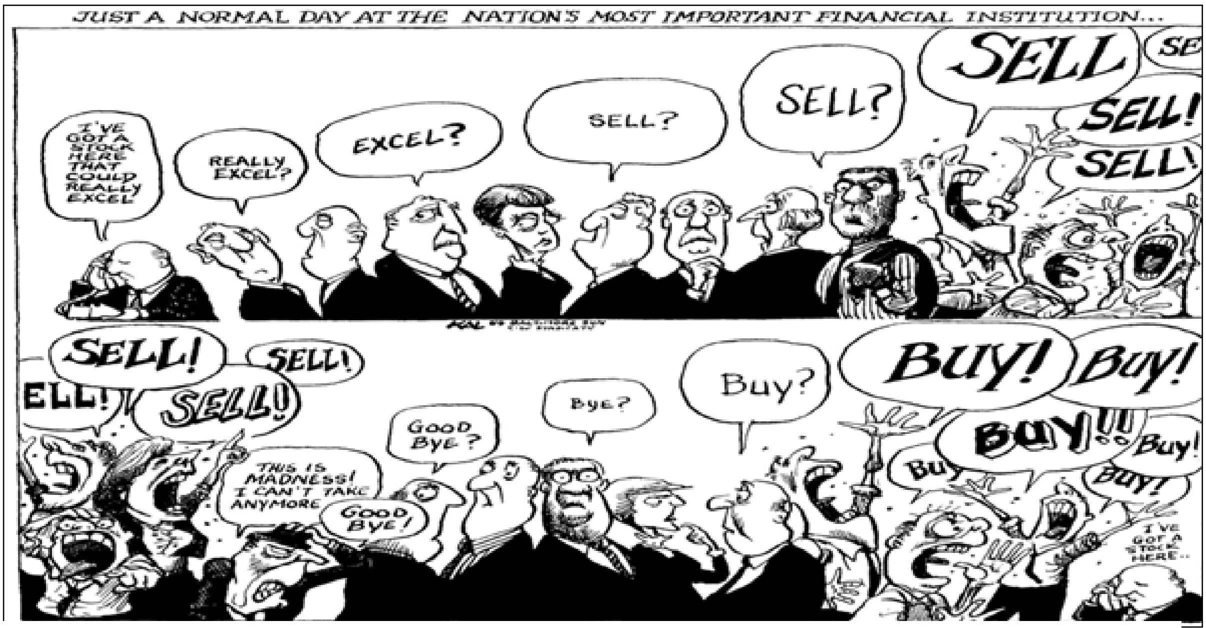


Figure 6-1: Relationship between exogenous factors and price formation.

On the other hand, Leroy and Porter (1981), Shiller (1981) and LeRoy (2008) have shown that major market movements far exceeded the characteristic market reaction to macro-economic news releases. Chapter 3 showed that most of price movements on the JSE could not be explained by macroeconomic news alone.

Page and Way (1992) tested the overreaction hypothesis on the Johannesburg Stock Exchange (JSE). The empirical results showed evidence of investor overreaction, indicating that the JSE is less than weak form efficient. Another study on the JSE conducted by Muller (1999) showed evidence of investor overreaction to economic news. Hsieh and Hornet's (2011) study on the JSE found that because of investor overreaction, mean reversals are strongest immediately after market crashes. These studies however do not give the extent to which economic news impact the JSE price movements and how the overraction has evolved over time. This study endevors to address these issues.

Bian et al's (2012) and Ivković (2007) studies found that the evolution of investors' behaviour is affected by the network structure of the stock market and the neighbour preference effect (investors prefer doing what everyone else is doing). Menkhoff and Nikiforow (2009) argues that many of the behavioural finance patterns exhibited by market participants are so deeply rooted in human behaviour that they are difficult to overcome by learning, despite the market participants' awareness of their existence. As illustrated in Figure 6-2 and 6-3, large stock market trends often start and end with periods of frantic buying (bubbles) or selling (crashes), (Liang, 2011). Many observers refer to these periods as apparent examples of herding behaviour that is irrational and driven by emotion and greed, in the case of bubbles, and fear in the case of crashes.



Source: The Economist: November 1997

Figure 6-2: Herding behaviour on the stock market

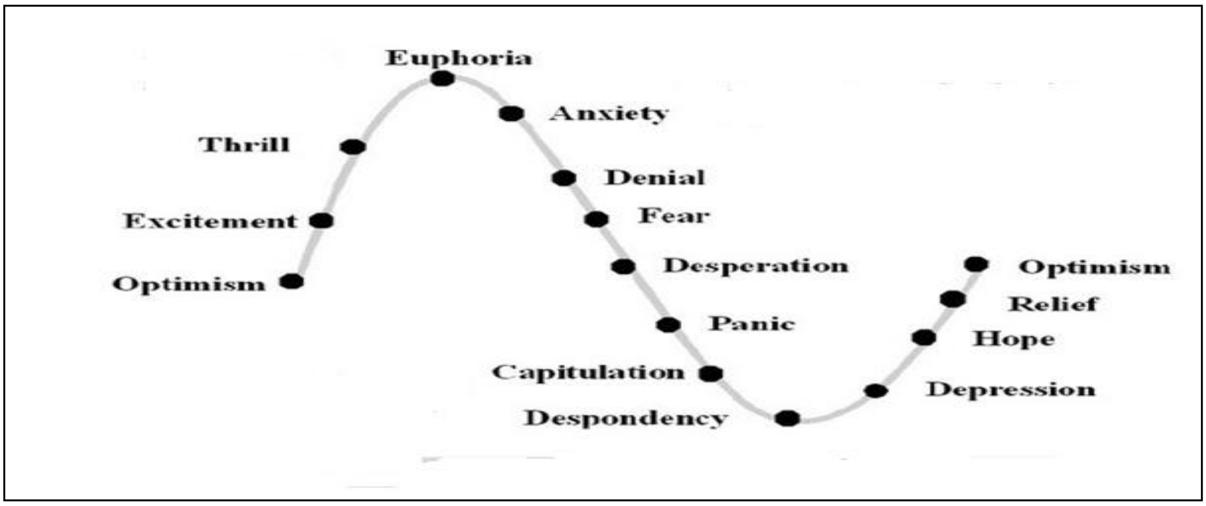


Figure 6-3: Market emotions cycle with price movements

Soros (1988) introduces an alternative theory to EMH on price formation called the reflexivity theory. He argues that investors are actors as well as observers of the economic systems that they are trying to predict and are always going to be biased in one direction or another. Umpleby (2010) postulates that earlier versions of the reflexivity theory date back as far as 1776 when Adam Smith used the idea to explain the process of innovation and competition among firms or nations. Darwin (1859) used the idea to describe natural selection. Karl Popper (1950)'s application of the term reflexivity in philosophy describes conjectures and refutations.

The implication of the reflexivity theory is that there is no unique way in which agents form expectations of the price and there is a two-way connection between the participants' view of the world and the situation in which they participate (Soros, 2008). Soros (1990; 2008) argues that agents' views are translated into events and these events in turn influence agents' views. The first relationship is the participating function and the second, the cognitive function. Perception and reality are linked by a two-way feedback loop illustrated in Figure 6-4. This link-up gives rise to a perpetual historical process in which neither the circumstances nor the market players' interpretations remain unaffected. Epistemology, a sub-discipline of philosophy, is dedicated to an examination of this subject, see (Popper, 1957).

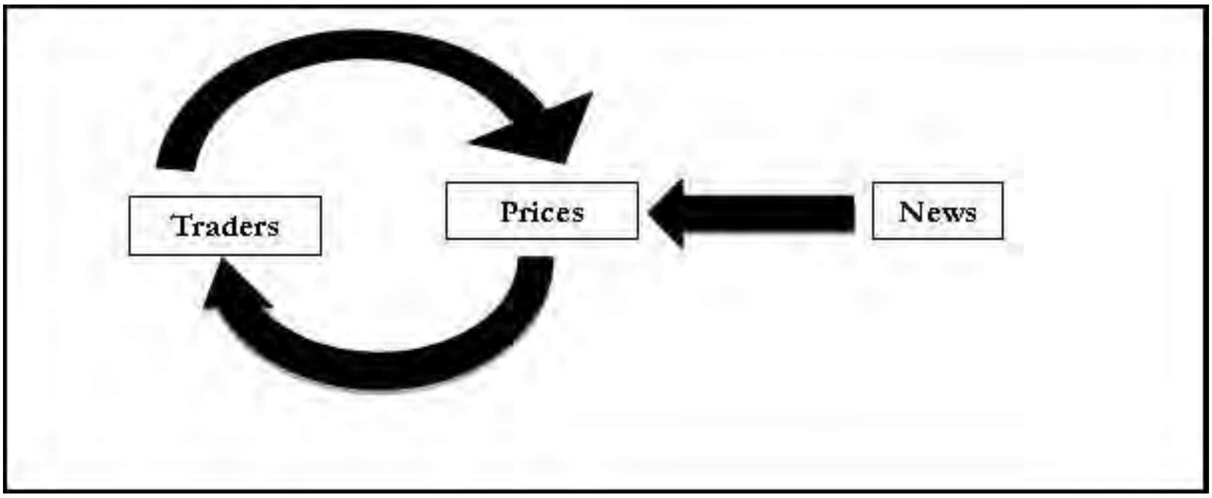


Figure 6-4: Relationship between endogenous factors and price formation

Soros (2008) elaborates that the typical sequence, the prevailing bias and the prevailing trend of prices start out as mutually self-reinforcing, but eventually, the relationship must become self-defeating because the divergence between perceptions and events cannot become forever wider. The major criticism levelled against Soro's reflexivity theory from the economics community has been its inability to quantify self-reflexivity, see (Shaikh (2010) and Bryant (2002)).

Zhong and Zhao (2012) suggest that the price formation mechanism is dependent on the relationship illustrated in Figure 6-5. They elaborate that the most important and interesting reflexive interaction takes place between the financial authorities and markets participants. They believe that because markets are not inclined towards equilibrium, they are susceptible to episodic crises and these crises lead to government regulatory reforms. Moreover, because government regulatory authorities and market agents equally act based on imperfect information, this makes the interaction between them reflexive.

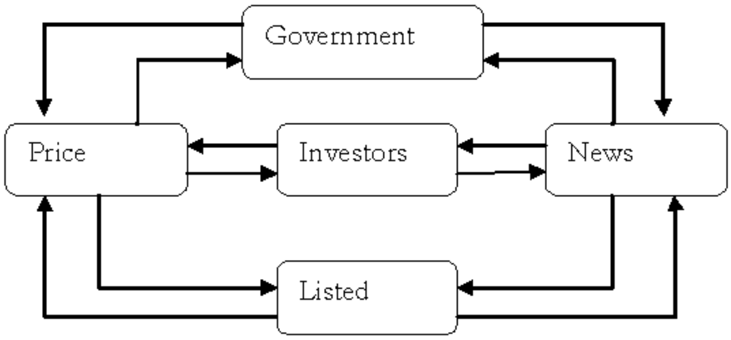


Figure 6-5: Price formation mechanisms with a government regulator

Filimonov and Sornette (2011) made the first notable attempt at quantifying reflexivity in financial markets. The study used a stochastic model to measure how much of the dynamics of a time series can be attributed to endogenous or internal causes. The study found evidence of reflexivity on the E-mini Standard & Poor 500 futures contracts. They also found that the level of endogeneity increased with time over the period of study. The study also came up with a prediction tool for flash crashes.

6.3 Data

The present study utilises the daily JSE All Share index futures with March, June, September and December expiry dates. These JSE futures used roll over on the second Thursday of the expiry date (JSE, 2010). The arithmetic average of the index taken every 60 seconds (100 iteration), between 12h01 and 13h40, is used. The data used in this study takes into consideration changes in supply and demand i.e. bid/ask prices and volumes. On the rollover date, the volume (which measures the liquidity) of the contract that is approaching expiry is switched to the proceeding contract at market opening. This study considers the JSE All Share index futures mid-prices (average of spread) as the best proxy for overall market movement.

