SEPARATION OF PRECIOUS METAL BETA FROM A JSE MULTIVARIATE MODEL WITH MACROECONOMIC VARIABLES

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Thesis submitted in partial fulfilment of the requirements for the degree of

MASTER OF COMMERCE in FINANCE (FINANCIAL & RISK MANAGEMENT)

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FEBRUARY 2015

DECLARATION

I Thabani Bonginkosi Mzobe, hereby declare that the work on which this thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work or any part of it has been, is being, or is to be submitted for another degree in this or any other university. I authorize the University to reproduce for the purposes of research either the whole or any portion of the contents in any manner whatsoever.

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ACKNOWLEDGEMENTS

I would like to first and foremost, thank the Lord God Almighty for His guidance, favour, grace and steadfast outpouring of wisdom and understanding which has helped me finally complete this dissertation. I am eternally grateful for the love and faithfulness.

I would also like to thank my family for their continued support through this entire journey. The completion of this dissertation would not have been possible without their support, patience, understanding and their unrelenting prayers. As a result, I would like to share this with them, my wife, Lufuno Mzobe, the Woman of God, Ziphokazi James and my sister, Sanelisiwe Ngaka, you have been the best and I am grateful for all the encouragement and assistance over these last few months. I would also like to dedicate this thesis to the rest of my family who have stood by me from our humble beginnings in rural KZN to this point in my life, may God bless you for all the assistance and the love.

I would also like to acknowledge and express my deepest and sincere thanks and gratitude for the supervision, assistance, encouragement and guidance from my supervisor, Glen Holman. Your availability for consultation and for giving direction has been amazing and made all the difference in my work and for that I am thankful.

ABSTRACT

This study examines a multifactor model of the Johannesburg Stock Exchange (JSE) framed within the Arbitrage Pricing Theory (APT). The APT has been set up such that it can be able to separate the beta for the precious metal factor within the model. The process goes via the investigation of macrovariables (with precious metals used as one of the macrovariables) and their effect on market (JSE) returns. A complete analysis and modeling of this relationship is likely to yield unparalleled rewards and cost-effective risk management, monitoring and mitigation. Using monthly data for the period 31/07/2002 to 30/04/2013 the dissertation focused on using a market (JSE) representative index as a basis for creating a wholly functioning APT model. This included creating a more liquid representative of the JSE All Share Index (ALSI) by using the top 100 stocks by market capitalization. Principal Components Analysis (PCA) was applied to the variables to ascertain a proper model for the JSE return structure. However, in the end an appropriate econometric structure in the form of Autoregressive Conditional Heteroscedastic (ARCH) and Generalized Autoregressive Conditional Heteroscedastic (GARCH) models was used and applied to test and create the APT model to address the objective.

The other purpose of this dissertation was to separate beta attributable to the precious metal macrovariable within the model. This is based on the establishment of the JSE in the late 1880s being primarily due to the discovery of precious metals in the former Transvaal (North West) and Pretoria, Witwatersrand and Vereeniging (PWV) region now Gauteng. This is to ascertain whether these metals still have as much influence on the JSE as they did for over half a century.

The results show that macroeconomic variables do influence the return generating process of the JSE, explaining almost 80% of variation in returns. The results show that the ALSI is characterized by a seven factor APT with, industrial production, money supply, SA consumer price index, ZARUSD exchange rate, crude oil, MSCI ACWI and precious metals statistically significant.

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LIST OF ACRONYMS

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
APT	Arbitrage Pricing Theory
BBL	Oil Barrel
BIC	Bayesian Schwartz Information Criterion
CAPM	Capital Asset Pricing Model
CRUDE	Brent Crude Oil price $/bbl
EMH	Efficient Market Hypothesis
ETF	Exchange Traded Fund
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GDP	Gross Domestic Product
GGM	Gordon Growth Model
GLD5PLAT	Precious Metal Variable (50% Gold price + 50% Platinum price)
HQC	Hannan-Quinn Criterion
INDPROSA	SA Industrial Production Index
INDPROOECD	OECD Industrial Production Index
JSE	Johannesburg Stock Exchange
MONEYSUP	M3 Broad Money Supply
MPT	Modern Portfolio Theory
MSCIACWI$	MSCI All Country World Index (US$)
OLS	Ordinary Least Squares
PCA	Principal Components Analysis
PP	Phillips-Perron
PVM	Present Value Model
SA	South Africa
SACPI	South African Consumer Price Inflation
SAGB10	SA 10-year Government Bond Yield
SARB	South African Reserve Bank
UK	United Kingdom
US	United States
ZARUSD	Nominal Rand/Dollar Exchange Rate

CHAPTER 1:
INTRODUCTION

1.1 BACKGROUND OF THE STUDY

The functioning and bustle of financial markets has been a source of intrigue and admiration for over a century given that they are an important aspect of the cogs of economic activity. Over the years stock prices have been identified as lead indicators of real economic activity and consequently business activity (Moolman, du Toit, 2005). As a result, stock market activity has been crucial in indicating whether it is a period of business investment or divestment. Financial markets also play an important role in indicating social moods, being linked with euphoria and misery of its participants and the general public as a result of activities within the exchanges e.g. the recent financial crisis in 2008. They can promote and stabilize economic growth by providing a sound base for the financial sector to thrive by serving as a channel that helps to attract domestic and foreign investments (Nkoro and Uko, 2013). According to Alile (1984), financial markets play a crucial role in mobilizing and allocating savings into investments in an efficient manner among competing usages which is imperative for any burgeoning economy.

It is for this reason that the link between the micro- and macroeconomy and the activities of financial markets have attracted a lot of interest from academics and policy makers for over half a century (Adjasi, 2009). This relationship continues to be investigated by different scholars to this day and a search for that parsimonious pricing model is ongoing (Nkoro and Uko, 2013). While a lot of research work has gone into this field, it is safe to say that no asset pricing model has been wholly accepted by practitioners within the academic fraternity.

The emergence of Harry Markowitz's (1952) modern portfolio theory, and its simple approach to maximizing expected return for a given amount of risk, gave rise to a thorough and imperative need to understand the portfolio construction process and the return generating process of underlying assets. This gave birth to the exploration and study into asset pricing models which led to the Capital Asset Pricing Model (CAPM). This pricing model was developed upon the mean-variance sufficiency framework (Shukla, 1997), and was introduced, separately, by Jack Treynor (1961, 1962) William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966). Although it is still popular and widely used in applications four decades later due to its simple practical approach and effectiveness in a wide range of situations, its empirical flaws have led to a pursuit and a flurry of more modern and empirically sound models. A popular one amongst these models is the arbitrage pricing theory, proposed by Stephen Ross in 1976.

These models serve a very important role within the financial markets industry as they continue to form a backbone for asset management decisions within the global landscape and consequently, South Africa. They provide stock market practitioners with a tool to be able to create an optimal portfolio based on a set of investment guidelines.

Similar to the underlying approach of the modern portfolio theory, the objective for most investors is always to get the maximum return for risk they can tolerate. This means that the objectives of portfolio managers are measured based on the expected return for the least amount of risk taken. As a result, portfolio managers must choose carefully from a list of seemingly infinite stocks and mix these with varying combinations to construct an optimal portfolio given utility preferences of investors. How do they make such selections with stocks on a global scale amounting to tens of thousands? They need, amongst other things, a properly functioning model that can assist in this process.

Modern portfolio theory also tells us that an investor does not get rewarded for taking on stock specific or unsystematic risk. MPT says that this type of risk can easily be eliminated through the process of diversification. As a result of this, a portfolio manager creates a portfolio of N>1 (N = number of stocks) to achieve diversification that eliminates this type of risk. However, there are limits to how diversified a portfolio can be. The concept of diversification means more diversification can be achieved as more and more stocks (subject to their covariance with the portfolio) are added to the portfolio. In fact, theory insists that a portfolio is not fully diversified until it holds all the possible investments across the world (Alexeev and Tapon, 2013). According to Grinold and Khan (2000), Bodie, Kane and Marcus (2011), Van Zyl et al, (2009) and a long list of literature, there are clearly diminishing marginal benefits to diversification with the “magical number” of adequate stocks required for sufficient diversification sitting anywhere between 21 and 30, depending on the market and covariance between assets (Alexeev and Tapon, 2013).

Due to the set of these “restrictions/constraints” along with a set of client guidelines, portfolio managers need a model that will enable them to select an optimal combination of these 21-30 stocks to create an optimum portfolio. Since the recent financial crisis, a great number of clients especially in the institutional space have been very finicky about risk management. They have kept a tight leash on the custodians of their investments, i.e. asset managers by keeping a close look on the amount of risk their investments are exposed to. They have done this by, amongst other things, placing tracking error[1] (TE) and ex-ante TE[2] constraints/limits. As a participant within an asset management firm, I have seen a rise in client requests for TE limits, and clients continue to require that managers closely monitor the ex-ante tracking error of the portfolio and ensure that it does not breach TE limits. How does a portfolio manager predict what ex-ante TE is? He needs a fully functioning model that will enable him to predict the return of shares in the portfolio and benchmark and then calculate ex-ante TE.

The fees that clients pay to asset managers that manage their portfolios have become a very touchy subject in financial markets over the last 5 – 6 years. This was on the back of the recent financial crisis and we have noticed investors increasingly scrutinizing fees they are required to pay as they are slowly less willing to pay for market beta. As a result of this, there has been a marked increase in the number of Index Tracker Funds (ITFs) and Enhanced Index Tracker Funds (ETFs) listed on the JSE as managers seek to provide a cheaper alternative for investors. The surge in these funds has resulted in the number of listed ETFs grow to 70 in 2014 (Williams, 2014). However, portfolio managers still require reliable quantitative models to create such funds.