6.4 Methodology

This models used in this chapter will help us understand the price formation process on the JSE. According to Masulis et al (2000) price formation is a function of exogenous and endogenous factors. The models below are going to measure how these two factor interact in price formation process on the JSE. Understanding the price formation will help asset manager better forecast price movement.

The self-excited conditional Poisson Hawkes model was adopted for measuring the level of reflexivity or endogeneity on the JSE. Filimonov and Sornette (2012) postulate that this technique is a natural and parsimonious way of observing the exogenous influences with self-excited dynamics. A general definition for a linear self-exciting process is given by:

$\lambda(t) = \mu + \int_{-\infty}^{t} \gamma(t-s)dN_s$	**Equation 6-1**

$= \mu + \sum_{t_i<t} \gamma(t-t_i)$	**Equation 6-2**

where $\mu = \lambda_0: \mathbb{R} \to \mathbb{R}_+$ is a deterministic base intensity and $\gamma: \mathbb{R} \to \mathbb{R}_+$ expresses the positive influence of past events t_i on the current value of the intensity process, which accounts for exogenous events. The value $\gamma(t)$ is a memory kernel function that weighs how much past events influence the generation of future events and thus controls the amplitude of the endogenous feedback mechanism. Hawkes (1971) proposes an exponential kernel $v(t) = \sum_{j=1}^{p} \alpha_j e^{-\beta_j t}$ so that the intensity of the model becomes:

$\lambda(t) = \mu + \int_0^t \sum_{j=1}^{p} \alpha_j e^{-\beta_j (t-s)} \, dN_s$	**Equation 6-3**

$\lambda(t) = \mu + \sum_{t_j<t} \sum_{j=1}^{p} \alpha_j e^{-\beta_j (t-t_i)}$	**Equation 6-4**

The Hawkes process presents two appealing properties. First, the exogenous influences on the system μ and the internal feedback mechanisms given by $v(t) = \sum_{j=1}^{p} \alpha_j e^{-\beta_j t}$ can be separated in their contributions to the conditional intensity $\lambda(t)$. Second, Daley and Vere-Jones (2008) showed that the linear structure of $\lambda(t)$ allows for its precise mapping onto a branching process which enables the direct measurement of the level of endogeneity.

6.4.1 The branching ratio

The branching ratio provides a robust measure of endogeneity, compared to the usual direct measures of market activity such as volume and trading rates. The branching process allows for the classification of different types of volatility shocks and to distinguish the exogenous (triggered by news) from the endogenous (self-excited) dynamics. Assuming constant background intensity μ, the rates of endogenous events are given by:

$R_{endo} = \mu.(n + n^2 + n^3 + \ldots\ldots) = \mu \sum_{i=1}^{\infty} n^i = \frac{\mu n}{1-n}$	**Equation 6-5**

Thus aggregate rate of all events is

$R = R_{endo} + R_{exo} = \mu + \dfrac{\mu n}{1-n} = \dfrac{\mu}{1-n}$	**Equation 6-6**

This means that $n = R_{endo/R}$ is the fraction of the average number of endogenously generated events among all events.

6.4.2 Estimation of the branching ratio

For the Hawkes process used in this study the branching ratio is given by expression

$n = \int_0^\infty \varphi(t)dt$	**Equation 6-7**

In particular, for the exponential kernel: $n = \alpha/\beta$

The Maximum Likelihood estimator

$\log L(\theta \mid t_1, \dots\dots, t_n) = -\int_0^T \lambda_t\,(t)dt + \int_0^T log\lambda_t(t)dN(t)$	**Equation 6-8**

In particular for the exponential kernel:

$logL = -\mu T + \sum_{t_i<T} \log(\mu + n\alpha \sum_{t_j<t_i} e^{-\beta(t_i - t_j)})$	**Equation 6-9**

6.5 Impact of liquidity on price movement

To rule out the impact of liquidity on price movement the section checks whether extreme movements could be due to failures in the liquidity provision. This is done by comparing price movements with volume movements. The price movement is calculated by taking the absolute values($|P_{t+1} - P_t|$) of the ALSI future index prices and dividing by P_t ;

$Price\ Movement = \dfrac{|P_t - P_{t-1}|}{P_{t-1}}$	**Equation 6-10**

where P_t and P_{t-1} are the ALSI levels at time t and $t-1$ respectively. As can be observed from Figure 6-6, some large price movements are associated with increase in trading activity, which implies that dynamical feedback between large market orders and price movement is important for the stability of markets.

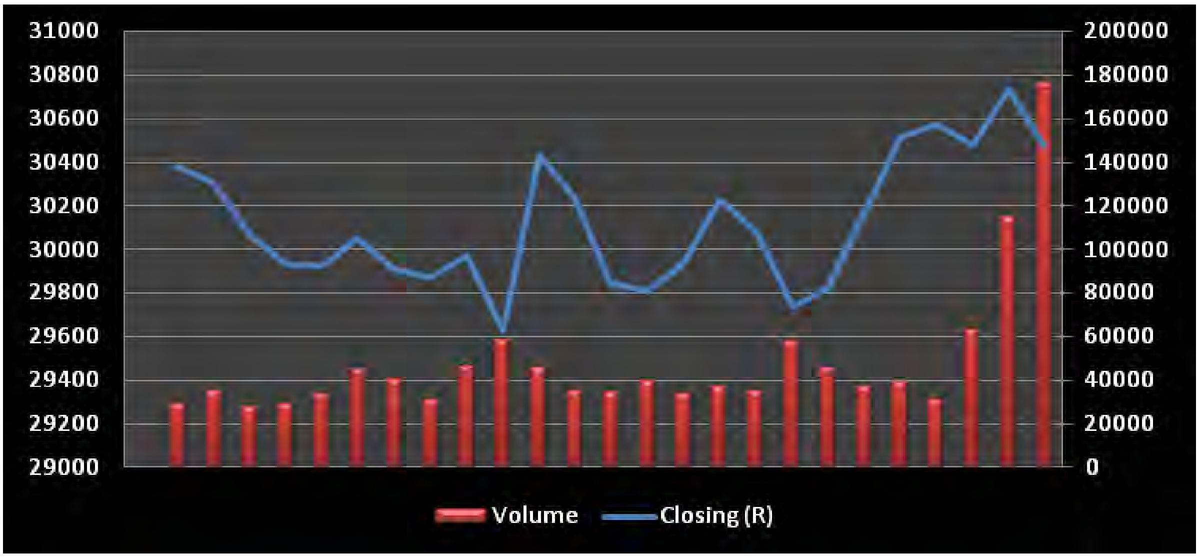


Figure 6-6: ALSI Future volume and closing price

It can also be inferred that the impact of volume is not linear or permanent as shown by the periods with high volumes but small market movements. The correlation results in Table 6-1 demonstrate a weak relationship between the liquidity and price movement.

Table 6-1: Correlation of |price movement| vs. volume

		Price Movement	Trading Volume
Price movement	Person Correlation	1.000	0.343
	Sig.(2- tailed)	.	0.064
	N	1971	1971

** Correlation is significant at 0.05 level (2-tailed)

According to the results in Table 6-1, the significance is above 0.05 (0.064) indicating that there is no evidence of interaction between price movement and volume at 5% significance level. These results are contrary to Kyle (1985)'s assertion that the relationship between volume and large price movement is linear and permanent.

6.6 Branching ratio n and level of endogeneity on the JSE market

The branching ratio (n) is defined as the fraction of market dynamics caused by internal dynamics. Figure 6-7 shows the fraction of events caused by internal and external dynamics.

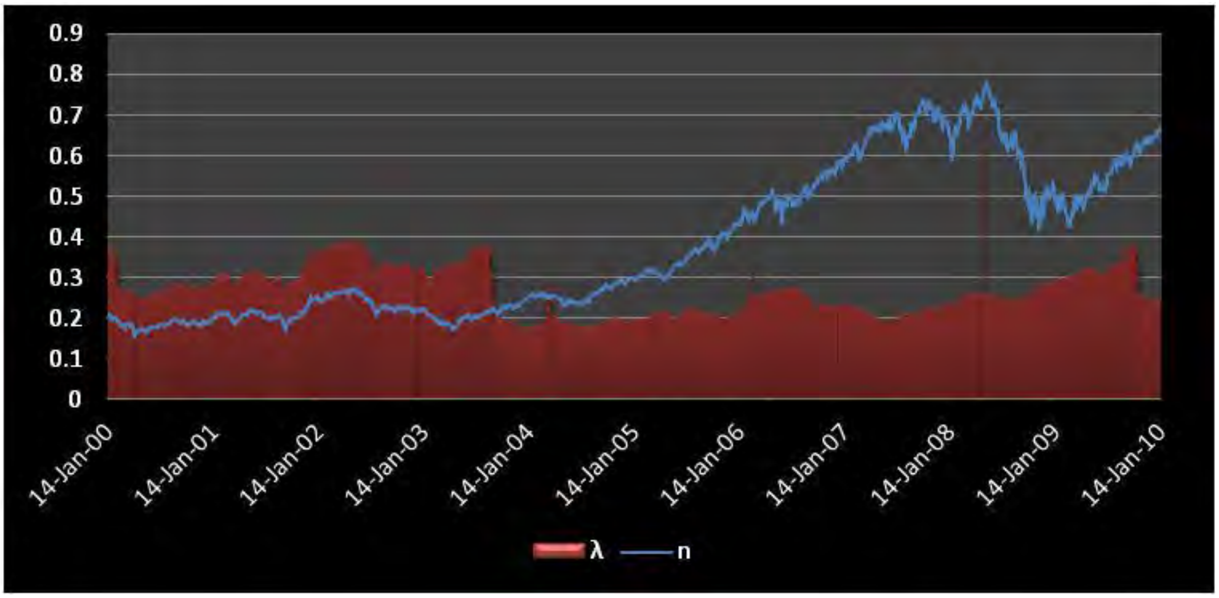


Figure 6-7: Endogenous vs. Exogenous contribution

The most interesting feature is the consistent rise in n (branching ratio) from mid-2003 to mid-2009. This result implies that there is an increasing influence of internal dynamics or events which causes further events through internal market mechanisms. In contrast, the exogenously driven dynamics generally remain more constant with major increases occurring just before market crashes. This means that exogenous shocks merely act as catalysts for the market fall. The branching ratio results can be divided into three period regimes shown in Table 6-2.

Table 6-1: Market regimes and explanations for their existence

Regime	Period	Explanation
Q1	2000-2004	Stationary branching ratio (n) fluctuation around 0.2, with minor disturbances caused by the September 11 (n= 0.37). Impact of exogenous shocks also constant and averaging 0.3.
Q2	2004-2007	This regime corresponds to the succession of market rallies and panics that characterized the aftermath of the burst of the dot-com bubble and an economic recession, n increases from around 0.2 to 0.7. Levels of exogenous shocks drops significantly, to an average of 0.2
Q3	2007-2012	The branching ratio stabilized between 0.7 and 0.8 corresponding to the start of the problems of the U.S subprime financial crisis. The large n is evidence of aftershocks of the biggest Global financial crisis since the great depression. The exogenous shocks also increase to between 0.28-0.4.

6.7 Implication of Study

Contrary to the existing paradigms which suggest that price formation are a function of exogenous factors (Masulis et al, 2000 and Hausman et al., 1992), the study has shown that endogeneity plays an important role in price formation especially in a market bubble or just before a market crash. The fact that endogeneity can now be measured in financial markets means that researchers can now extrapolate the branching ratios to model market bubbles and with some measure of accuracy predict market crashes.

6.8 Conclusion

The main purpose of this chapter was to find the extent to which reflexivity (endogeneity) affects price formation on the JSE. To address this issue, stock markets were characterized as paradigms of intricate human societies in which external news impose exogenous influences on investors whose interactions via complex social and economic systems lead to price formation. To demonstrate, the self-excited Poisson Hawkes model was adopted to model price movements on the All Share Index (ALSI) futures contracts traded on **SAFEX** from 2000 to 2010. The most interesting feature is the consistent increase in endogeneity from mid-2003 to mid-2009. The trend only levels off after 2009. This result implies that there is an increasing influence of internal dynamics on the price formation on the JSE. In contrast, the background of exogenous shocks information-driven dynamics generally remain more constant with major increases occurring just before market crashes. This result indicates that market crashes are caused by endogenous dynamics and exogenous shocks merely act as catalysts.

6.9 Appendix

6.9.1 Derivation of the Hawkes process equation

Here we model the intensity λ_t of the counting process by the particular form of Hawkes process that satisfies the following Stochastic Differential Equation (SDE);

$$d\lambda_t = \kappa(\rho(t) - \lambda_t dt + hdN_t$$

The solution for λ_t takes the form

$$\lambda_t = c(t) + \int_0^t he^{-k(t-s)}\, dN_s$$

where

$$\mathrm{c(t) = c(0) + k\int_0^t e^{-k(t-s)} \varrho(s)ds}$$

verify by Ito formula on $e^{kt}\lambda_t$

$$e^{kt}\lambda_t = c(0) + k\int_0^t e^{ks}\,\rho(s)ds + \int_0^t he^{ks}\,dN_s$$

$$ke^{kt}\lambda_t dt + e^{kt}d\lambda_t = ke^{kt}\rho(t) + he^{kt}dN_t$$

$$k\lambda_t dt + d\lambda_t = k\rho(t) + hdN_t$$

$$d\lambda_t = k(\rho(t) - \lambda_t dt) + hdN_t$$

Consider the limit $lim_{t\to\infty}c(t)$

$$\lim_{t\to\infty} \mathrm{c(t)} = \lim_{t\to\infty}\left\{c(0)e^{-kt} + \chi\int_0^t e^{-i\omega t}\rho(s)ds\right\}$$

$$= \lim_{t\to\infty} k\int_0^t e^{-i(t-s)}\rho(s)ds$$

$$= \lim_{t\to\infty} ke^{-kt}\int_0^t e^{ks}\rho(s)ds$$

$$= \lim_{t\to\infty} k\frac{e^{kt}\rho(s)}{ke^{kt}}$$

$$= \lambda_\infty$$

Treating $\rho(t)$ as a constant $\rho(t)$= λ_∞

$$c(t) = c(0)e^{-kt} + k\int_0^t e^{-k(t-s)}\,\rho(s)ds$$

$$= c(0)e^{-kt} + k\lambda_\infty e^{-kt}\int_0^t e^{(ks)}\,ds$$

$$= c(0)e^{-kt} + \lambda_\infty e^{-kt}\lambda_\infty(e^{kt} - 1)$$

$$= \lambda_\infty + e^{-kt}(c(0) - \lambda_\infty)$$

Notice that if we set $c(0) = \lambda_\infty$ then the process is simply

$$\lambda_t = \lambda_\infty + h\int_0^t e^{-k(t-s)}\,dN_s$$

Where we can think of λ_∞ as the long run "base" intensity, i.e. the intensity if there have been no past arrival.

CHAPTER 7

HYBRID ADAPTIVE INTELLIGENT MODELS AS AN ALTERNATIVE TO THE STANDARD PARADIGM

Prediction is very difficult, especially if it is about the future.

Niels Bohr, *Danish Physicist*, 1890.

7.1 Introduction

It is widely accepted that predicting stock returns is not a simple task since there are many market dynamics involved and their structural relationships are non-linear and difficult to control, see (Nygren, 2004; Langley et al, 2004 and Chen, 2005).). Several researches conducted on these highly nonlinear systems have shown that they are difficult to control, particularly when they have complex dynamics, see (Abarbanel et al, 1990; Morel and Leonessa, 2009). This apparent complexity of the problem paves the way for the importance of intelligent forecasting models (Abraham et al., 2001).

The objective of this chapter is to examine whether all the main findings given in the previous chapters on the dynamics of the Johannesburg Stock Exchange (JSE) market movement can lead to improvements in stock return forecasting. Given evidence of non-linearity, fat tails, heterogeneous agents, reflexivity and the fractal nature of the JSE financial market, neural networks, fuzzy logic, and fractal theory are combined to obtain a hybrid adaptive intelligent model (HAIM technique). This method combines the neural network's ability to classify and control with fuzzy logic's ability to make judgment and fractals' ability to characterize the processes in modelling to create a robust adaptive model for the JSE.

The HAIM technique proposed in this chapter is compared with a standard neural network and an Auto-regressive integrated moving average (ARIMA) model. The results show that the HAIM technique provides significantly better forecasting when compared to the neural and the ARIMA approaches. A comparative study into the prediction performances of the three models over different horizons showed that the HAIM technique outperformed all the other models under study. Out of sample forecast was also performed and the HAIM outperformed the other three models for the three period used for the experiment.

The chapter is organized as follows. The next section reviews the available literature on the intelligent prediction. The third section focuses on the methodology used while the fourth section discusses the forecasting results. The fifth section concludes the study.

7.2 Literature Review

Adaptive hybrid intelligent systems are computational systems that integrate different techniques to develop the next generation of intelligent systems (Abraham, 2005). These systems are being used for modelling complex problems and decision making in different fields like robotics, security and agriculture, see (Zhang and Zhang, 2002; Hachour, 2009). According to Zhang and Zhang (2002), hybrid intelligent systems allow the representation and manipulation of different types and forms of data and knowledge, which may come from various sources.

Intelligent prediction techniques, such as neural networks, fuzzy logic, and genetic algorithms, are being widely applied to the problem of forecasting complex time series, see (Zadeh, 1994; Jang et al, 1997). A survey conducted by Maddala (1996) on adaptive intelligence showed that these methods have an advantage over traditional statistical methods. The most important advantage being that, there is no need to identify the structure of a model a-priori, which is obviously needed for the traditional statistical models, see (Castillo et al 1996; Melin et al, 2007). However, intelligent prediction techniques have been criticised for their black-box nature and the large number of data for training the system, see (Qi, 1999; Dunis et al, 2002).

According to McNelis (2005), stock markets of emerging economies represent a fertile ground for the application of intelligent prediction modelling techniques for two reasons. Firstly, emerging market data are often very noisy due to the thinness of the markets such that there are obvious asymmetries and non-linearities that cannot be ignored (McNelis, 2005), see also section 3.5 in Chapter 3. Secondly, in many instances, the participants in these markets are learning through trial and error about policy news, legal and other changes taking place in the structuring of their markets, (McNelis, 2005).

Much of the difficulty in forecasting stock markets and other complex time series come from the complexity of the variables that cannot be controlled (Blanche et al, 2004). According to Marlin and Castillo (2003), complications are often presented by restrictions, either on the control factors or in the operational regime of the modeling system. In the stock market prediction problem, the complexity often lies in the heterogeneous nature of the market and the dynamic change in the economy that present many different sources of uncertainty, (Zhang and Zhang, 2002).

Melin and Castillo (2003) developed the original version of intelligent prediction techniques, the analytical tool adopted in the current study to capture the dynamics of aircraft movements. The original goal was to capture the dynamics of aircrafts to control them to avoid dangerous behavior of the aircraft dynamic system (Melin and Castillo (2003)). The study succeeded in showing that the technique could be used to control chaotic, non-linear and unstable behaviour in aircraft systems. According to Sornette (2004) the similarities of dynamics (nonlinearities and instabilities) found in aircraft systems just like in stock markets allow for the extension of the technique to stock market forecasting.

7.3 Hybrid adaptive intelligent model

The study combines neural networks, fuzzy logic and fractal theory to obtain a new hybrid adaptive intelligent model (HAIM technique) for modelling stock market returns. This method adopts the strengths of the three modelling techniques to achieve a robust adaptive control model for the JSE stock market dynamics. The overall structure of the adaptive system proposed in this chapter is shown in Figure 7-1.

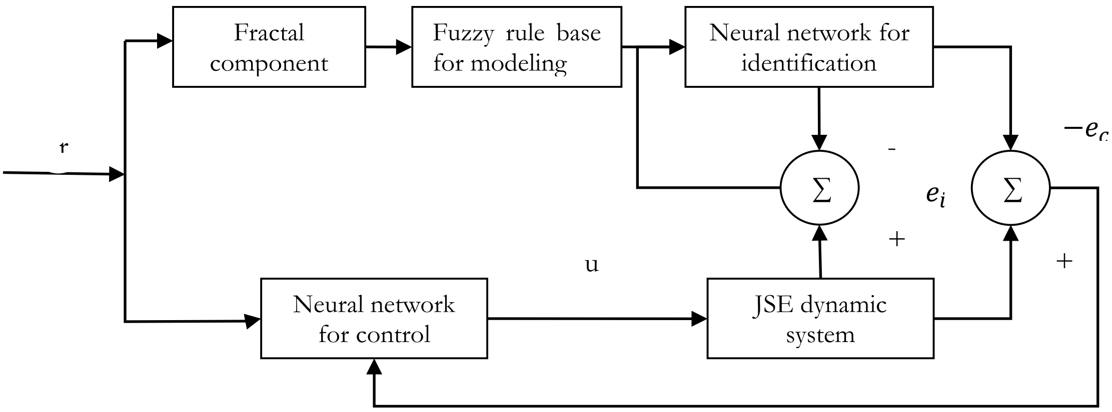


Figure 7-1: General architecture for an HAIM technique

The delayed prices of the market form the inputs to the neural network N_c which generates the feedback for the system referred to in Chapter 6. The study makes adjustments to parameters of Neural Network N_i by back propagating the identification error e_i while those of Neural Network N_c are adjusted by back propagating the control error e_c through the identification model (Melin and Castillo, 2003). The mathematical model for the nonlinear dynamic system is generated by the fuzzy system of rules. On the other hand, fractal dimensions are used to characterize the process and this information is used to specify the mathematical model allowing it to pick up the changes in economic variables.

The conceptual model underlying the computational model will be derived from a representation of financial markets as complex dynamics systems, whose stochastic behaviour is influenced by exogenous shocks and endogenous uncertainty, the latter caused by interaction among market participants (degree of consensus and tendency to crowd behaviour). Inspiration for this approach came from Vaga (1990). The system will be fed with information from different sources, namely

- macroeconomic and macro-financial indicators

- risk appetite of investors in securities, measured on the basis of correlation between returns in risky and safe markets
- returns and historical volatility in financial markets
- signal of trend, reversal and change of regime from technical analysis of financial prices (moving averages, resistance and support levels, relative strength indicators etc.) these signals will serve as proxy variables for endogenous uncertainty
- implied volatility in option markets and expected distributions extracted from them
- recent episodes of instability in other markets that can exert a contagion effect

The system is to produce a rich informative output consisting of descriptive reports and warning signals. Secondly, the system will provide signals and indicators reflecting the likelihood of a market crash. An extensive set of symptoms of financial fragility will be monitored and new events will be checked against typical patterns of evolution of financial crises.

7.3.1 Fuzzy modeling of dynamical systems

For a complex stock market dynamic system, it is necessary to consider a set of statistical models to represent adequately all of the possible dynamic behaviours of the system. To do this a fuzzy decision procedure for the selection of a suitable model to adopt according to the value of a selection factor vector α is used. To execute this decision procedure, the study makes use of the fuzzy logic rules shown below which use non-linear differential equation.

IF α_1 is A_{11} AND α_2 is A_{12}...AND α_m is A_{1m} THEN dy/dt = f_1(y,α)

IF α_1 is A_{21} AND α_2 is A_{22}...AND α_m is A_{2m} THEN dy/dt = f_2(y,α)

.. ..

IF α_1 is A_{n1} AND α_2 is A_{n2}...AND α_m is A_{nm} THEN dy/dt = f_n(y,α)

where A_{ij} is the linguistic value which may be defined as variables whose values are expressed as words. Large price movements, for example, which are a common concern in equity investments, may be viewed both as numerical values ranging over the interval [0,100%], and linguistic variables that can take on values like high, not very high, and so on. The value $\alpha \in R_m$ is defined by $\alpha = [\alpha_1 ... \alpha_m]$, and $y \in R_p$ is the output obtained by the numerical solution of the corresponding differential equation.