Based on the above requirements, it is clearly important for financial market participants to have a wholly functioning, theoretically and empirically proven and sound model. This can either be used to ascertain the right mix of shares that will prevent TE limit breaches, predicting the best performing shares to be included in a quantitative driven portfolio or to enable asset managers to perform many of their fiduciary duties by making better informed decisions.

Gold shares have predominantly made the bulk of the FTSE/ JSE All Share Index (henceforth ALSI) through most of its history (Shapiro, 2013). This makes sense given that it was the very discovery of this and other precious metals that facilitated the establishment of the Johannesburg Stock Exchange (henceforth JSE) to enable newly discovered mines and their financial backers to raise capital. However, we have seen this sector diminish considerably in terms of size and relative stature within the ALSI over the last three decades to a position of obscurity (Van Rensburg, 2002). One of the byproducts of the financial crisis was the reemergence of precious metals, like gold, as safe haven and portfolio balancing assets. This has thus put the spotlight back on gold and the role it plays, not only as an instrumental asset within the broader economy of South Africa but also the

[1] Tracking error: *It is is a measure of how closely a portfolio follows the index to which it is benchmarked (Wikipedia)*. It is a *divergence between the price behaviour of a portfolio and the price behaviour of a benchmark. It is calculated as a standard deviation of the differences. This measure reports the difference between the return an investor receives and that of the benchmark he or she was attempting to imitate (Investopedia).*

[2] Ex-ante Tracking error: If a model is used to predict tracking error it's called ex-ante as opposed to ex-post which uses actual past returns.

effect its daily movements have on the returns of the ALSI.

Investing in the stock market is complicated and challenging, it involves an element of risk and uncertainty due to the fact that stock price movements are difficult to forecast, let alone understand (Moolman and du Toit, 2005). This creates a need for a thorough structural study and analysis which can help ascertain some of the characteristics of stock price movement and hopefully assist in developing a model for forecasting the stock market as a whole.

The introduction of MPT had a lot of influence on investors' decision making process. This led to an increase in interest and focus in the field of financial economics. As a result, a number of studies have been undertaken; focusing on asset pricing models and this is evident with the abundance of research literature in this field. However, it is deplorable that in emerging markets, there continues to be a considerable lag in this field compared to the voluminous work in developed markets (Iqbal & Haider, 2005). Although it has started to pick up in recent years, there still exists a necessity to conduct more research in this area to ascertain whether the results measure up to those in developed markets (Cauchie, Hoesli & Isakov, 2002).

This study aims to investigate the relationship between pre-specified macroeconomic variables and the JSE ALSI with a special emphasis on the beta of the precious metal factor. These pre-specified macroeconomic variables include; South African Industrial Production as a proxy for economic activity, OECD Industrial Production as a proxy for developed markets economic activity, Money Supply, Consumer Price Index, Bond Yields, Exchange Rate, Oil, Gold Price/Platinum Price/ 50% Gold & 50% Platinum and MSCI AC World as a proxy for foreign markets. The study uses the Arbitrage Pricing Theory (APT) introduced by Ross (1976), within the framework proposed by Chen *et al*. (1986).

It is important to set the background and examine the methodology used to reach the decision to use APT as the basis for this research. According to Singh (2008), one of the most essential issues in the field of financial economics is the price an investor pays to mitigate or reward they get for bearing risk. According to Markowitz's (1952) selection theory, investors cannot simply base their investment decisions purely on return maximization but have to be mindful of risks inherent in financial assets. As a result of this, it is always important for market practitioners to dig deeper and understand an asset's risk-return relationship before an investment decisions can be made. For this reason, a lot of theoretical and empirical research in finance has been dedicated to understanding the behavior of stock prices and thoroughly examining factors that affect prices of these risky assets. It is through this search for better understanding of stock pricing that the field of financial economics, on the back of Markowitz's modern portfolio theory, went down the road of discovering asset pricing models and it is safe to assume that the field has not looked back since.

The intricacies of asset pricing are the buttresses of financial markets functionality. The intertwined relationship between asset prices and their drivers is the core of all market activity and it is what keeps the ever so dynamic nature of markets going. This on the whole keeps market practitioners intrigued and interested and ultimately drives supply and demand which is the overriding economic force that drives prices and consequently market returns (Moolman and du Toit, 2005). The constantly changing nature of the economic phenomenon of supply and demand means that there will always be different equilibriums established leading to different prices and volatility thereof. This makes the search and identification of asset price drivers and factors that influence them ever more critical.

1.2 HISTORY, STRUCTURE AND MODERNISATION OF THE JOHANNESBRG STOCK EXCHANGE

Before we start with any work or analysis on this thesis we start by analysing the stock exchange, looking at its brief history[3]. The main objective of this thesis warrants that we trace the JSE's history given its roots of precious metals discovery and changes that have taken place over the years.

The biggest "bourse" in Africa and the 18th largest in the world and 8th largest in emerging markets by market capitalization (World Federation of Exchanges, 2012), has gone through a lot of changes since it was founded in 1887. The physical location, market capitalization, management, technology, association, membership, demutualization and a lot more changes have taken place in almost its 120 years of existence.

The Johannesburg Stock Exchange was established in November 1887. This was 14 months after the discovery and proclamation of the Witwatersrand goldfields in September 1886. The exchange was formed to enable the mining companies of the newly discovered mines and their financial backers to centrally and easily raise capital for further development of the industry. This further led to the formation of investment companies that were established with the intention of participating in the mining boom taking place at the time. The exchange was founded by a London business

[3] This is a well-covered topic in literature and to prevent reinventing the wheel, the discussion of this subject matter makes reference to the JSE as a source of most of this information.

traveler, Ben Minors Woollan, as the Johannesburg Exchange and Chambers Company, housed in central Johannesburg.

Strong unprecedented growth in the number of traders necessitated a change in buildings a number of times culminating with the move to the present offices based in Sandton in the year 2000.

The JSE went through more changes along with changing buildings over the years, with the open outcry system being replaced after 108 years of operation by an electronic trading system on 7 June 1996. The amendment of the legislation with introduction of limited corporate liability of foreign membership led to a plethora of foreign buyers flocking into the country in search of better excess returns, prior to this foreigners were not legally allowed to practice. Preceding this, sanctions imposed on the country due to apartheid also limited foreign participation. However, after the first democratic elections in 1994; a big impact on the JSE in terms of foreign participation was witnessed.

In anticipation of impending 1994 elections and the uncertainty of what was to follow given the turmoil that had been experienced in the lead up to this time, a number of individuals and companies aimed to take money offshore. As a result of this, the government looked to review exchange controls to better control flow of capital out of the country. At the same time there was renewed vigor to invest into the "new country" and this led to sizeable flow of capital into SA. Coupled with the fact that the world was entangled and gripped by the globalization phenomenon, the integration of the South African economy into world economy presented new avenues for the bourse. The market has benefited from capital flows into the country which have in some parts helped ease the pressure on the current account as portfolio flows plug the gap (Moolman and du Toit, 2005). This along with demutualization (all share certificates migrated to electronic settlement environment) in 2002 led to a complete change of guard on the JSE as this ushered in a new era and since this period there has not been a failed trade on the JSE. These developments have further enhanced the attractiveness of the JSE as an investor's destination and entry into Africa. The Exchange Controls Act has since been slowly relaxed.

The mining and financial companies that were originally listed on the JSE were joined by industrial shares which were nonexistent at the beginning due to the lack of industrial development and activity in the secondary sector of the economy at the time (Mabhunu, 2004). The JSE was and has always been a symbol of riches of gold mining companies and industry as shown by the reasons for its establishment (Murray, 1987).

However, we have seen a shift from this, in the 1980s, gold companies were the darlings of the exchange and made up over 50% of the JSE market capitalization, but the mining companies have been joined by a number of industrial companies which have transformed the look of the JSE (Moolman and du Toit, 2005). According to JSE index data, this has resulted in the portion of the JSE represented by gold companies shrinking to below 2% (see appendix II). How the mighty have fallen, the industrial companies have since overtaken not only gold companies but mining companies as a whole and now make up over 50% of the JSE All Share Index.

The roots of the JSE are deeply embedded in the mining industry, although a lot has changed over the years in terms of the role played by precious metals in the economy and stock market. Although the weight of gold and platinum shares has waned on the JSE and their contribution to the South African economy, Gold and Platinum as an investment and assets still play a big role in the financial markets and to the South African economy. A lot of investors continue to view the precious metals basket as the purest safe haven currency. As a result, the movement of precious metals as an asset still has a big influence on the economy and JSE with the fortunes of these still heavily linked to those of these metals.