A statistical model for the description of the nonlinear dynamic system is necessary. For this particular case, this may require testing several models before obtaining the appropriate model for the process. Several models for different set of parameter values for representing all the possible behaviours of the system might be necessary. A general model for the dynamic system can be expressed as follows:

$$\frac{dx}{dt} = f_1(x, D, \alpha) - \beta f_2(x, D, \alpha)$$	**Equation 7-1**

$$\frac{dp}{dt} = \beta f_2(x, D, \alpha)$$	**Equation 7-2**

where $x \in R^n$ a vector of state variables is, $p \in R^m$ is a vector of outputs, $\beta \in R$ is a constant measuring the efficiency of the conversion process, $D \in (0,1)$ is the fractal Hurst of the process while $\alpha \in R$ is a selection parameter.

7.3.2 Neural networks for control

Neural networks were adopted in this study for parametric adaptive control. This process involves controlling the output of a system with a known structure but unknown parameters. Assuming p is known, the parameter vector θ of a controller can be chosen as θ^* so that the system and the fixed controller act like a reference model described by a differential equation with constant coefficients, see (Marlin and Castillo 2003; Narendra and Annaswamy, 1989). If p is unknown, the vector $\theta(t)$ has to be adjusted using all the existing information pertaining to the system. There are two approaches to the adaptive control of an unknown system given by:

(i) direct control and

(ii) Indirect control.

The direct control approach adjusts the parameters of the controller to reduce some of the output error. On the contrary, the indirect control estimates the parameters of the system at any point in time and the parameter vector of the controller is selected under the assumption that $p(t)$ represents the correct value of the parameter vector. This study employs the indirect approach to control a nonlinear system as it allows the parameters of the model to be updated using the identification error. The back propagation is then applied to adjust the controller parameter errors identified through the selected model.

7.3.3 Fractal dimension for process characterization

A fractal dimension is an index for characterizing fractal patterns or sets by quantifying their complexity as a ratio of the change in detail to the change in scale. Much progress has been made in understanding the complexity of systems through the application of fractal analysis theory, see (Peters, 2004 and Mandelbrot, 1987). The fractal dimension of a geometrical object is defined as follows;

$d = \lim_{r \to 0} \frac{In\, N(r)}{In(1/r)}$	**Equation 7-3**

Where $N(r)$ is the number of boxes along the surface of the object and r is the dimension of the box. The relevance of the fractal dimension for this study lies in its capacity to measure the geometrical complexity of objects

7.3.4 Adaptive control of stock market systems

The mathematical model for the stock market system can be represented as nonlinear differential equations, (Ismail, 2008). In this case a fuzzy rule base is used for modelling. This enables the use of the appropriate mathematical model according to the changing economic conditions or states of the economy and classification of the index (sector) under investigation. Summary of the fuzzy rules are given in table 7-1.

Table 7-1: Fuzzy rule base for modeling stock market dynamic system

IF		THEN	
H-exponent	Previous Price	Following Price	Probability of Event
>0.5	Positive	Positive	H exponent
>0.5	Negative	Negative	H exponent
=0.5	Positive	Negative/Positive	0.5
=0.5	Negative	Positive/Negative	0.5
<0.5	Positive	Negative	H exponent
<0.5	Negative	Positive	H exponent

It can be shown that the possible outcomes using this notion are given by the equation 7-4:

$$P'_{t+1} = \frac{1}{2}[H(P'_t + L(e,s)) + (1-H)(P'_t - L(e,s))] \qquad \textbf{Equation 7-4}$$

where e and s are fuzzy decision variables and represent the state of the economy i.e. crisis or non-crisis (see Chapter 3) and sector of the index respectively since degree of price movement are dependent on the sub-sector, (see Chapter 2).

7.4 Model Performance

The performance of the model results is compared to the traditional statistical approach such as auto-regression integrated moving average model (ARIMA) and artificial neural network (ANN). While there are undoubtedly other linear and non-linear methods against which performance of the adaptive model can be compared with, but the study chooses these two models as benchmarks because they are widely used and are the most familiar methods of applied researchers for forecasting, (McNelis, 2005). The study presents the estimates of the linear model as the first point of reference. The statistical analysis indicated that the ARIMA (1, 1, 1) model for the return index series is given by:

$\hat{r}_t = 0.012 + 0.356r_{t-1} - 0.877a_{t-1}$	**Equation 7-5**

The ANN will use the same parameters as those of the HAIM, so as to allow for more accurate comparison. The performance of each model is compared using the following measures; the R-square Mean Absolute Percent Error (MAPE) and Root Mean Square Error (RMSE). As shown in the previous chapters, the JSE market is a quite complex, evolutionary and has multiple factors interacting through it. These include political events, general economic conditions, and heterogeneous agents with varying expectations. Therefore, another relevant evaluation measure is employed, for the accuracy of the prediction of change in direction (POCID), defined by

$\text{POCID}=100\,\frac{\sum_{t=1}^{N} D_t}{N}$	**Equation 7-6**

$$D_t=\begin{cases}1, & if\ (r_t - r_{t-1})(\hat{r}_t - \hat{r}_{t-1}) > 0\\ 0, & otherwise\end{cases}$$

where *N* is the number of patterns, *r* the desired output and $\hat{r}_t$ the model output.

The biggest criticism of the ARIMA model is that model identification techniques is subjective and the reliability of the model can depend on the skill and experience of the forecaster. The ANN estimation on the other hand is often criticized because of its black box nature and the large number of parameters required for training. The hybrid model suggested in this study attempt to counter most of the criticism raised for the ANN and ARIMA (1, 1, 1). We believe that hybrid model can better capture the mechanisms of the human mind

7.5 Performance of Models

In this section, the HAIM, ANN and ARIMA are estimated and compared. A database of historical daily prices were used to evaluate the performance of the ANN and ARIMA models. Using statistical criteria, the experimental results in Table 7-2 reveal that the HAIM model provides a promising alternative to stock market predictions, resulting in low errors in comparison with the ARIMA and ANN models. The R-squared value represents the proportion of variation in the dependent variable that is explained by the independent variables. The better the model explains variation in the dependent variable, the higher the R-squared value. Without further comparison, the HAIM best explains variation in the dependent variable, followed by the ANN and ARIMA models. These statistics are all based on the difference between the desired value and the model output for one-step ahead forecasting.

Table 7-1: One-step ahead forecasting for the JSE index

	ARIMA(1,1,1)	**ANN**	**HAIM**
R-Square	0.912	0.926	0.954
RMSE	1342.3	1128.6	956
MAPE	1.43%	1.35%	1.12%
POCID	48.70%	55.20%	64.50%

7.5.1 Performance over different prediction horizons

Predictions of the three modelling techniques are compared over different prediction horizons. The study compares the errors of the training data with the validation daily, weekly and monthly data. As is evident from the results in Table 7-3, the HAIM outperformed all the other techniques when forecasting at all the prediction horizons. The reason for this result is that the HAIM combines the power of neural networks in short term predictions with the fuzzy logic's ability to contain more general knowledge about the dynamic behaviour of the process. Hence it has the potential to forecast better in the long term. The ANN technique also does a good job for the three prediction horizons when compared to the linear model (ARIMA).

Table 7-2: SSE of the predictions models over different time horizons.

Model	Training data	Validation data		
	SSE	SSE (daily)	SSE (weekly)	SSE(monthly)
ARIMA	0.0230	0.062	0.154	0.554
ANN	0.0012	0.039	0.256	0.312
HAIM	0.0002	0.014	0.047	0.064

7.6 The out-of-sample forecast performance of the models

The in-sample forecast performance of the model is often a poor indication of the forecasting ability of the models, therefore various out-of-sample performances were conducted to test the robustness of the HAIM model. The coefficients of the various models were re-estimated using three different sample periods from 1994-2004. The results over the three periods are tabulated in Table 7.4, Table 7.5 and Table 7.6.

In order to get some idea of which model performed better in the out sample forecasts, the average RMSE, R-Square, MAPE and POCID were calculated over all the forecasting periods. The results are summarized in Table 7.7. The forecasting accuracy of the HAIM is superior to that of the ARIMA and ANN based on the average out-of sample forecast in table 7.7.

The HAIM managed to outperform the **ARIMA (**1, 1, 1) and ANN models in all the three periods of the out-of-sample forests, using the **RMSE** and **MAPE** and **POCID** criteria. The ARIMA only managed to perform the ANN for the R-Square and POCID criteria in the second out of sample forecast period (1997-2000). The ANN outperformed the ARIMA model in the first and third out-of-sample periods.

*T***able 7-4: Out-of-sample forecast performance of the models from 1994-199***6*

	ARIMA(1,1,1)	ANN	HAIM
R-Square	0.902	0.931	0.943

RMSE	1378.2	1237.78	840
MAPE	1.93%	1.70%	1.18%
POCID	46.24%	48.30%	66.70%

Table 7-5: Out-of-sample forecast performance of the models from 1997-2000

	ARIMA(1,1,1)	ANN	HAIM
R-Square	0.903	0.892	0.947
RMSE	1342.3	1128.6	789
MAPE	1.52%	1.50%	1.11%
POCID	51.60%	49.44%	66.82%

Table 7-6: Out-of-sample forecast performance of the models from 2001**-2004**

	ARIMA(1,1,1)	ANN	HAIM
R-Square	0.912	0.926	0.954
RMSE	1176.80	894.64	667.84
MAPE	1.89%	1.65%	1.15%
POCID	51.45%	59.43%	70.43%

Table 7-7: Average out-of-sample forecast performance of the models from 1994-2004

	ARIMA(1,1,1)	ANN	HAIM
R-Square	0.906	0.916	0.948
RMSE	1299.1	1087.01	765.61
MAPE	1.78%	1.62%	1.15%
POCID	49.76%	52.39%	67.98%

7.7 Implication of study

One of the most important issues when designing a model is the question of providing a methodology for their development. A good forecast will go a long way in helping portfolio managers to exploit all the potential investment opportunities that the JSE stock market offers as well as hedge them from disastrous choices.

7.8 Conclusions

A HAIM time series prediction has been developed for the JSE dynamic system by combining neural networks' ability for identification and control with fuzzy logic's ability for decision and use of expert knowledge and fractal theory's ability to characterise a system. The HAIM was compared with the traditional ARIMA model and the classic Artificial Neural Network and it outperformed the latter in all respects. The prediction accuracy over longer horizons was also significantly better than with the other models under investigation. The HAIM also managed to outperform other traditional models in the out-of-sample forecasts experiments. The designed HAIM model ensures greater accuracy in tracking of the JSE stock market movements.

CHAPTER 8

SUMMARY AND CONCLUSIONS

"Now it seems evident that, if this conclusion were formed by reason, it would be as perfect at first, and upon one instance, as after ever so long a course of experience. This question I propose as much for the sake of information, as with an intention of raising difficulties. I cannot find and imagine any such reasoning. But I keep my mind still open to instruction, if anyone will vouchsafe to bestow it upon me."

David Hume, *Philosopher*, *Extract from* Essential Works of David Hume (1965).

8.1 Summary and Conclusions

This thesis explores the dynamics of the Johannesburg Stock Exchange returns to understand how they impact stock prices. This increasing complexity and volatility coupled with the recent wave of financial crises in several markets sparked off a debate about the nature and characteristics of stock markets. Given the paucity of research into the market dynamics, this research contributes to a broader understanding of these issues by exploring different market dynamics that affect stock prices. This study draws attention to market dynamics amid continuing uncertainty over the role of investors, economic and other fundamental factors in shaping the stock market dynamics.

This first chapter gives a brief overview of financial markets in general, the Johannesburg Stock Exchange and equity investment management. The chapter also gives a brief overview of the Johannesburg Stock Exchange and current developments. It also discusses issues of liquidity and market concentration. Collectively, these issues lay a strong foundation for a comprehensive grasp of the immediate and broader structural context of operation of the JSE market dynamics including a clear background for understanding the proceeding chapters.

The second chapter examines the JSE indices using the fractal analysis technique for estimating the Hurst exponent. Evidence supporting a fractal nature in the market was found, implying a long-term predictability property for the overall market index. The results also suggest a logical system of variation of the Hurst exponent by firm size, market characteristic and sector grouping. These results contradict the widely popularized EMH. The conclusion suggests that market participants are incapable of efficiently valuing some equities, though not necessarily all. Future research can examine whether the fractals observed on the JSE are time varying or fixed along the time series.

The third chapter investigates the economic and political events that affect different JSE sectors and how they explain the appearance of non-linear windows on the Johannesburg Stock Exchange. It also draws conclusions on the degree of sensitivity of different market sectors to positive and negative news. There was evidence of transient burst of nonlinear periods on the JSE that can be attributed largely to the occurrence of economic events and the state of the market. Mixed results for the sensitivity reactions to different news announcements by different sectors were observed. Future research should also consider extending the results of this study to individual firms to examine the adjustment of stock price to firm-specific events. This will provide deeper insight into issues on listed companies' corporate actions.

Chapter 4 examines the distribution of stock market returns on the Johannesburg Stock Exchange (JSE). Evidence of leptokurtosis (fat tails and high peaks) and that a student-t distribution is an excellent fit for the JSE stock returns is found. The stock returns also exhibit positive skewness indicating a high probability of observing positive returns. There was evidence of volatility clustering suggesting a price formation process with heterogeneous beliefs. The study also shows that the Gaussian based Value-at-Risk model is an ineffective risk measurement tool under high market volatility. Future research should also consider whether the clustering of large fluctuations in financial time series is a consequence of long memory effects or other effects such as human psychology.

In chapter 5, simulations are used to demonstrate how different agent interactions affect market dynamics. The study also highlights how the homogenous agent assumption adopted in the CAPM and other versions of the model affect asset pricing. The results demonstrate that it is possible for traders to switch occasionally their characteristics between trading strategies and this evolutionary switching of traders is dependent on the state of the market. Through an analysis of correlations of the market states and agent strategies the fraction of technical analysts is shown to be large in times of crashes and bubbles. The results also seem to indicate that CAPM models with the homogenous belief assumption underestimate stock prices. The results suggest that traditional asset pricing models can be greatly improved by considering heterogeneity.

Chapter 6 discusses the extent to which reflexivity (endogeneity) affects price formation. For this, the self-excited Poisson Hawkes model, which combines exogenous influences with self-excited dynamics, is adopted. The most interesting feature is the consistent prevalence of endogeneity from mid-2003 to mid-2009. This played out in a manifold of critical economic events such as the U.S sub-prime and European debt crises. This result implies that there is an increasing influence of internal dynamics or events on stock price formation. In contrast, the background of exogenous shocks information driven dynamics generally remains more constant with major increases occurring just before market crashes.

The last chapter presents the HAIM model for financial time series prediction. Given evidence of non-linearity, reflexivity, heterogeneous agents and the fractal nature of the JSE financial market from preceding chapters, neural networks, fuzzy logic and fractal theory are combined to obtain a hybrid adaptive intelligent model (HAIM technique). By combining the advantageous strength of neural networks (ability for identification and control) with the strength of fuzzy logic (ability for decision making and use of expert knowledge) and fractal theory (for process characterisation), a robust adaptive model for the JSE dynamic system is developed. The proposed system is compared to the traditional linear model (ARIMA) and classic Artificial Neural Networks model and the system outperformed them in all respects. The prediction accuracy over longer horizons is also significantly better than the other models considered in this study.

8.2 Implications and Future Research

The results presented in this study have important implications for the pricing and risk analysis of equities on the JSE and other developing markets. The main problem with the current paradigms is that they are based on the notion that an ensemble of heterogeneous and interacting agents can be replaced by a unique representative one. With the results of this research, it is hoped that financial practitioners are now in a better position to understand and explain the JSE stock market behaviour. We also hope that the methods and evidence presented here will spur the investment community to look beyond modern portfolio theory and related theories, toward more practical market models for pricing and risk analysis of equities.

REFERENCES

Abarbanel, H. D. I., Brown, R. and Kadtke, J. B. (1990): Prediction in chaotic nonlinear systems: Methods for time series with broadband Fourier spectra, Phys. Rev, 1782–1807.

Abbod, M. F., Linkens, D. A, Mahfouf, M. and Dounias, G. (2002): Survey on the use of smart and adaptive engineering systems in medicine, Artificial Intelligence in Medicine, 179–209.

Abraham, A. (2005): Hybrid Intelligent Systems: Evolving Intelligence in Hierarchical Layers, Studies in Fuzziness Soft Computation, 159–179.

Abraham, A., Nath, B., Mahanti, P. K. (2001): Hybrid Intelligent Systems for Stock Market Analysis, International Conference on Computational Science, 337-345.

Alfarano, S., Lux, T., Wagner, F. (2007): Empirical validation of stochastic models of interacting agents. European Physical Journal B, 55, 183-187.

Altı, A, Kaniel, R, Yoeli, U. (2012): Why do institutional investors chase return trends? , Journal of Financial Intermediation, 21(4), 694-721.

Arrow, K. (2004): The Changing Face of Economics. Conversations with Cutting Edge Economists Colander, D. Holt R.P.F and Barkley Rosser, J (Eds.), The University of Michigan Press, Ann Arbor, 2004, 301.

Amilon, H. (2008): Estimation of an adaptive stock market model with heterogeneous agents, Journal of Empirical Finance, 342–362.

Andersen, T. G., & Bollerslev, T. (1997): Heterogeneous Information Arrivals and Return Volatility Dynamics: Uncovering the Long-Run in High Frequency Returns. The journal of Finance, 52(3), 975-1005.

Andersen, T. G., Bollerslev, T, Diebold, F. X. and Ebens, H. (2001): The Distribution of Realized Stock Return Volatility, Journal of Financial Economics, 43-76.

Andersen, T. G. Bollerslev T, Meddahi. (2005): Correcting the errors: Volatility forecast evaluation using high-frequency data and realized volatilities, Econometrica, 279–296.

Andersen, T. G, Bollerslev, T., Francis, X. Diebold, and Vega, C. (2002): Micro-effects of Macro announcements: Real-time price discovery in foreign exchange, National Bureau of Economic Research Working Paper 8959.

Andersen, T. G, Bollerslev, T., Francis, X. Diebold, and Vega, C. (2005): Real-time price discovery in stock, bond and foreign exchange markets, National Bureau of Economic Research Working Paper w11312.

Andrew C. J, Mills, TC, & Roberts, J. (1995): Misspecification of the market model: the implications for event studies, Applied Economics Letters, 2(5), 163-165.

Axelrod R., T. L. (2006): A Guide for Newcomers to Agent-Based Modelling in the Social. In K. L. L. Tesfatsion, Handbook of Computational Economics 2. (pp. 1648–1659). Amsterdam: Elsevier.

Baca, S., Garbe, B., and Weiss, R. (2000): The rise of sector effects in major equity markets, Financial Analysts Journal, 56, 34-40.

Bachelier, L. (1900): Théorie de la speculation , Annales Scientifiques de L'École Normale Supérieure: 17-21.

Bahat, D., Rabinovitch, A and Frid, V. (2005): Tensile Fracturing in Rocks: Tectono-fractographic and Electromagnetic Radiation Methods, Springer-Verlag, Heidelberg.

Barr, G. D. I. and Kantor, B. S. (2002): The South African Economy and its Asset Markets: An Integrated Approach, SAJE, 70, 1, 53-77.

Barber, B. M and Odean, T. (2001): Boys will be boys: Gender, overconfidence and common stock investment, Quarterly Journal of Economics, 261-292.

Barrow-Green, J. (1996): Poincare and the Three-Body Problem (History of Mathematics Vol 2), Rhodes Island: American Mathematical Society.

Baumohl, B. (2012): The Secrets of Economic Indicators: Hidden Clues to Future Economic Trends and Investment Opportunities, New Jersey.

Benedetti, H., Romero, R., & Bonilla, C. A. (2013): Testing for Intensity, Persistence and Financial Contagion in Latin America: A New Use of the Hinich Bicorrelation Test. Persistence and Financial Contagion in Latin America: A New Use of the Hinich Bicorrelation Test.

Bian, Y., Xu, L., Li, J., He, J. and Zhuang, Y. (2012): An Evolution Model of Trading Behaviour Based on Peer Effect in Networks, Hindawi Publishing Corporation Discrete Dynamics in Nature and Society, 15.

Birz, G. and Lott, J. R. (2011): The Effect of Macroeconomic News on Stock Returns: New Evidence from Newspaper Coverage, Journal of Banking & Finance, 2791–2800.

Black, F., & Litterman, R. (1992). Global portfolio optimization. *Financial Analysts Journal*, *48*(5), 28-43.

Blanchet. O (2004): A Hybrid Approach with Modular Neural Networks and Fuzzy Logic for Time Series Prediction. Soft Computing Journal, 50-62.

Blanchard, O. J. (1979): Speculative bubbles, crashes and rational expectations, Economics Letters, 387–389.

Bloomfield, R. A. (1999): Market Transparency: Who Wins and Who Loses? The Review of Financial Studies, 5-35.

Brock, V. A. (1986): Distinguishing Random and Deterministic Systems. Journal of Economic Theory, 168-195.

Brock A. W, LeBaron, B. (1996): A Dynamic structural model for stock return volatility and trading volume, The Review of Economics and Statistics, 64-89.

Brock, W. A., Hsieh, D. A., & LeBaron, B. D. (1991): Nonlinear dynamics, chaos, and instability: statistical theory and economic evidence. MIT press.

Brooks, C. and Hinich, M. J. (1998): Episodic nonstationarity in exchange rates. Applied Economics Letters, 719-722.

Brooks, C., Hinich, M. .J and Molyneux, R. (2000): Episodic nonlinear event detection: political epochs in exchange rates. In: D. Richards and A. Arbor, (Eds), Political Complexity: Non Linear Models of Politics, (pp. 83–98). MI: University of Michigan Press.

Brunnermeier, M. K. (2001): Asset Pricing under Asymmetric Information- Bubbles, Crashes, Technical Analysis and Herding, Oxford: Oxford University Press.

Bryant, C. G. (2002). George Soros's theory of reflexivity: a comparison with the theories of Giddens and Beck and a consideration of its practical value, Economy and Society, 31(1), 112-131.

Bloomfield, R. J.,and O'Hara, M. (1999): Market Transparency: Who Wins and Who Losses? The Review of Financial Studies, 5-35.

Bunde, A. J. (2005): Long term memory: A natural mechanism for the clustering of extreme eventsand anomalous residual times in climate records. Phys. Rev. Lett, 85, 3736

Bunde, A., Halvin, S., and Roman, E. H. (1990): Multifractal features of random walks on random fractals. The American Physical Society, 74-89.

Bocker, K, & Kluppelberg, C. (2005): Operational VaR: a closed-form approximation, Risk Magazine Limited, 18(12), 90.

Bollerslev, T. (1986): Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics, 307-327.

Bowley, G. (2010): Lone $4.1 Billion Sale Led to 'Flash Crash' in May. The New York Times, Retrieved 28 October 2010.

Cajueiro, D. O., Tabak, B. M. (2004). Ranking efficiency for emerging markets. Chaos, Solitons & Fractals, 22(2), 349-352.

Casavalone, S. (1996): Drivers of market illiquidity on the JSE, Unpublished PhD thesis University of Cape Town.

Case, K. E, & Shiller, R.J. (1988): The behavior of home buyers in boom and post-boom markets.

Castillo, O. A. (1996): Automated Mathematical Modelling for Financial Time Series Prediction using Fuzzy Logic, Dynamical System Theory and Fractal Theory. CIFEr'96, New York, NY: IEEE Press, 120-126.