1.3. OBJECTIVE OF THE STUDY

The main objective of this thesis is to identify and extract the beta attributable to the precious metal factor within a JSE multifactor pricing model. This thesis aims to go back to the grassroots of the JSE; precious metals were once instrumental in the formation and performance of this market and though size of these stocks has waned over time, the study aims to ascertain whether these metals still play an important role in the return generating process. For this study to achieve this, it is imperative to first empirically test the return generating process of JSE returns and develop a wholly functioning model within the confines of the APT multifactor model using ARCH/GARCH econometric framework. In the first part of the study, the validity of APT theory and its soundness as an asset pricing model is investigated and reviewed. The process to identify and select risk factors to test alongside the precious metal factor follows and is motivated by theory on APT. This study also investigates properties and characteristics of time series data of the JSE. This process analyses both returns and the volatility of data by considering innovations of both the mean and variance of returns and selecting an appropriate econometric framework that can handle the observed properties. In setting out to achieve the main objective of this study a few hypotheses are directly and indirectly analyzed along the way:

Hypothesis 1: *JSE returns are characterized by a multifactor model framed with the APT.*

Hypothesis 2: *JSE returns are characterized by non-normality, dependence and as a result the residuals have ARCH effect*

Hypothesis 3: *The risk premium of the precious metal factor within the multifactor model is statistically significant and non-zero.*

Hypothesis 4: *Global and past variance influences and explains the variance of JSE returns.*

The contribution of this study is in three ways. It first aims to investigate the influence of precious metals on the returns of the JSE. It then seeks to ascertain the true properties of time series return data on the JSE then identify and select an appropriate econometric framework to correctly account for these properties in the modeling process. This provides an improvement over a number of studies that heavily rely on the Least Squares methodology. Lastly, it looks at both the mean and conditional variance equation of these returns to capture both the moments of the mean and stochastic residual term. According to this author's knowledge, this has not been attempted or done within the South African market.

1.4. METHODOLOGY

This study relies upon the literature of the APT multifactor model and uses the ARCH/GARCH econometric framework (specifically GARCH (1,1)) to model the return generating process of JSE returns. This framework is well suited for financial time series data which frequently departs from normality and characterized by leptokurtosis and skewness and treats time varying variance as a variable that needs to be modeled. This framework is more robust in the presence of heteroscedasticity and adequately deals with ARCH effects in residuals compared to other frameworks.

1.5. ORGANIZATION OF THE STUDY

Chapter 2 reviews the theoretical literature of the APT and some of its predecessors. Chapter 3 focuses on empirical literature review and introduces different approaches and applications of APT, the statistical and preselected macroeconomic variables approach. It also reviews the ARCH/GARCH framework. Chapter 4 discusses the properties of time series returns. Chapter 5 discusses the creation of the FTSE/JSE ALSI Top 100 Index, the criteria used to identify and select risk factors used for the analysis. It also discusses the methodology in the form of ARCH/GARCH framework. Chapter 6 looks at the a priori expectations of factors, preliminary analysis of data and the correction of data. Chapter 7 presents the results of the study and observations. Chapter 8 provides a summary and conclusions of the study and possible areas of further research.

CHAPTER 2:

LITERATURE REVIEW: THEORETICAL BACKGROUND

2.1.1 THEORETICAL BACKGROUND: MORDERN PORTFOLIO THEORY & ASSET PRICING MODELS

Before we can go into detail about the asset pricing models, it is imperative to consider and review theoretical underpinnings that have given rise to such models. As a result, this chapter looks at the theoretical groundwork of the information effect on asset prices and the relationship between asset prices and the macroeconomy. Asset pricing models are based on assumption that markets are efficient, that makes it important to take a look at Efficient Market Hypothesis (EMH) to underline the important role it plays and the effect it has on pricing and behavior of asset prices. The next step is to then turn our focus to asset pricing theory and the underlying theoretical groundwork. The start will be looking at Capital Asset Pricing Model (CAPM) and then proceed to discuss the Arbitrage Pricing Theory (APT) and compare the latter model to CAPM. CAPM and APT represent the onset of asset pricing models following on the heels of Markowitz's Modern Portfolio Theory (MPT). These models assert that a linear relationship exists between the expected return of a stock and its identifiable risk factors. These models form the backbone of this research paper as will be discussed later.

2.2.1 EFFICIENT MARKET HYPOTHESIS

The Efficient Market Hypothesis (EMH) can be traced back to the independent works, with different research agendas, of Paul A. Samuelson (1965) and Eugene F. Fama (1963, 1965a, 1965b, 1970). However, it was Fama who operationalized and presented it – by summarizing it succinctly that "*prices fully reflect all available information*."

It is based on the principle that price of a stock at any given time fully reflects all available information. As a result of this, Fama (1970) believes stock markets to be entirely efficient, and captured by the idea of a "random walk". This concept deals with the highly elusive issue of why and how stock market prices change. The concept of random walk is of the view that, the flow of all available information is seamless and without delay and is immediately reflected in stock prices. This means that a stock price at any given time reflects news released at that particular time and future stock prices fully reflect and account for information and financial news available and released at that particular future time. The characterization of this news according to Fama is that it is unpredictable. According to Malkiel (2003), this means that by virtue of this unpredictability of news, news and stock prices of today cannot be used to predict stock prices tomorrow.

This means that arbitrage opportunities are impossible and as a result, market participants are unable to earn risk adjusted returns that are higher than those of the market by simply using publicly available information. According to Fama (1970) it is safe to assume that market prices will always fully reflect and thus equal the fundamental or true value of the stock. If these two prices are not equal, the difference will be too small for an investor to profitably exploit them given transaction costs.

2.2.2 PRESENT VALUE MODEL/GORDON'S CONSTANT GROWTH MODEL

The dividend discount model (DDM) or present value model (PVM) is the most commonly and used framework for evaluating share prices using the present value of all future dividends or earnings. The theoretical underpin of this model was provided by John Burr Williams in his 1938 study called; The Theory of Investment Value. It was then published by Gordon and Eli Shapiro in 1956. This model is based on the premise that a company's value is given by the sum total of its entire future dividend stream adjusted for length of time until the payment date and using the company's risk-adjusted rate. This means that security prices are determined by dividends and a discount rate (Smith, 1925). This is captured in the formula below:

$$P_{i,t} = \sum_{n=1}^{\infty} \frac{E(D_{i,t+n})}{(1+k_i)^n} \tag{2.1}$$

where P_i is the is the price of share i at time t, $D_{i,t+n}$ represents the future dividend payments and $(1+k_i)^n$ is the discount factor to be used to discount dividends to present value with k as the discount rate.

2.3.1 MORDERN PORTFOLIO THEORY & ASSET PRICING MODELS

After taking a look at the behavior of stock prices using EMH and the cause thereof as well as pinpointing the building blocks of stock pricing, the next step is to see how these filter through to the grassroots of various stock pricing models this study is exploring (CAPM & APT).

Rationality is the keystone of all utility theory and it is on this concept that the foundation of modern portfolio theory is based. The development of Capital Asset Pricing Model is based on the assumption that all individuals are utility maximizers and therefore everyone behaves rationally otherwise the concept falls apart (Mossin, 1966).

This subsection focuses on and highlights the foundation into research work on asset pricing models and transitions into the seminal paper by Stephen Ross (1976) on the Arbitrage Pricing Theory. This is done by looking at theoretical work that precedes this groundbreaking work, in particular the theoretical and empirical limitations of the Capital Asset Pricing Model. It also looks at the development of the APT and its theoretical and empirical advantages over CAPM.

2.3.2 MORDERN PORTFOLIO THEORY

The origins of MPT go back to Markowitz's (1952) paper on portfolio selection by introducing the concept of mean-variance optimization. This paper had far reaching implications insofar as it provides the theoretical and empirical rationalization of the process of diversification as practiced in financial markets today. He shows that when done right, diversification leads to an investor being rewarded by the market only for bearing systematic risk (Page, 1993).

As mentioned in chapter 1 section 1.1, Treynor (1961, 1962), Sharpe (1964), Lintner (1965), and Mossin (1966) expanded on Markowitz work merging it with Tobin's (1958) research of liquidity preference and separation theorem as behavior towards risk (Page, 1993). This gave rise to the groundbreaking equilibrium theory of asset pricing models in the form of Capital Asset Pricing Model (Sharpe, 1964).

The development of the theories, literature and models as presented here closely follows that presented in the articles by Treynor (1961, 1962), Sharpe (1964), Lintner (1965), and Mossin (1966), Ross (1976), Roll & Ross (1980) and Burmeister, Roll and Ross (2003). They delved extensively into the methodology and steps used to come up with these models. Given the measure and extent that they have gone to in providing complete clarity about the development steps, not much can be gained from trying to reinvent the wheel and thoroughly modifying the approaches used in these papers.

2.3.3 THE CAPITAL ASSET PRICING MODEL: ASSUMPTIONS AND LIMITATIONS

It is impossible to go into any study or research of asset pricing models without first touching on Capital Asset Pricing Model (CAPM). Beside the fact that it marked the birth of asset pricing theory as we know it, CAPM is still widely used today in a range of applications, five decades later. This is due to the simplicity of its application (Bodie *et al*, 2003), it is still used to estimate the cost of capital, comparing the performance of portfolios, using the Security Market Line (SML) to ascertain an expected return of assets at Initial Public Offerings (IPO) and evaluating the performance of portfolios against their benchmarks (Van Zyl *et al*, 2009).

It is a single factor model, with the return of the market assumed to be the only macroeconomic variable necessary, along with the individual stock return through beta, for stock valuation (Damodaran, 2002). As a result, investors are only rewarded for and should only be willing to pay a premium to avoid systematic risk. It seeks to minimize systematic risk, which the portfolio theory could not manage (though it was able to minimize unsystematic risk through diversification). This model can be mathematically represented as:

$$\boldsymbol{E(R_i) = R_f + \beta[E(R_m) - R_f]} \qquad (2.2)$$

where $E(R_i)$ is the expected return on asset i, R_f is the risk-free rate, $E(R_m)$ is the expected return on the market portfolio, $[E(R_m) - R_f]$ is the risk premium and β is beta of asset i.
As seen in equation 2.2, beta (β) (which is the relationship between the stock and the market) plays a big role in determining the expected return of asset i. This tells us that the higher the asset's beta (β) the higher its return is expected to be (ceteris paribus).