Cenesizoglu, T. (2006): Asymmetries in the Reaction of Stock Prices to Macroeconomic News, Working paper, HEC Montreal, 13-16.

Charpentier, A. and Siba, D. (2008): Dynamic flood modelling-combining Hurst and Gumbel's approach, Environmetrics, 20, 32-52.

Chen, S. H. (2005). Computational intelligence in economics and finance: Carrying on the legacy of Herbert Simon. Information Sciences, 170(1), 121-131.

Chen, J. T, Gupta, A. K, and Troskie, C. G. (2003): The distribution of stock returns when the market is up. Communications in Statistics-Theory and Methods, 32(8), 1541-1558.

Chen, S. H, Lux, T, & Marchesi, M. (2001): Testing for non-linear structure in an artificial financial market. Journal of Economic Behavior & Organization, 327-342.

Chen, S. and Yeh, C. (2001): On the emergent properties of artificial stock markets: the efficient market hypothesis and the rational expectations hypothesis, Journal of Economic Behavior & Organization, 217–239.

Chiarella, C., Dieci, R. and Gardini, L. (2002): Speculative behavior and complex asset price dynamics: a global analysis, Journal of Economic Behavior & Organization, 49, 173-197.

Chiarella, C., Iori, G., and Perelló, J. (2009): The impact of heterogeneous trading rules on the limit order book and order flows, Journal of Economic Dynamics and Control, 33, 525-537.

Christiansen, C. H. and Ranaldo, A. (2007): Realized Bond-Stock Correlation: Macroeconomic Announcement Effects Journal of Futures Markets, 27, 439-469.

Chimanga, A., S. (2007): Hedging an Investment Portfolio using Options, Financial Engineering Project report, UWC-FEPR 2007.

Chimanga, A., and Kotze, D. (2009): A Multivariate Analysis of Factors Affecting Stock Returns on the JSE, African Journal of Finance , 80-94.

Chitrakala Rani, T. and Indrakala, S. (2012): A Fractal Analysis of Indian Stock Markets: International Journal of Research and Reviews in Computer Science, 1367-1369.

Colander, D., Föllmer, H., Haas, A., Goldberg, M., Juselius, K., Kirman, A., Lux, T., Sloth, B. (2008). The Financial Crisis and the Systemic Failure of Academic Economics. 98th Dahlem Workshop.

Colquitt, L. L, Hoyt, R. E, & Lee, R. B. (1999): Integrated risk management and the role of the risk manager. Risk Management and Insurance Review, 2(3), 43-61.

Competition Commission (2009): Unleashing Rivalry Ten years of enforcement by the South African competition authorities, Pretoria, South Africa.

Connolly R.A and Stivers C. T (2000); Evidence on the Economics of Equity Return Volatility Clustering, Economic Society, 24-37.

Cont, R. (1997): Scaling and correlation in financial data. European Physical Journal, 12-17.

Cont, R. (2005): Long range dependence in financial markets, Fractals in Engineering, Springer, 159-179.

Cox, J. and Glapa, L., (2009): Credit crisis timeline, The University of IOWA Center for International Finance & Development.

Curtler, D. M, Poterba, M, J., Summers, L. H. (1989): What moves stock prices?, Journal of Portfolio Management, 4-12.

Daley, D. J. and Vere-Jones, D. (2008): An Introduction to the Theory of Point Processes Volume II: General Theory and Structure, Series: Probability and Its Applications, 2nd edition, Springer, Heidelberg.

Damodaran, A. (2007): Valuation Approaches and Metrics: A Survey of the Theory and Evidence, Foundation and Trends in Finance, 693–784.

Daniel, K. H. (1998): Investor Psychology and Security Market Under and Overreactions, Journal of Finance, 1839-1885.

Darwin, C. (1859): On the Origin of Species, London: John Murray.

David, A. (2008): Heterogeneous beliefs, speculation, and the equity premium. The Journal of Finance, 63(1), 41-83.

De Cesari, A., Espenlaub, S., Khurshid, A and Simkovic, M. (2011): The effects of ownership and stock liquidity on the timing of repurchase transactions,

Debreu, G. (1974): Excess demand functions, Journal of Mathematical Economics , 15–21.

DeLong, J. B. (2005): Financial Markets, Noise Traders, and Fundamental Risk, Background Memo, U.C. Berkeley and NBER.

De Long, J, Shleifer, A, Summers, L. H., Waldmann, R. (1990): Noise trader risk in financial markets, Journal of Political Economy, 703-38.

DG trade statistics (2011): South Africa-EU Bilateral Trade and Trade with the world, Trade G.2, 5-8.

Dunis, C., Williams, M. (2002): Modelling and trading the EUR/USD exchange rate: do neural network models perform better? Derivatives: use, trading and regulation, 211–239.

Edmister, R. O. (1982): Margin Analysis for Consumer Deposit Interest Rate Policy, Journal of Bank Research, 179-84.

Engle, R. (1982): Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica , 987-1007.

Fair, R. (2002): The Events that Shook the Market, Journal of Business, 713–731.

Fama, E. J. (1970): Efficient capital markets: a review of theory and empirical work, Journal of Finance 25, 383-417.

Fama, E. J. (1991): Efficient capital markets: II, Journal of Finance 46 (5), 1575-1617.

Fama, E., Fisher, L., Jensen, M. and Roll, R. (1969): The adjustment of stock prices to new information. International Economic Review 10, 11-21.

Farmer, J. D., Patelli, P., & Zovko, I. I. (2005): The predictive power of zero intelligence in financial markets. Proceedings of the National Academy of Sciences of the United States of America, 102(6), 2254-2259.

Falconer, K. (2003): Fractal Geometry. New York: Wiley, pp 308.

Fernández, C, and Steel, M. F. J. (1998): On Bayesian modelling of fat tails and skewness. Journal of the American Statistical Association, 93(441), 359-371.

Filimonov, V and Sornette, D. (2011): Quantifying reflexivity in financial markets: towards a prediction of flash crashes, Proc. Natl. Acad. Sci., USA.

Frankel, J. and Froot, K. (1988): Chartists, Fundamentalists, and the Demand for Dollars, Greek, Economic Review 10.

Flatters, F., and Stern, M. (2008): Trade and Industrial Policy in South Africa, TIPS Annual Forum, Cape Town.

Flood, M. D. (1999): Quote disclosure and price discovery in multiple-dealer financial markets. The Review of Financial Studies , 37-59.

Foss, N. J. (2001): The Problem With Bounded Rationality:On Behavioral Assumptions in the Theory of the Firm. DRUID Working Paper No 01-15 .

Gabaix, X and David, L. (2006): Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets, Quarterly Journal of Economics, 505-540.

Gençay, R., Xu, Z. (2003): Scaling, Self-Similarity and Multifractality in FX Markets, Physica A, 578 – 590.

Geweke, J., Porter-Hudak, S. (1983): The estimation and application of long memory time series models, Journal of time series analysis, 4(4), 221-238.

Greenblatt, S. A. (1998): Atomic Decomposition of Financial Data, Computational Economics, 275-293.

Ghura, D. (1990): Exchange Rate Shocks, Macroeconomic Announcements and Commodity Price Behavior. NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. Chicago.

Gilmore, C. G. (2001): An examination of non-linear dependence in exchange rates, using recent methods from chaos theory, Global Finance Journal , 139–151.

Granger, C. W. J. (1980): Long memory relationships and the aggregation of dynamic models, Journal Econometrics, 227–238.

Greene, M. T. and Fielitz B. D. (1977): Long-term dependence in common stock returns, Journal of Financial Economics, 339-349.

Godogo, K. (2007):The JSE Investment Case, Afena Capital Report.

Goodhart, C. A., O'Hara, M. (1997): High frequency data in financial markets: Issues and applications. Journal of Empirical Finance, 4(2), 73-114.

Google Finance (2010): Dow Jones Industrial Average Historical Prices, Google Finance, Retrieved August, 2010.

Hachour, O. (2009): The proposed Fuzzy Logic Navigation approach of Autonomous Mobile robots in unknown environments. International journal of mathematical models and methods in applied sciences, 204-218.

Harlow, W. V. (1991): Asset allocation in a downside-risk framework. Financial Analysts Journal, 28-40.

Hancocks, R. E. (2010): The influence of domestic macroeconomics variables on the performance of the JSE sectoral indices, Unpublished MSc thesis (Rhodes University)

Hawkes, A.G. (1971): Spectra of some self-exciting and mutually exciting point processes. Biometrika, 58, 83–90.

Hausman, JA., Lo, AW. and Mackinlay, AC. (1992): An ordered probit analysis of transaction stock prices. Journal of Financial Economics 31, 319–379.

Hinich, M. J and Patterson, D. M. (1995): Detecting epochs of transient dependence in white noise. Austin: University of Texas.

Hommes, C. H., (2006): Heterogeneous agent models in economics and finance. In: Tesfatsion, L, Handbook of Computational Economics, Vol. 2: Agent-Based Computational Economics. Elsevier Science B.V., 1110-1186.

Horta, P. C., Mendes, I. and Vieira (2008): Contagion effects of the US Subprime Crisis on Developed Countries, CEFAGE-UE Working Paper 2008/08.

Hume, D. (1761): An Enquiry Concerning Human Understanding, The Harvard Classics, 1909–14.

Hume, D. (1965): Essential Works of David Hume, Douglas Editions.

Hsieh, D.A. (1991). Chaos and Nonlinear Dynamics: application to financial markets. The Journal of Finance, 46(5), 1839-1877.

Hsieh, H. H and Hodnett, K. (2011): Tests of the Overreaction Hypothesis and the Timing of Mean Reversals on the JSE Securities Exchange (JSE): the Case of South Africa, Journal of Applied Finance & Banking, 107-130.

Ismail, M. T. A. (2008): Modelling Nonlinear Relationship among selected ASEAN Stock Markets. Journal of Data Science, 533-545.

Ivković, Z., and Weisbenner, S. (2007). Information diffusion effects in individual investors' common stock purchases: Covet thy neighbours' investment choices, Review of Financial Studies, 20(4), 1327-1357.

Jafta, R.C. (1998): Is South African Competition Policy keeping up with world developments?, Annual Legislation & Policy Review Conference. Randburg.

Jang, J. R. (1997): Neurofuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. Prentice Hall.

Jegadeesh, N and Titman, S. (1993): Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, The Journal of Finance, 65-91.

J.P Morgan Asset Management (2009): Non-normality of Market Returns-A framework for asset allocation decision-making, J.P Morgan Chase Report, 1-31.

Jorion, P. (2007): Value at Risk – The New Benchmark for Managing Financial Risk. McGraw–Hill.

JSE website (2011): http//www.jse.co.za/home, 11 November 2011.

JSE fact sheet, 08/05/2012, http://www.jse.co.za/Libraries/SAFEX ED Products-Equity Index Futures/contract specifications.sflb.ashx.

Judd, K. J. (1996): Handbook of Computational Economics, vol. 2, Agent-Based Computational Economics, North-Holland, Amsterdam, 1109–1186.

Kahneman, D. and Tversky, A. (1979): Prospect theory: An analysis of decisions under risk, Econometrica (2): 263–291.

Kalman, R. E. (1963): Mathematical Description of Linear Dynamical Systems, SIAM Journal on Control, 152-192.

Kasman, A and Torun, E. (2007): Central Bank Review, Central Bank of the Republic of Turkey.

Khalsa, A. S. (2008): Decoupling theory: a study of global markets in the present era of volatility, Report Paradigm, Institute of Management Technology Report.

Kirchler, M., Huber, J. (2007). Fat tails and volatility clustering in experimental asset markets. Journal of Economic Dynamics and Control 31, 1844–1874.

Kydland, F. E., & Prescott, E. C. (1988): The workweek of capital and its cyclical implications, Journal of Monetary Economics, 21(2), 343-360.

Kyle, A. S. (1985): Continuous auctions and insider trading, Econometrica, 53, 1315-1335.

International Political and Military Affairs. February 8,(2010). http://www.worldmonitor.info/.

Janssen, M. (1993): Microfoundations; A critical inquiry. Routledge.