2.3.3.1 CAPM Assumptions

The CAPM in defined by the following assumptions for its equilibrium to hold: (Perold, 2004; Focardi & Fabozzi, 2004; Taylor, 2005):
All investors:

- *Are rational and risk-averse seeking to minimize portfolio risk through Markowitz's method of diversification and maximize wealth;*
- *Trade in perfect frictionless markets with no taxes or transaction costs, with all information available to simultaneously to them;*
- *Have homogenous risk and expected return expectations and investment horizon;*
- *Can borrow and lend unlimited amounts at the risk-free rate and are price takers*

The CAPM assumes that all investors have homogenous expectations i.e. they are mean variance optimizers meaning according to CAPM all investors will hold the market portfolio (Elton, Gruber, Brown & Goetzmann, 2003). This assumption is based on Harry Markowitz portfolio selection theory, with one of the conditions of Markowitz's modern portfolio theory being that it is essential for all investors to act according to the mean-variance axiom (Markowitz, 1952).

A lot of research has been published questioning and scrutinizing the effectiveness of the model in practice. Friend and Blume (1970), Blume and Friend (1973) and Fama and MacBeth (1973) are some earliest studies to scrutinize the work of CAPM. More recent studies by Ang and Chen (2005), Fama and French (2006) and Kassimatis (2008) have also delved into an investigation of the performance of CAPM and in more cases its validity has been found wanting with irregularities found in the performance of the model. Koo and Olson (2007) show that the model is not a good fit for portfolio management with it being better with smaller betas. Friend and Blume (1970) found that the CAPM's estimates of performance are seriously biased. The magnitude of the bias was seen to be related to the amount of portfolio risk. These empirical results cast a serious shadow over the validity, usefulness and applicability of the model. As a result of this, Blume and Friend (1973) concluded that the CAPM, as an explanation of observed returns on all financial assets, should be rejected (Erdugan, 2012).

As a result of the noted deficiencies of CAPM a lot of research went into trying to address specific certain assumptions in an effort to extend and improve the model. However, the additional theoretical research failed to make any improvements as such, empirical research into the model continues to be subject to much debate. Roll (1977), has gone to an extent of stating that validity of the model is an impossible hypothesis to test given the difficulty of identifying and measuring the true market portfolio. Apart from Roll's (1977) critique however, an abundance of empirical research has been undertaken and it is widely accepted that the pure theoretical form of the model does not fit well with reality.

2.3.3.2 A CONCLUDING REMARK ON CAPM

Although unquestionably the foremost theoretical breakthrough in the field of asset pricing models and a great expansion of the work of portfolio theory, CAPM has been demonstrated to have a multitude of limitations (Roll, 1977). From both a theoretical and empirical standpoint the model has been measured and found to be wanting in a number of aspects. It is apparent that some of the assumptions of the model, apart from being restrictive, are contrary to fundamental evidence concerning investor behavior and security returns' distribution (Fama, 1970).

2.3.4 ARBITRAGE PRICING THEORY

As a result of CAPM's documented inadequacies to capture risk sources of assets and the risk-return relationship, the Arbitrage Pricing Theory, developed by Ross (1976) emerged as an alternative asset pricing model. The APT gained much adoration and popularity amongst financial economics scholars as a result of its ability to overcome theoretical and empirical snags demonstrated by CAPM (Damodaran, 2002). The restrictive nature of CAPM's assumptions and its dependence on the not so clear-cut market portfolio have long been its Achilles heel and have led both market practitioners and academics alike to view it with much skepticism. This made the APT the next logical step in the evolution of asset pricing models. The APT was also shown to perform better than CAPM according to most empirical research (Priestley, 1994). Chen (1983) used factor analysis to prove that APT performs better than CAPM in US stock markets, this was also confirmed by Conner and Korajczyk (1988) using principal component analysis (PCA).

In this section we review, present and discuss briefly the development and advancement of multifactor asset pricing models. The multifactor pricing models are primarily based on the Arbitrage Pricing Theory (APT) dealing with a factor equilibrium ambit in which there are more sources of risk other than the singular market factor of CAPM.

As mentioned above the development of the theories, literature and models as presented here diligently tracks that presented by Ross (1976), Roll & Ross (1980) and Burmeister, Roll and Ross (2003) in their research articles. These authors wrote extensively on this subject and methodology thereof of this model. Given their approach and clarity, not much can be gained by trying to massively alter the approach they used in these papers.

THE DEVELOPMENT OF THE ARBITRAGE PRICING THEORY (APT)

The basis of APT is that stock prices react to sets of shared factors in a systematic way. This has had far reaching implications over the years on financial markets participants and the evidence of this is in the evolution of an array of sector specific indices e.g. financials, industrials, resources, etc.

The APT was developed by Stephen A. Ross (1976a, 1976b) as a response to the deficiencies of CAPM. According to Page (1993), Ross presented this model as an experimental argument with its basis on the preclusion of arbitrage and showing that the linear pricing relationship is a necessity for equilibrium of utility maximization. In the APT Ross (1976) identified that a set of k common factors are dominant return generating factors and there is no market portfolio requirement as the main source of risk.

The model begins with a set of neoclassical assumptions of perfectly competitive and frictionless markets (Fama, 1995; Van Rensburg, 1996), with homogenous expectations from investors that a return on any risky asset is a linear combination of various (k) risk factors rather than just one. It also assumes that investors are wealth maximisers and therefore risk averse (Reinganum, 1981; Van Rensburg, 1996). The APT assumes that return generating process can be described by a simple factor generating model of the form (Roll and Ross, 1980):

$$R_i\,(t) = E_i + b_{i1}f_1(t) + ... + b_{ik}f_k(t) + e_{i,}(t) \qquad i = 1,...., n \qquad (2.3)$$

where, $R_i(t)$ is the return on asset *i* at time *t,* E_i is the expected return on the i^{th} asset at the beginning of the period. The next k terms are of the form $b_{jk}f_j$ where f_j is the non-zero *j*th factor common to returns of all stocks. The b*ij* represents sensitivity of stock *i* to the movement of factor *j*. The factors are assumed to be pervasive i.e. affect all the securities similarly (Roll and Ross, 1980; Berry *et al.*, 1988). The last term e_i is the idiosyncratic risk of stock *i* i.e. unsystematic risk specific to asset *i*, it is independent enough to permit the law of large numbers to apply with $E(e_i) = 0$. It reflects the random noise that influences stock *i* and is unrelated to that of other stocks. As a result, the error term is the key restriction of the equation with $E(e_i^2) = \sigma_i^2$, $E(e_ie_k) = 0$, $i = k$ and *cov* $(e_if_j) = 0$ (Ross, 1976). Another assumption posited by Burmeister, Roll and Ross (2003), is that expectations at the beginning of the period, for all factor sensitivities and for asset specific error term are zero, i.e.;

$$E(f_1) = \ldots\ldots = E(f_k) = E(e_i) = 0 \qquad (2.4)$$

Roll and Ross (1980) suggested that, there should not be too strong a dependence on the error term for the asset return as this suggests that there are simply more than k factors and these extra factors have not been incorporated into the analysis.

The second postulate for the APT is that pure arbitrage profit is impossible (Burmeister *et al.*, 2003). This follows on the EMH concept of perfect competition in financial markets and it states that it is impossible for any market participants to make a positive expected rate of return on any combination of assets without taking more risk and without undertaking some net investment funds (Burmeister *et al.*, 2003). Dhrymes, Friend, Gultekin and Gultekin (1985), reckon that it is all the aforementioned assumptions about the nature of risk factors and arbitrage that make the APT model simple and easy to apply to derive any financial economic model on asset pricing.

The focal point for APT is the expected *ex post* return, the first term on the right hand side of equation 2.3 above (Paavola, 2007). As a result, APT theorem states that for equilibrium expected return for stock *i* there exists k + 1 numbers $P_0, P_1, \ldots\ldots, P_k$, not all equal to zero, such that;

$$E[r_i(t)] = P_0 + \beta_{i1}P_1 + \ldots\ldots + \beta_{ik}P_k \qquad (2.5)$$

This means that the expected return on asset *i,* is equal to P_0 plus the sum over j of β_{ij} multiplied by P_j (Burmeister *et al.*, 2003).

where; the P_j represent the risk premia for the j-th risk factor and thus can be used by any investor to determine the risk-return tradeoff while β_{ij} represents the stocks sensitivity to this risk factor (Chen, 1983; Berry, Burmeister & McElroy, 1988; Paavola, 2007). If we assume that we have a well-diversified portfolio, resulting in idiosyncratic risk being equal to zero, with zero sensitivity to all risk factors (i.e. $\beta_{i1}= \beta_{i2}=\ldots\ldots.= \beta_{ik} = 0$) this portfolio has zero risk and is equal to P_0 according to equation 2.5 (Ross, 1976). Therefore this means that if there is a risk-free asset with return R_f, then $R_f = P_0$. Similarly, by inference the risk premium for the j-th risk factor, P_j, is the excess return over the risk-free rate on asset *i* with a sensitivity exposure to P_j of one (i.e. $\beta_{ij} = 1$) and zero sensitivity to all other factors (i.e. $\beta_{ih} = 0$; for all $h \neq j$) (Burmeister *et al.,* 2003 and Pitsillis, 2005). According to Burmeister *et al.* (2003), the full APT model is obtained by substituting equation 2.5 into equation 2.3 ending up with;

$$R_i (t)- P_0 = \beta_{i1} [P_1 +f_1 (t)] + ... + \beta_{ik} [P_k + f_k (t)] + e_i \qquad (2.6)$$

This equation helps us make a distinction between CAPM and APT, where the stock's excess return in the CAPM equation is given by the beta times the market's excess return (Burmeister *et al.*, 2003). However, for the APT the investor can control and determine this excess return by adjusting the portfolio's exposure to a certain factor. This can be done through increasing or decreasing exposure to a certain factor. As a result, this means that investors can control expected return through stock selection (Roll and Ross, 1980; Burmeister *et al.*, 2003; Ouysse and Kohn, 2008).