Langley, P. A., and Morecroft, J. D. (2004): Performance and learning in a simulation of oil industry dynamics. European Journal of Operational Research, 715-732.

LeBaron, B. (1994): Chaos and nonlinear forecastability in economics and finance, Philosophical Transactions: Physical Sciences and Engineering, 397-404.

LeBaron, B. (2006): Time scales, Agents, and Empirical Finance, Medium, Econometrics, 20-25.

LeBaron, B., Arthur, W. B., and Palmer, R. (1999): Time series properties of an artificial stock market, Journal of Economic Dynamics and Control, 1487-1516.

LeBaron, B. and Yamamoto, R. (2008): The impact of imitation on long-memory in an order driven market, Eastern Economic Journal 34, 504-517.

Lee K and Pesaran, M. H. (1995): Econometric Analysis of Nonlinear Dynamic Models with Applications in International Macroeconomics, End of Award Report.

LeRoy, S. F. (2008): Excess Volatility Tests, The New Palgrave Dictionary of Economics.

LeRoy, S. and Porter, R (1981): The present-value relation: Tests based on implied variance bounds, Econometrica, Journal of the Econometric Society, 555–574.

Levy, D. (2007): Chaos theory and strategy: Theory, application, and managerial implications, Strategic Management Journal.

Li, M and Parker, M. E. (2005): Cross-sectional Analysis of Asymmetric Information after Decimalization, Journal of Business and Economic Perspectives, No 2.

Li, S. (2000): The development of a hybrid intelligent system for developing marketing strategy, Decision Support Systems, 395–409.

Liang, H. (2011): A Neural Basis of Herd Behaviour in Stock Market: An Experiment, Design, SSRN working paper.

Lillo, F. Micciche, J, Tumminello M, Piilo J and Mantegna R, N. (2012): How news affect the trading behaviour of different categories of investors in a financial market, Quantitative Finance Journal.

Lim., K. P. (2007): Ranking of efficiency for stock markets: a nonlinear perspective. Physica A 376: 445–454.

Lim, K. P. (2008): Sectoral efficiency of the Malaysian stock market and the impact of the Asian financial crisis, Studies in Economics and Finance, 196-208.

Lim, K. P, Brooks, R. D. and Hinich, M. J. (2008): Nonlinear serial dependence and the weak-form efficiency of Asian emerging stock markets, Journal of International Financial Markets, Institutions and Money.

Limam, I. (2003): Is long memory a property of thin stock markets?. International evidence. Review of Middle East Economic Finance: 251–266.

Lintner, J. (1965): The valuation of risk assets and selection of risky investments in stock portfolios and capital budgets. Review of Economics and Statistics: 13-37.

Liu, J, and Longstaff, F. A. (2004): Losing money on arbitrage: Optimal dynamic portfolio choice in markets with arbitrage opportunities. Review of Financial Studies, 17(3), 611-641.

Lo, W. A. (1991): Long-term memory in stock market prices. Econometrica, 1279-1313.

Lo, W. A. (2005): Reconciling Efficient Markets with Behavioral Finance: The Adaptive Markets Hypothesis, Journal of Investment Consulting, 21-44.

Lo, W. A. (2008): Efficient markets hypothesis. In S.N Durlauf and L.E Blume (eds), The New Palgrave Dictionary of Economics Online, New York: Palgrave Macmillan.

Longstaff, F. A. (2010): The subprime credit crisis and contagion in financial markets. Journal of Financial Economics, 436–450.

Lucas, R. E. (1972): Expectations and the Neutrality of Money. Journal of Economic Theory, 103-124.

Lux, T, & Marchesi, M. (2000): Volatility clustering in financial markets: A micro-simulation of interacting agents. International Journal of Theoretical and Applied Finance, 3(04), 675-702.

Machiavelli, N. (1950): The Prince and the Dis-courses. Luigi Ricci, Trans. New York, Modem Library, 3-98.

Maddala, G. (1996): Introduction to Econometrics. Prentice Hall.

Maheswaran, S., & Sims, C. A. (1992): Empirical implications of arbitrage-free asset markets. Cowles Foundation for Research in Economics at Yales University.

Mala, R. and White, M. (2006): Assessment of an emerging stock market: The case for Fiji's Stock Market. International Research Journal of Finance and Economics, 116-132.

Mandelbrot, B. (1963a): The Variation of Certain Speculative Prices, Journal of Business, 394-419.

Mandelbrot, B. (1963b): New Methods in Statistical Economics, Journal of Political Economy, 421-440.

Mandelbrot, B. (1964): Random walks, fire damage amount, and other Paretian risk phenomon. Operation research, 582-585.

Mandelbrot, B. (1967a): On the distribution of stock price differences. Operations Research , 1057-1062.

Mandelbrot, B. (1967b): How Long Is the Coast of Britain?. Statistical Self-Similarity and Fractional Dimension. Science, New Series, Vol. 156, No. 3775, 636-638.

Mandelbrot, B. (1972): A statistical methodology for non-periodic cycles: from the covariance to R/S analysis. Annals of Economic and Social Measurement, 259-290.

Mandelbrot, B. (1987). The Fractal Geometry of Nature. New York: W.H. Freeman and Company.

Mandelbrot, B. (2004): The (Mis)behaviour of Markets. London: Profile books.

Mandelbrot, B. and Taleb, N. (2006): A focus on the exceptions that prove the rule, Financial Times.

Mandelbrot, B. and Vanness, J. W. (1968): Fractional Brownian motions, fractional noises and applications. SIAM Review: 422-437.

Mangani, R. D. (2004): Non-linear dynamics and stock return predictability on the JSE securities exchange of South Africa, Unpublished PhD thesis (University of Cape Town).

Mangani, R. (2007): Distributional properties of JSE prices and returns. Investment Analysts Journal, 66, 52-72.

Mantegna, R. and Stanley, E. (2000): An introduction to econophysics. New York,: Cambridge. Mantel, R. (1974): On the characterization of aggregate excess demand. Journal of Economic Theory , 348–353, 421-440. University Press.ress.

Markowitz, H. (1952): Portfolio Selection. Journal of Finance, 77-91.

Markwat, T., Kole, E. and Dick van Dijk (2009): Contagion as a domino effect in global stock markets. Journal of Banking & Finance, 1996-2012.

Masih, A. M, & Masih, R. (1997): Dynamic linkages and the propagation mechanism driving major international stock markets: an analysis of the pre-and post-crash eras. The Quarterly Review of Economics and Finance, 37(4), 859-885.

Masulis, R. W. and Shivakumar, L. (2002): Does market structure affect the immediacy of stock price responses to news?. Journal of Financial and Quantitative Analysis, 37, 617–648.

Mboweni, T. (2008): Governor's Address at the eighty-eighth annual general meeting of shareholders. Johannesburg: Reserve Bank of SA.

McDonald, M. A. (2004): From miasma to fractals: the epidemiology revolution and public Health nursing. Public Health Nursing, 21(4), 380-391.

McMillan, D. G. (2004): Nonlinear predictability of short run deviations in UK stock market returns. Economics Letters, 149-154.

McNelis, P. D. (2005): Neural Networks in Finance: Gaining Predictive Edge in the Market, Elsevier Inc, Burlington, MA.

McQueen, G. and Role, V. V. (1993): Stock Prices, News, and Business Conditions. Review of Financial Studies, 683-707.

Mehra, R., Prescott, E. C. (1985): The Equity Premium: A Puzzle. Journal of Monetary Economics, 145–161.

Menkhoff, L. and Nikiforow, M. (2009): Professionals' Endorsement of Behavioral Finance: Does It Impact Their Perception of Markets and Themselves?. Journal of Economic Behavior & Organization, 71, 318–329.

Melin, P. and Castillo, O. (2003): Adaptive intelligent control of aircraft systems with a hybrid approach combining neural networks, fuzzy logic and fractal theory, Applied Soft Computing, 353–362.

Melin, P., Mancilla, A., Lopez, M., Trujillo, W., Cota, J. and Gonzalez, S. (2007): Modular Neural Networks with Fuzzy Integration Applied for Time Series Forecasting, Analysis and design of intelligent systems using soft computing techniques, 217-225.

Milani, F. (2007): Expectations, learning, and macroeconomic persistence. Journal of Monetary Economics, 2065–2082.

Mitzenmacher, M. (2003): A brief history of generative models for power law and lognormal distributions. Internet Mathematics, 226–250.

Mistry, A. (2008): Momentum Trading, Volatility Feedback, and the Distribution of Stock Returns New York University, Graduate School of Business Administration.

Mitra, S. K. (2011): Influence of Range to Standard Deviation Ratio on Results of a Trading Rule. Canadian Center of Science and Education, Asian Social Science, 42-53.

Mlonzi, V.F, Kruger, J. and Nthoesane, M. G. (2003): Share price reaction to earnings announcement on the JSE-ALtX: A test for market efficiency. Journal of Economic Literature, 478–539.

Morel, Y., Leonessa, A. (2009): Prediction-based Observation of Nonlinear Systems Non-affine in the Unmeasured States, Joint 48th IEEE Conference on Decision and Control and 28th Chinese Control Conference Shanghai, P.R. China, 16-18.

Morera, A. T. (2008): In Search Of Pockets of Predictability, MSc thesis, Swiss Federal Institute of Technology of Zurich.

Moolaman, E. and Du Toit, C. (2005): An Econometric Model of the South African stock market, SAJEMS NS, 77-91.

Mossin, J. (1966): Equilibrium in a Capital Market . Econometrica: 768-783.

Muller, C. (1999): Investor overreaction on the Johannesburg Stock Exchange, Investment Analyst Journal, 5-17.

Mulligan, R. F. (2000): A fractal analysis of foreign exchange markets, International Advances in Economic Research, 33-49.

Mulligan, R. F. (2004): Fractal analysis of highly volatile markets: An application to technology equities. The Quarterly Review of Economics and Finance, 155–179.

Muslomow, A., Guler, and, Cenktan, O. (2005): Macroeconomic stabilization programs and financial performance of small and medium sized enterprises in Turkey. Journal of International Business and Entrepreneurship, 19-40.

Muth, J. F. (1961): Rational Expectations and the Theory of Price Movements reprint. The new classical macroeconomics, 3-23.

Myers, S. C. (1984): Finance theory and financial strategy. Interfaces, 14(1), 126-137.

Narendra, K., Annaswamy, G. (1989): Stable adaptive systems. Englewood Cliffs: NJ: Prentice-Hall.

Nawrocki, D. N .(1996): Portfolio Analysis with a Large Universe of Assets. Applied Economics, 28, 1191-98.

Nevmyvaka, Y. (2005): Normative Approach to Market Microstructure Analysis, Doctoral dissertation, University of Pennsylvania.

Nichols, D. (2012): http://www.fractalgoldreport.com/fmr-analysis.php Fractal Publishing LLC.

Nolan, J. P. (2009): Stable Distributions: Models for Heavy Tailed Data, American University Unpublished, Retrieved 2010-02-21.

Nygren, K. (2004), Stock Prediction – A Neural Network Approach, Master Thesis, Royal Institute of Technology, KTH.

Odean, T. (1998): Volume, Volatility, Price, and Profit When All Traders Are Above Average. The Journal of Finance , 1887-1934.

Osborne, M. F. M. (1964): Brownian Motion in the Stock Market. In The Random Character of Stock Market Prices, by Cootner PH. Cambridge: MA: MIT Press. 100-128.

Osler, C. (2012): Market Microstructure and the Profitability of Currency Trading. Annual Review of Finance Economics, 4(1), 469-495.

Ottaviani, M, and Sørensen, P. N. (2006): The strategy of professional forecasting. Journal of Financial Economics, 81(2), 441-466.

Ozun, A. (2006): Theoretical Importance of Artificial Neural Networks For The Efficiency of Financial Markets. 5th International Finance Symposium: Integration in the Financial Markets, Istanbul Vienna

Page M. J. and Way C. V. (1992): Stock Market Over-reaction: The South African Evidence. Investment Analysts Journal, 35-49.