Equation 2.5 gives us the expected return for asset *i* at time *t* but the actual return is hardly ever equal to the expected return due to surprises that always take place in any economic situation (Burmeister *et al.*, 2003). Thus putting all of this together, the return on asset *i* is given by;

$$R_i (t) = E[r_i (t)] + U[r_i (t)] \qquad (2.7)$$

where $U[r_i (t)]$ is the unexpected return, equation 2.7 looks a lot like equation 2.3 which means the unexpected return is given by the second part of equation 2.3 (Chen, 1983 and Elton & Gruber, 1988) meaning;

$$U[r_i (t)] = b_{i1}f_1(t) + ... + b_{ik}f_k(t)+ e_{i,}(t) \qquad (2.8)$$

However, given equation 2.4 and that by all construction an investor does not expect or anticipate any economic surprises when constructing a portfolio and these are usually unintended bets. The second term of equation 2.7 can thus be seen as a measure of good or bad luck for the investor depending on the contribution of these unintended exposures to portfolio return (Burmeister *et al.*, 2003). As a result of equation 2.4 and according to Chen, Roll and Ross (1986) and Burmeister *et al.* (2003), given the fact that all economic factors over long historical periods their sample means will be approximately zero. As a result, by inference, over extensive historical sample time periods the contribution to return from unexpected return will be approximately zero. This means that over sufficiently long periods realized return on a perfectly diversified portfolio is given only by the expected return in equation 2.5.

While equation 2.5 may look and be interpretable as a multifactor or multi-beta CAPM Ross (1976) argues that the APT holds in all but the most extreme cases of disequilibrium and in so doing is able to provide a forward looking pricing structure that is not central or based on the market portfolio which has proved very hard to identify.

THE SELECTION AND NUMBER OF FACTORS USED TO ESTIMATE THE APT MODEL

After the development process, the next step is to touch on the process followed to estimate and test the model. Roll and Ross (1980) used a three-part test to ascertain the model's ability and their data seemed to support the APT as a model. However, Shanken (1985) questioned the problems presented by the model, especially the fact that the number of factors needed by the model seem to be indeterminate. He argues that there exists an embarrassing gap between the theoretical importance of priced pervasive factors and actual identification of these factors (Nkoro and Uko, 2013). It is understandable that each market may have its own pervasive factors which may not be necessarily similar to the next. However, given the relative importance that has been attributed to these factors across decades of literature, it would be safe to assume that a lot of work could have been dedicated to identifying these common factors.

Burmeister *et al.* (2003) hypothesizes that there are three different methods that one can use to estimate risk factors of the model;

i. *"They can be computed using statistical techniques such as factor analysis or principal analysis*
ii. *K different well-diversified portfolios can substitute for the factors*

iii. *Economic theory and financial markets knowledge can be used to pre-specify K risk factors that can be measured from available macroeconomic and financial data"*

Each of these methodologies can be used and each is suited for a certain kind of analysis depending on the end user. The first approach is essential and useful in helping to ascertain the value K. This approach includes making assumptions and using theory to specify variables of the equation and then using a covariance matrix to build and test the theory. The second approach is straight forward and normally leads to a lot of insights about which portfolios investors can choose and invest in given their factor loadings.

The third approach seems to be the most intuitive as it involves examining ex post/realized stock returns and then linking these to macrovariables that apply or that may have been responsible for these moves. According to Chen (1983) this is the most important approach for APT and represents the future of research since it allows for the interpretation of common factors. In this approach, contrary to the statistical approach which generates the factors through factor or principal component analysis, macroeconomic factors are prespecified or preselected. This involves marrying both theory as well as practical experience in the financial markets to create a model that is theoretically and practically applicable (Chen, 1983; Burmeister *et al.,* 2003).

The first and second approach usually have an undesirable property which makes it almost impossible to understand because the process used leaves these factors non-unique linear combinations (Burmeister *et al.*, 2003). The other reason is that these factors almost never remain the same from sample to sample, meaning that a combination that may have been factor 2 in one sample is almost guaranteed not to be in the next (Chen *et al.*, 1986). The statistical procedures also use artificial variables and lack intuitive appeal given that they use stock returns to estimate stock returns (Shukla, 1997 and Burmeister *et al.* 2003).

These issues make it difficult to infer which specific economic factors underlay the analysis and as a result, pure statistical analyses may lead to incorrect conclusions (Brown, 1989). It is for this reason of the apparent lack of intuitive appeal of the statistical methodology that this research shied away from it. It would have become problematic to separate the precious metal beta or identify which factor was represented by this. As a result, no conclusion could be drawn from the approach that would have been helpful in the investigation being carried out in this paper. The factor analytic and PCA approaches are explored in brief detail in the empirical literature review with some pioneering results of this approach, also included in the appendix for reference purposes and completeness of the thesis.

Due to the scrutiny associated with the use of statistical techniques for the APT, Chen (1983) believes that the model is more suited to macroeconomic variable analyses. However, selection of appropriate set of macroeconomic variables, although it is easier, still requires as much skill as it does science. The factors need to be easy to interpret as a result surpassing the difficulty presented by statistical procedures. According to Berry *et al.* (1988) different stocks and/or portfolios are influenced differently by different factors and as should be expected to very varying degrees. This is very important for portfolio diversification purposes, as a well-diversified portfolio can be constructed by selecting different stocks depending on how they react to factors.

The selection of these macroeconomic variables is where this method encounters shortcomings; as there is still no discipline that guides this selection process making it a concern that needs addressing. This however, is the same problem encountered by statistical procedures as there is no process for deciding and selecting the identity and number of factors within APT literature.

What bodes well for the macroeconomic methodology though is the fact that Chen and Jordan (1993) critically analyzed the APT using both factor analysis and macroeconomic variable procedure of Chen *et al.* (1986). They found no significance differences between results of the two different procedures. This means that not much is lost when switching from factor analysis, which was predominantly used for the APT, to using the macroeconomic variable approach. They also showed that the macroeconomic procedure may actually be better when the two procedures are tested against a test period or a holdout sample. Nevertheless, due to the desirable simplicity of the macroeconomic model, Chen and Jordan (1993) state their preference for it over the statistical procedures and they prefer it due to the economically interpretable factors. They ascertain that the macroeconomic methodology APT models expected returns very well and does not take away from the accuracy. This is a big plus for this simple model that does not need big computational power to ascertain returns. As a result, this is the methodology that will be used for this paper albeit the statistical procedure results have been included in the appendix.

2.4 CONCLUSION

In this chapter we outlined and retraced the initial development and progress of asset pricing theory from its roots to the APT to fully highlight the evolution that has taken place in this field of financial economics. We showed that the APT is a multifactor generalization offering a testable alternative to the CAPM, which can be applied on a subset of many risky assets and it does not require nor heavily rely on the market portfolio which is the bedrock of CAPM.

Further to this a review of the Capital Asset Pricing Model (CAPM), as a pioneer of the asset pricing models was done. However, the restrictive nature of the assumptions of CAPM and its dependence on the market portfolio proved to be its undoing. This led to the development of a new model which was perceived to be better and has been proven to be so over the years by various scholars, the Arbitrage Pricing Theory (APT).

The APT provided an advantage over CAPM because of its use of the multifactor structure and being able to identify and make use of more than one source of risk (Paavola, 2007). The various procedures used to derive the APT were also explored and reviewed. It was determined from the above review that the APT model derived from preselected macroeconomic variables is preferable and advantageous over the statistical procedure, especially for this study. The APT though is not without its shortcomings, it fails to identify these multiple factors that need to be used in the model. It is also silent on the number of these factors or selection thereof.

In the next chapter a full review of empirical literature of the APT with specific focus on macroeconomic variables and their link to stock pricing is conducted to provide an overview of the application of the model.

CHAPTER 3:
EMPIRICALLITERATURE REVIEW

3.0 INTRODUCTION

In the preceding chapter we discussed various asset pricing models and expanded on the presence of multifactor model which is used in the return generating process. This implies existence of multiple risk sources pervasively influencing stock prices and returns. This chapter looks at empirical literature which exists in this field where macroeconomic variables are used as these multiple risk factors to explain fluctuations in stock market returns.

The chapter consists of two sections, a very brief empirical review of literature that utilizes statistical methods to model the return generating process in APT. The second section, which is the focus of this paper, reviews empirical literature that uses preselected macroeconomic variables to model the return generating process within APT. However, for completeness of the thesis and to fully encapsulate all the literature that was reviewed and relevant for this study we will first take a look at the original method of the APT, the statistical procedure.

The second section is further divided into subsections with focus on literature from global and developed markets before looking into emerging markets and South Africa. The chapter also reviews literature on ARCH/GARCH framework which is the methodology used in the study. The chapter ends by taking a look and summarizing the chapter sections.

3.1 APT EMPIRICAL TESTS AND EVIDENCE

There are numerous different studies that exist that have investigated the applicability of the APT framework in various markets and under different situations and time periods. The one embarrassing gap in this literature continues to be that of the identification and number of factors (Grinold and Kahn, 2000). This makes the bounds of possible factors open and makes the task even more difficult as there is a wide variety of possible factors (Grinold and Kahn, 2000). Roll and Ross (1980) posit that the number of factors is not as important as priced factors in the model. As a result, this still means that the fundamental requirement for the APT is having the right priced factors to have a properly functioning model (Burmeister, Roll and Ross, 2003). As discussed in the previous chapter, there are two different schools of thought when deciding or ascertaining factors for the APT model (Padron *et al.,* 2006). The first is the original approach which was used by Roll and Ross (1980) in their seminal paper. This method was originally proposed and used by Gehr (1978) and was mostly used in the original studies of the applicability of the APT model. This method is known as the statistical procedure and is further divided into two parts, the factor analysis and principal component analysis (PCA). The latter was suggested by Chamberlein and Rothschild (1983) to deal better with large data samples. These statistical techniques simultaneously compute the entire model, including both factors and the stocks sensitivities to the underlying factors (Altay, 2003).

The second school of thought relies on preselected macroeconomic variables as factors to be used in the APT model. This procedure is using the method of Chen, Roll and Ross (1986), it does not rely on statistically extracted latent factors but on intuitively selected macroeconomic variables as systematic factors within the APT model.

These different methods will be reviewed in sections 3.2 and 3.3, respectively

The main reason for this chapter is to review the potential factors and how they are identified for the APT model, the methodologies used in producing these factors and which econometric techniques are used in ascertaining the risk-return relationship in the return generating process.

3.2 EMPIRICAL TESTS AND EVIDENCE: STATISTICAL PROCEDURE

There is a wealth of literature on this subject as a number of theoretical and empirical tests have been conducted to ascertain the applicability of the model and more so with the aim of critiquing, refining and improving various facets of Ross's original work. Gehr (1978) did the first empirical test of the APT in 1978; however the work of Roll and Ross (1980) is widely considered as the foundation of all empirical work done on this subject. A host of academic scholars have since followed suite trying to identify, measure and test effectiveness of the factors affecting share returns. The failure of the original theory to specify and classify factors needed in the return generating process is an embarrassing gap and has had various scholars looking to identify and discover the true nature and number of these factors and consequently somewhat has contributed to the volume of research in this area.

3.2.1 STATISTICAL PROCEDURES: Factor Analysis

The statistical technique is the approach that was used in the initial empirical tests of the APT to extract relevant factors for the return generating process. In this section we will start by reviewing the Factor Analysis technique.

The main idea of this technique is to describe the covariance relationships among multiple variables in terms of minimized unobserved underlying factors. It assumes that variables can be grouped together by their correlations to one another, assuming that they are not or have very small correlation to any other group within the same data. As a result, it is possible that each group can be assumed to represent a single underlying factor responsible for the correlation presented by the group (Johnson and Wichern, 2007).

The factor analytic approach tests of the APT are based on a two-step procedure (Priestley, 1994). In the first step the main aim is to select a time period and use a sample of stocks, sample portfolio sets or stock index to estimate the factor structure of the sample (Burmeister, Roll and Ross, 2003). This means that in this process the analysis simultaneously estimates b_{ik}'s and f_k's (in equation 2.3 by setting E_i equal to a constant) in a way that a preset proportion of the covariance of the residual terms is minimized (Elton *et al.*, 2007). In this process the analyst can preset a level of probability at which below this level the probability of extracting an extra factor is negligible meaning that the factors identified before this level make up the number of factors in the return generating process. This has further implications, meaning that any analyst or researcher can set their own arbitrary level as a cutoff for addition of extra factors. This makes the process of setting the number of factors very subjective. In the first step the estimated sensitivities (b_{ik}'s) which are estimated from the time series data form the backdrop for the procedure's second step. The second step of this procedure involves estimating price of risk or risk premia.

According to the APT, the estimated risk premia should be the same across all different assets, portfolios and/or index supporting the assumption that systematic factors are pervasive (Priestley, 1994).

3.2.2 FACTOR ANALYSIS: Empirical Tests

Due to the large volume of research in this field, the statistical section will only cover pioneering work. As mentioned above, to our knowledge, Gehr (1978) was the first to perform an empirical test of the APT. He used factor analysis on a set of 41 companies selected from various industries and used these as a sample for factor mimicking portfolios. In the second set of data he used 24 industry indices. He extracted three factors and discovered that only one of these had a statistically significant premium and thus ascertained that the stock returns within the US market were characterized by a one factor model.

Although, Gehr (1978) is credited with the first empirical test of the APT, the groundbreaking work was done by Roll and Ross (1980). They used a much more comprehensive test of the APT which was the first to use the two-step factor analysis procedure developed by Fama and MacBeth (1973). Their main aim was to extract factors and their risk premia (size, sign and significance of these) and test the restrictions of the APT by using daily data of 1260 stocks from NYSE and AMEX, for the period July 1962 to December 1972. They discovered that as many as four risk factors are priced i.e. have significant risk premia.

Chen (1983) looked to develop a method that will be better able to handle large scale data to avoid using small samples due to computational constraints. He used factor analysis on daily US stock returns from 1963 to 1984 to test the superiority of the APT over its predecessor, the CAPM. He proceeded to test whether the residuals from CAPM are explained by the APT to prove that the model is indeed correct, and the results proved that to be so. As a result, Chen (1983) proved that the APT outperforms the CAPM and is better at explaining the empirical irregularities found in CAPM.

Beenstock and Chan (1986) used an approach similar to Chen (1983). They used monthly returns of 220 UK stocks listed continuously from December 1961 to December 1981 (their analysis period). They imposed a restriction of at least one trade per month on the data to avoid estimation problems due to non-trading. Due to the fact that smaller capitalized firm are less likely to trade than their large capitalized counterparts, their data was more biased towards large capped stocks. They concluded that a 20 factor model performed much better than a four factor model. However, they did admit that since they could not prove outright that none of these factors were idiosyncratic there is a chance that there may be less than 20 factors but greatly more than four.

3.2.3 STATISTICAL PROCEDURES: Principal Component Analysis

All the tests discussed until now have employed factor analysis on testing the APT. However, as indicated above that factor analysis cannot handle large sets of data, development of an alternative approach had to be explored. The work of Chamberlain and Rothschild (1983) pioneered the use of principal component analysis (PCA) a statistical method that preserves the diversifiable property of stock specific returns while weakening the diagonality condition (Shukla, 1997). Priestley (1996) called it the natural way to estimate parameters from an approximate model. According to Chamberlain and Rothschild (1983); PCA can be used to estimate the decomposition for large samples, using eigenvectors as factor loadings (Shukla, 1997). This gets around the computational constraints cited by Roll and Ross (1984) as the reason they used smaller samples. Shukla (1997) believes that the relative ease of calculating the principal components makes the technique attractive as it also does not violate the stationarity assumption. Another great advantage of PCA approach is that it gives the factor scores directly without the need to use two steps used by factor analysis of first estimating the risk premia and then getting the factor scores.

In the extension of the work of Chamberlain and Rothschild (1983), Trzcinka (1986) used PCA on weekly data and was one of the first ones to pioneer the work into APT using PCA along with Connor and Korajczyk (1986). He looked at 865 stocks and reached a conclusion similar to that of Roll and Ross (1980) that the return generating process is characterized by more than one factor.

Cauchie, Hoesli and Isakov (2004) used Xu's (2003) maximum explanatory component analysis (a form of principal component analysis) to study monthly returns of nineteen industrial sector portfolios of the Swiss stock market. These covered a period from 1986 to 2002 and looked to derive risk factors using PCA to compare against the macroeconomic procedure. PCA produced five significant factors versus four from the macroeconomic approach (industrial production, market return, term structure and changes in inflation).

In trying to ascertain risk factors that drive hedge fund returns, Fung and Hsieh (2004) used principal component analysis to construct a seven factor model. The constructed model proved very robust explaining about 80% of variation in monthly returns of hedge funds.

Building on the work of Fung and Hsieh (2004), Teo (2009) attempted and succeeded in using principal component analysis to increase the number of factors from seven to nine and was able to account for the returns of Asian portfolios using the model.

According to Connor and Korajczyk (1993) the one weakness of the PCA technique is that it has fewer restrictions in assuming that the idiosyncratic term is diagonal, this method will recognize these idiosyncratic factors as common, distorting findings (Xu, 2007). This means that in finite economies where perfect diversification cannot be achieved the model will be contaminated by idiosyncratic factors (Shukla, 1997; Xu, 2007). This was evident in the research conducted by this researcher for this paper. Using the top 100 stocks listed in the Johannesburg Stock Exchange between August 2002 and April 2013, the extracted factors contained a large proportion of firm-specific components in the factor model (please see

Appendix II) and as a result total variation presented a large percentage of firm-specific variation.

However, Shukla and Trzcinka (1990) show that most researchers do not believe that the eigenvalues of PCA will perform better that factor loadings extracted using factor analysis in estimating the return generating process of the APT. As a result, most researchers have shunned this methodology despite it presenting advantages over its counterpart.

After looking at the APT factors extracted using statistical techniques one conclusion is clear, that these techniques appear to be unfavorable (Brown, 1989). The problem that we have discussed above is that of the inability to interpret factors extracted through statistical techniques. Statistical factors rely on stock returns to explain stock returns and this does not have economic appeal since the factors cannot be linked to economic forces (Shukla, 1987; Burmeister, Roll and Ross, 2003; Graham and Burrus, 2000). This would make for interesting observation allowing us to marry the factors extracted to some kind of market or macroeconomic phenomenon that is driving stock returns. This could be beneficial for stock market participants to better apply results of the APT analysis by better isolating the drivers of certain risks and being able to position their portfolios in a way that militates against this risk or hedge against it.