Palmer, R. G., Arthur, W. B, Holland, J. H., LeBaron, B. and Tayler, P. (1994): Artificial economic life: a simple model of a stock market, Physica D: Nonlinear Phenomena, 264–274./

Peron, T. K. D, Costa, L. D. and Rodrigues, F. A. (2012): The structure and resilience of financial market networks. Chaos, 22.

Peng, C. K., Buldyrev, S. V., Havlin, S., Simons, M., Stanley, H. E., Goldberger, A. L. (1994): Mosaic organization of DNA nucleotides. Physical Review E, 49(2), 1685.

Pesaran, M. H. and Potter, S. M. (1992): Nonlinear dynamics and econometrics: AN introduction. Journal of Applied Econometrics, S1–S7.

Peters, E. (1989): Fractal Structure in the Capital Markets. Financial Analysts Journal, 45, 4, 32-37.

Peters, E. (1991): Chaos and Order in The Capital Markets: A New View of Cycles, Prices, and Market Volatility. New York: John Wiley & Sons.

Peters, E. (1991b): R/S Analyais using Logrithmic Returns: A technical Note. Financial Analyst Journal: 50-62.

Peters, E. (1994): Fractal Market Analysis- Applying Chaos Theory to Investment and Econmics. New York: John Wiley & Sons.

Peters, E. (1999): Complexity, Risk, and Financial markets. New York: John Wiley & Sons.

Poon, S. H and. Granger, C.W. J. (2003): Forecasting Volatility in Financial Markets: A Review. Journal of Economic Literature, 478–539.

Popper, K. R. (1950): Indeterminism in Quantum Physics and in Classical Physics. British Journal for the Philosophy of Science 1 (2):117-133.

Popper, K. R. (1954): Self-Reference and Meaning in Ordinary Language. Mind 63 (250), 162-169.

Popper, K. R. (1957): The Poverty of Historicism, Harper and Row, New York.

Qi, M. (1999): Nonlinear Predictability of Returns using Economic and Financial Variables. Journal of Business and Economic Statistics , 419-429.

Rachev, S. (2003): Handbook of heavy tailed distributions in finance. Amsterdam: Elsevier.

Rachev, S. (2005): Desirable properties of an ideal risk measure in portfolio theory. International Journal of Theoretical and Applied Finance, 19-54.

Ramanauskas, T. (2008): Agent–based Financial Modelling as an Alternative to the Standard Representative Agent Paradigm. Pinigų studijos, 5-21.

Reilly, F. K, Brown, K. C. (2002): Investment Analysis and Portfolio Management. South-Western: South-Western Educational Publishing.

Reilly, F., & Brown, K. (2011). Investment analysis and portfolio management. Cengage Learning.

Ricardo, D. (1810). The high price of bullion, a proof of the depreciation of bank notes.

Richards, G. R. (2000): The fractal structure of exchange rates: measurement and forecasting. Journal of International Financial Markets and Money, 163–180.

Roache, S. K., Rossi, M. (2010): The effects of economic news on commodity prices. The Quarterly Review of Economics and Finance, 377-385.

Romero-Meza, R., Bonilla, C. and Hinich, M. (2006): Nonlinear Event Detection in the Chilean Stock Market, Applied Economics Letter, 987 - 991.

Ross, S. (1976): The Arbitrage Theory of Capital Market Asset Pricing. Journal of Economic Theory, 341-360.

Sahalia, Y., Cacho-Diaz, J., and Roger JA (2011): Modelling Financial Contagion using mutually exciting jump processes.

Sargent, T. (1993): Bounded Rationality in Macroeconomics. Oxford, UK: Oxford Univ.Press.

Sargent, T. J. (1996): Expectations and Non-neutrality of Lucas, Journal of Monetary Economics, 535-548.

Samouilhan, N. (2006): The Relationship between International Equity Market Behaviour and the JSE. ECONRSA, Working Paper Number 42.

Samuelson, P. A. (1939): Interactions between the multiplier analysis and the principle of acceleration, The Review of Economics and Statistics, 21(2), 75-78.

Samuelson, P. A. (1965): Proof that properly anticipated prices fluctuate randomly. Industrial Management Review 6, 41-49.

Samuelson, P. A. (1970): The Fundamental Approximation Theorem of Portfolio Analysis in terms of Means, Variances, and Higher Moments. Review of Economic Studies, 537-42.

SAS Elementary Statistics Procedures, (2010): SAS Institute (section on Kurtosis), http://support.sas.com/onlinedoc/913/getDoc/en/proc.hlp/a002473332.htm.

Scheinkman, J. A and LeBaron, B. (1986): Nonlinear Dynamics and Stock Returns. Journal of Finance, 26-48.

Schmitt, F., Schertzer, D. and Lovejoy, S. (1999): Multifractal Analysis of Foreign Exchange Data, Applied Stochastic Models and Data Analysis, 29-53.

Seo, M. G, Barrett L. F. (2007): Being emotional during decision making, goood or bad? An emprical Investigation. Academy of Management Journal: 923–940.

Sharpe, W. (1964): Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. Journal of Finance: 425-442.

Shaikh, A. (2010): Reflexivity, path dependence, and disequilibrium dynamics. Journal of Post Keynesian Economics, 33(1), 3-16.

Shiller, R. J. (1981): Do Stock Prices Move Too Much to be justified by Subsequent Changes in Dividends, The American Economic Review, 421–436.

Simon, H. A. (1957): Models of Man, John Wiley & Sons, New York.

Simon, H. A. (1979): Rational decision making in business organizations. American Economic Review, 493–513.

Smith, A, (1776): The Wealth of Nations, In: R.H. Campbell and A.S. Skinner (Ed.), The Wealth of Nations, Glasgow edition.

Sonnenschein, H. (1973): Do Walras' identity and continuity characterize the class of community excess demand functions?, Journal of Economic Theory, 345–354.

Sornette, D. (2004): A complex system view of why stock markets crash. New Thesis, 1(1), 5-17.

Soroka, S.N. (2006): Good news and bad news-Asymmetric responses to economic information, The Journal of Politics, 68, 372–385.

Soros, G. (2003): The Alchemy of Finance: Reading the Mind of the Market, J. Wiley.

Soros, G. (1990): Opening the Soviet System, London, Weidenfeld and Nicolson, New York: Distributed in the USA and Canada by Rizzoli International Publications.

Soros, G. (2008): The New Paradigm for Financial Markets: The Credit Crisis of 2008 and What it Means, New York: Public Affairs.

Summers, A. and Shleifer, H. S. (1990): The Noise Trader Approach to Finance. Journal of Economic Perspective, 19-33.

Stamps, A. E. (2002): Fractals, skylines, nature and beauty. Landscape and Urban Planning, 60, 163–184.

Statsa (2011): Natural resources accounts-Energy accounts for South Africa, 2005–2010, Discussion document.

Stein, E. M, and Stein, JC. (1991): Stock price distributions with stochastic volatility: an analytic approach. Review of financial Studies, 4(4), 727-752.

Stiglitz, J. (2002): Globalization and its Discontents, W.W. Norton & Company, Penguin books, New York.

Strate website, (2011): http://www.strate.co.za, 12 November 2011.

Taqqu, M.S. (1975): Weak convergence to fractional Brownian motion and to the Rosenblatt process. Mathematical Reviews, 287-302.

Taleb, N. (2007a): The Black Swan ; Impact of highly improbable events. New York: Random House.

Tang, T, Shieh, S. J.(2006): Long-memory in Stock Index Futures Markets: A Value-at-Risk Approach. Journal Of Business Finance, 21-55.

Taylor, R., Newell, B., Spehar, B, and Clifford, C. (2001): Fractals: A Resonance between Art and Nature Symmetry: Art and Science, 1, pp. 194–18197.

Taqqu, M. S. (1975): Weak convergence to fractional Brownian motion and to the Rosenblatt process. Mathematical Reviews, 287-302.

Teoh, S.W. (1999): The effect of socially activist investment policies on the financial markets: Evidence from the South African boycott. Journal of Business, 35-89.

Thornton, M. (2004): Who Predicted the Bubble? Who Predicted the Crash?. The independent Review, 5-30.

Toth, B. (2008): From multi-agent modelling to microscopic market dynamics: A statistical physics approach, PhD thesis, Budapest University of Technology and Economics.

Umpleby, S. (2010): From Complexity to Reflexivity: The Next Step in the Systems Sciences, Cybernetics and Systems '10 Robert Trappl (ed.) Austrian Society for Cybernetic Studies Vienna, Austria.

U.S. SEC Futures Trading Commission, (2010): Findings Regarding the Market Events of May 6, 2010, New York.

Vaga, T. (1990): The coherent market hypothesis. Financial Analysts Journal, 46(6), 36-49.

Van Ransburg, P. (1995): Economic forces and the Johannesburg Stock Exchange: A multifactor approach, De Ratione, 45-63.

Van Ransburg, P. (1998): Economic forces and the Johannesburg Stock Exchange, unpublished doctoral thesis, University of Natal, Natal.

Van Ransburg, P. (1999): Macroeconomic identification of candidate APT factors on the Johannesburg Stock Exchange. Journal for Studies in Economics and Econometrics, 27-53.

Velasquez, T. (2010): Chaos Theory and the Science of Fractals in Finance, ODEON Working Paper No. 5.

Veronesi, P. (1999): Stock Market Overreaction to Bad News in Good Times: A Rational Expectations Equilibrium Model, Review of Financial Studies, 975-1007.

Wall Street Journal Reporter (2010): Senators Seek Regulators' Report On Causes Of Market Volatility. Wall Street Journal, 15.

Wang, A. F. (2001): Over-confidence, Investor Sentiment, and Evolution. Journal of Financial Intermediation 10, 138–170.

Watanabe, T. (2001): Price volatility, trading volume, and market depth: evidence from the Japanese stock index futures market. Applied Financial Economics, 11(6), 651-658.

Weil, P. (1989): The Equity Premium Puzzle and the Risk-free Rate Puzzle. Journal of Monetary Economics 24, 401-421.

Wikipedia (2012), http://en.wikipedia.org/wiki/Black_Monday (1987), Date retrieved 23/05/20112.

Wray, D.B. , Papadimitriou, R.L. (2009): In The Elgar Companion to Hyman Minsky. In The Psychology of Financial Markets:Keynes, Minsky and Emotional Finance, by Sheila Dow. London: Cheltenham Press, 31-48.

Xiong, J and Idzorek, T, M. (2011): The Impact of Skewness and Fat Tails on the Asset Allocation Decision. Financial Analysts Journal, 2, 23-38.

Yalama, A., Celik, S. (2013): Real or spurious long memory characteristics of volatility, Empirical evidence from an emerging market. Economic Modelling, 30, 67-72

Yalçın, K. C. (2010): Market Rationality: Efficient Market Hypothesis versus Market Anomalies. European Journal of Economic and Political Studies, 23-38.

Yamamoto, R. (2006): What Causes Persistence of Stock Return Volatility? One Possible Explanation with an Artificial Market, New Mathematics and Natural Computation, 261–270.

Yamamoto, R. (2010): Order-splitting and long-memory in an order-driven market. Europe Phys, 51-57.

Yamasaki, R. (2005): Evolution with Individual and Social Learning in an Agent-Based Stock Market, Computing in Economics and Finance.

Yue, W. T., Chaturvedi, A. R., and Mehta, S. R. (2000): Is More Information Better? : The Effect of Traders' Irrational Behavior on an Artificial Stock Market. International Conference in Information Systems, Brisbane, Australia.

Zadeh, L. (1994): Soft computing and fuzzy logic. IEEE Software, 48 - 56.

Zeckhauser, R., Patel, J. and Hendricks, D. (1991): Non-rational actors and financial market behavior. Theory and Decision Journal, 257-287.

Zhang, L. (2011): Fractal Properties of the Industry Indices for Chinese and Japanese Stock Markets, Conference on Information and Financial Engineering (IPEDR), IACSIT Press, Singapore.