3.3 MACROECONOMIC FACTORS

The difficulty encountered by this study in trying to extract precious metal factor beta from a model derived using statistical factors coupled with the problems mentioned in the previous section motivated for a look into an alternative methodology that uses prespecified variables. The financial market is believed to be a leading predictor of the underlying and future economic state. As a result, most participants are always watching closely for economic data releases (e.g. Non-Farm Payroll numbers in the US) to effect and inform their investment decisions (Glen Holman, PowerPoint Presentation, February, 2011).

According to Padron and Boza (2006), the need to correctly identify the factors that impact returns led a plethora of academics and researchers to pursue this technique. Also from a statistical point of view this technique has an added advantage of using economic information plus stock returns to provide estimates with better properties (Burmeister *et al.,* 2003). One caveat is that, there is still no theory behind the selection of these presepecified variables, the selection is based on each author's understanding and knowledge of the underlying financial market and its possible drivers.

3.3.1 MACROECONOMIC FACTORS: GLOBAL AND DEVELOPED MARKETS

Nai-Fu Chen (1983) was the first researcher to postulate that the APT factors be given some kind of economic interpretation. However, this would not happen until the pioneering work he did with Roll and Ross in 1986 that used, *ex* ante, a set of prespecified variables as proxies for pervasive factors (Connor and Korajczyk, 1993). The work of Chen, Roll and Ross (1986) provided a watershed in terms of this approach. Chen *et al.* (1986) used the dividend discount model as the basis for selection of candidates for factors and they looked to select variables that could affect the discount rate and thus affect the current stock price and then those which could have an effect on the stock price through company earnings and consequently dividends (Poon & Taylor, 1991). Their work laid the foundation from which APT models that prefer to bypass statistical procedures could draw reference (Elton and Gruber, 1995).

They selected a change in industrial production; a measure of unexpected inflation, a change in expected inflation as variables that could affect future dividends. They used a measure of the term structure (long government bond return less the return on short term government bonds (Treasury bills)) and a measure of risk premium or default risk (a difference in returns on low-grade corporate bonds and government bonds. They also included two stock market indices to capture any factors that may have not been included in the list above but have pervasive effect on returns and also to leave room for the model to collapse into the CAPM with market being the single factor. They also included oil and consumption as possible factors.

They used Fama and MacBeth's (1973) two step procedure. They used data from January 1953 to December 1983 and formed 20 equally weighted portfolios based on market value. They divided the analysis period into three sub-periods. They used 60 months of data to estimate betas in the first stage and used betas as independent variables to ascertain estimates of sensitivities in the second stage. They then tested these sensitivities for statistical significance and the results showed that the APT is characterized by five factors with the risk premia for industrial production, unexpected inflation, changes in expected inflation and term structure premium statistically significant through the entire period whilst the risk premium factor was marginally significant.

They used portfolios because these provide for a good spread of risk and return which improves the discriminatory power of cross-sectional regression tests (Priestley, 1994), portfolios reduce the noise that is present in individual stocks and they also reduce the errors in variables (EIV) problem inherent in the two-step procedure caused by the use of estimated betas rather than actual ones. According to Black, Jensen and Scholes (1972) forming portfolios produces estimates of betas which are closer to actual betas.

A number of studies followed suite on the work of Chen *et al.,* (1986) using the same framework to prove the validity and superiority of APT over CAPM. Berry, Burmeister and McElroy (1988), also followed on the work of Chen *et al.* (1986) and using the same five prespecified variables ascertained that the five factor APT model performed superior that the single factor CAPM model.

Priestley (1996) used pre-specified factors in the UK market and found seven macroeconomic and financial factors that are statistically significant, the default risk, industrial production, exchange rate, retail sales, money supply, unexpected inflation, change in expected inflation, term structure of interest rates, commodity prices and market portfolio.

Ratanapakorn and Sharma (2007) used six macroeconomic variables to investigate a relationship between macroeconomic factors (long-term interest rates, short term interest rates, industrial production, inflation, Yen/USD exchange rate and M1 money supply) and monthly returns of the S & P 500 index from January 1975 to April 1994. They discovered that there is a long-term relationship between US stocks via the S & P 500 index and six macroeconomic factors. These variables

Humpe and Macmillan (2007) looked into the relationship between macroeconomic variables and stocks in the US and Japan. They used monthly returns of S & P 500 and Nikkei 225, respectively, from 1960 to 2004 and four macroeconomic factors (industrial production, M1 money supply, CPI and 10-year Treasury bond yield for the US and the officiala discount rate for Japan). Their results showed that there is a relationship between stock returns and Industrial production, CPI and bond yields for the US and Industrial production, CPI and M1 money supply for Japan. M1 money supply and discount rate were found to be insignificant for US and Japan, respectively. Japanese stocks were more sensitive to Industrial production than US stocks proving that macroeconomic variables have a different impact on stock prices in different markets (Humpe and Macmillan, 2007).

The results of Humpe and Macmillan (2007) in Japan seemed to be in the same vein as those of Brown and Otsuki (1990) who found that the APT in the Japanese stock market is characterized by five factors; money supply, a production index, crude oil price, exchange rates and call money rates. Also, Mukherjee and Naka (1995) investigated the APT within the Japanese stock market and found cointegration between the stock market and six variables; exchange rate, inflation rate, money supply, real economic activity, long-term government bond rate and call money rates (Nkoro and Uko, 2013).

McSweeney and Worthington (2007) took a look at the impact of oil and other macroeconomic factors in the Australian market. They used excess returns from January 1980 to August 2006 and investigated the impact of; the market portfolio, oil prices, exchange rates and the term premium. Their results indicate that the market portfolio, oil prices, exchange rates and the term premium are priced in the Australian stock market.

This followed on the work of Faff and Chan (1998) that took a look at the price determinants of the gold industry shares in Australia. They investigated the effect of macroeconomic variables on these shares, namely; market return; gold prices, interest rates and exchange rates using data from 1979 to 1992. They found that only the market return and gold prices provided significant explanatory power.

Cheung and Ng (1998) looked at data from five countries, Canada, Germany, Italy, Japan and US and found a link between some country specific economic variables and stock returns. These were real output, real oil price, real consumption and real money supply.

These were pioneering studies in various markets and results show the APT to be an intuitive concept that can be applied to any market with significant results. The studies provide enough support for the APT and *ex ante* macroeconomic variables. However, Taylor (1991) used the same factors as those used by Chen, Roll and Ross (1986) and found no evidence of a relationship between share returns and macroeconomic variables in the UK and noted that different markets may be characterized by different sets of macroeconomic factors. Their observation provided great insight into the APT model that uses macroeconomic variables as candidates for factors; it shows that factors that are applicable in one market may not be so in another. Their results also had the significance of growing the number of possible factors that are investigated in different markets as the need arose to capture, determine and add more country specific factors (Huberman and Wang, 2005).

3.3.2 MACROECONOMIC FACTORS: EMERGING MARKETS

As demonstrated above, there is irrefutable evidence of a link between macroeconomic variables and stock returns within the APT framework. However, the wealth of this empirical work has been from developed markets; however, emerging markets are slowly catching up in this field. This may have something to do with the late development of stock exchanges in these markets especially with the onset of globalization and markets opening more and more to external investors. However, stock exchanges in emerging and frontier markets continue to be characterized by thin trading and remain unstable and shallow (Nkoro and Uko, 2013). This has major implications for the APT model as this affects the effectiveness of the model especially in economies with a finite number of securities because it means that the unsystematic risk is not completely diversifiable (Shukla, 1997).

The work available in these markets has tended to focus on using models that do not have any theoretical basis, vector autoregressive (VAR) and vector error-correction (VECM) models (Peng, Cui, Groenwold and Qin, 2009). These methodologies have been widely because there's no theoretical framework a priori requirement before these can be used in ascertaining the relationship between macroeconomic factors and stock returns. This means that the results from these should be treated with a bit of caution as they tend to be undependable.

However, Adjasi and Biekpe (2005) used these models; in analyzing macroeconomic factors from 7 African countries and found that the depreciation of exchange rates in the long-run leads to higher share prices in some countries while it causes a drop in share prices in the short term (Salihu, 2013).

Maysami and Koh (2000) used VECM and looked at data from the Singapore market using seven-year data from January 1988 to December 1995 and concluded that there is a relationship between share returns and changes in money supply (positive), short and long-run interest rates and exchange rates (negative relationship).

Some studies in emerging market have however used Chen, Roll and Ross's (1986) APT framework to analyze the relationship between macroeconomic variables and stock returns. Fifield, Power and Sinclair (2002), looked at the relationship between macroecoomic factors and stock returns of thirteen emerging stock markets over a ten-year period, 1987 to 1996. They looked at data from Chile, Greece, Hong Kong, India, Korea, Malaysia, Mexico, the Philipines, Portugal, South Africa, Singapore, Thailand and Turkey. They looked at both local and global macroeconomic variables, in keeping with Chen *et al.* (1986) they used six local factors; inflation, exchange rates, short-term interest rates, gross domestic product, the money supply and trade balance. They used world market return, world inflation, commodity prices, world industrial production, oil prices, and US interest rates for global factors. They concluded that GDP, inflation, money supply, interest rates, world industrial production and world inflation explain fluctuations in returns of emerging stock markets. As expected, the significance varied across different markets and factors.

In the Croatian market Benakovic and Posedel (2010) looked at 14 stocks for the period of January 2004 to October 2009. They test five variables, namely; inflation, industrial production, interest rates, market index and oil prices as factors. They use the two-step testing methodology and the results show that the market, interest rates, oil prices and industrial production have a positive relationship with stock returns while inflation has a negative influence.

Zhu (2012), tests nine macroeconomic variables for the period between January 2005 and December 2011 for stocks listed in energy sector of the Shanghai stock market. He employed OLS and found that exchange rates, exports, foreign reserves and unemployment rate have an impact on the returns of the stocks in the energy sector.

Butt and Rehman (2010), use GARCH technique to examine the effect of macroeconomic variables on the returns of different industries of the Karachi stock exchange. They used data from July 1998 to June 2008. The results reveal that the market return is the biggest driver while the inclusion of other macroeconomic variables increases the explanatory power of the model.

On the other hand Iqbal, Khattak, Khattak and Ullah (2012) use a two-step methodology to identify the macroeconomic factors that have an effect on a sample of 26 stocks listed in the Karachi stock market. They use data from 2004 to 2008 and the results showed that inflation, exchange rate, money supply and oil prices are priced in the APT framework of the Karachi stock market.

In the Turkish market, Kandir (2008) used six macroeconomic variables and applied OLS methodology for the period 1997 to 2005; he concluded that the consumer price index, exchange rate, interest rate and return on the MSCI World significantly affected the return of stocks in this market. On the other hand, industrial production, money supply and oil prices showed no relationship with stock market returns.

Ramadan (2012) tested the applicability of the APT model in the Amman stock market in Jordan from 2001 to 2011. He used OLS methodology to test; interest-rate term structure, inflation, money supply and risk premium and two market indicators; the dividend yield and productivity of the industry. The results show that interest-rate term structure, money supply, risk premium and dividend yield are priced in the Jordanian stock market.

Nguyen (2010) used a two-pass methodology proposed by Fama and MacBeth (1973) to investigate the APT framework in the SET (Stock Exchange of Thailand) using data from January 1987 to December 1996 and concluded that exchange rates consistently explain returns along with industrial growth rate.

Moving closer to home, Eita (2012) used VECM methodology in Namibian market data from 1998 to 2009. He discovers that economic activity, money supply, inflation, interest rates and exchange rates are variables that are priced in this market.

Nkoro and Uko (2013), use GARCH in Mean technique to estimate the impact of macroeconomic variables on the Nigerian stock market returns using annual returns from 1985 to 2009. Their results show that inflation, government expenditure, index of manufacturing output and interest rates are priced in while money supply and exchange rates show no statistical significance.

Adjasi (2009) also uses one of the models of the GARCH family of models as a technique to analyze the impact of macroeconomic forces on stock price movement in Ghana. He uses EGARCH for data from January 1991 to January 2007 and finds that cocoa prices, interest rates, gold price, money supply and oil price have an effect on stock market returns of the Ghana stock exchange.

In this section we have taken a look at some of the work that has been done to apply studies similar to Chen *et al.* (1986) in emerging markets. Researchers have used similar macroeconomic variables as those used back in 1986 but have also added a lot of country specific ones. In the end we have a wide range of variables that can be candidates for risk factors. These include industrial production (as a proxy for economic activity), interest rate, inflation, oil price, exchange rates, money supply, gold price and some global indices to capture the international element. However, as mentioned, the literature is silent on the selection process and with no theoretical background as a base the best course of action is to provide motivation for the selection of variables before proceeding with the analysis.

3.3.2.1 MACROECONOMIC FACTORS: SOUTH AFRICAN STUDIES

The study of macroeconomic variables and their relationship to stock market returns has received a reasonable amount of attention in South Africa (Moolman and du Toit, 2005). However, most of these studies have focused on the structural models or the like within the South African stock market, these include studies by; Barr and Kantor (2002), Van Rensburg and Robertson (2003a, 2003b, 2004), Moolman and du Toit (2005), Auret and Sinclaire (2006), Basiewicz and Auret (2009). They focused and placed much emphasis on size and value effects following on multifactor models that focus on firm-specific attributes developed by Fama and French (1992) as well as testing the efficiency of the market. Some studies however also investigated the effect of multiple macroeconomic factors on returns of the Johannesburg Stock Exchange (JSE) using the APT framework and using testing technique of Roll and Ross (1980) and Chen *et al.* (1986). These include studies by Page (1986), Page (1996), Van Rensburg (2001), Mangani (2007b), Manageni (2008b), Mangani (2009), Chinzara and Aziakpono (2009), Chinzara (2011), to mention but a few.

The early pacesetters and pioneers in the field of APT framework within South Africa were Page (1986) using Roll and Ross's (1980) technique and Van Rensburg (1995, 1998, and 1999). Van Rensburg is considered to have contributed the largest to the literature of modeling returns and macroeconomic variables within the JSE (Moolman and du Toit, 2005). The study of this nature helps determine whether the APT is applicable only to developed markets or whether it is still structurally sound in an emerging market like South Africa lending much weight and underpinning to the theoretical foundation of the model (Altay, 2003).

The initial analysis of the APT in South African used the Roll and Ross (1980) technique of factor analysis. Page (1986) used the factor analysis approach of Roll and Ross (1980) to test the APT framework within the JSE and found that the market is characterized by a two-factor model.

Van Rensburg and Slaney (1997) also applied the same methodology (maximum likelihood factor analysis) and came to the same conclusion that the JSE is characterized by a two-factor return generating process. They went further and used McElroy and Burmeister's (1988) approach by trying to link the two factors to observable proxies and give them economic interpretation. They found that these two factors can be proxied by the Gold and Industrial indices of the JSE. After the movement from the I to the J series by the JSE which necessitated the classification of the sub-indices and sectors within the JSE, Van Rensburg (2002) updated the proxied indices and in keeping with the original conclusion of Van Rensburg and Slaney (1997) found that FINDI (Financials and Industrials) and Resources indices can be utilized as the observable proxies of the first two factors in the APT model of the JSE and thus these could be substituted into the original APT equation.

Aside from Van Rensburg and Page, Barr (1990) also followed factor analytic approach to try and identify macroeconomic factors that affect stock returns on the JSE. He found that short-term interest rates, the gold price, foreign stock markets and business confidence are priced in the return generating process of the JSE.

Van Rensburg also investigated the APT framework within the JSE using Chen *et al* (1986) pre-specification of variables approach. Van Rensburg (1995) investigated the relationship between four macroeconomic factors; namely the unexpected changes in the term structure, unexpected changes in inflation expectations, unexpected changes in the gold price and unexpected returns on the NYSE against the JSE. He concluded that all four factors significantly affected returns on the JSE.

Van Rensburg (1999) investigated the effect of several macroeconomic variables on the JSE overall index, industrial and gold index. He reached a conclusion that returns of these three indices are significantly influenced by long-run interest rates, gold and foreign reserves and the balance of the current account. He also found out that the return of the industrial index is influenced by short-term interest rates and Dow Jones industrial index and the gold index is affected by the exchange rate and the gold price.

Moolman and du Toit (2005) developed a structural econometric model for the JSE estimated using co-integration and error-correction techniques. It aimed to identify the macroeconomic variables that affect the returns of the South African stock market and their conclusion was that the JSE is determined according to the dividend discount model with short-term rates, exchange rates, S&P 500 index, the gold price and risk premium being the key drivers of returns.

Barr, Kantor and Holdsworth (2006) looked into the effect of exchange rates on the JSE top 40 companies and the JSE. They used GARCH (1,1) technique to estimate betas and concluded that short-term movements in the JSE are dominated by movement and direction of the rand.

Mangani (2009) used a GARCH (1,1) framework to analyze the effect of the discount rate and gold price changes on JSE stocks. The results show that the discount rate influenced the mean returns of stocks while the gold price influenced the volatilities of return of these stocks. Following on his earlier work, Mangani (2011) used the same GARCH (1,1) model to investigate the effects of monetary policy on JSE portfolios. He found that the discount rate affected both the mean return and return volatilities of JSE stocks.

Chinzara and Aziakpono (2009) show that returns and volatility within the South African market are linked to global markets with Australia, China and USA shown to have the most impact. This means that there is a need for an international factor to capture the effect of these global influences.

Chinzara (2011) looked into the macroeconomic uncertainty and stock market volatility on the JSE and found that volatility of exchange rates, short-term interest rates; oil prices, gold prices and inflation affect stock market volatility.

Hsing (2011) looked into the effects of certain macroeconomic variables on the South African stock market using EGARCH (1,1) technique of Nelson (1991) with data from 1980 to 2010. He finds that the stock market in South Africa is influenced by growth rate of real GDP, ratio of money supply to GDP, US stock market index, ratio of government deficit to GDP, domestic real interest rates, nominal exchange rate, domestic inflation and US government bond yield.

All the studies reviewed above introduced an interesting phenomenon in the field of finance, by giving market participants (and researchers) the opportunity to link stock returns with real underlying economic factors. They changed the consensus in the market and this led to a plethora of publications in this field. Due to the volume of research in this field both in developed and emerging markets, not all literature could be reviewed but rather the focus was on the pioneering literature as well as that literature that helped formulate this paper. As a result, a plethora of literature which looks into the relationship between macroeconomic variables and the market was researched and explored but not included in this paper[4].

[4] For further reading on this topic one can make use of these studies. These include, but not limited to, Burmeister and Wall (1986) who re-examined the factors proposed by Chen et al. (1986), McElroy and Burmeister (1988), Chen and Jordan (1993), Connor and Uhlaner (1988) and Rahman et al. (1998), Mukherjee and Naka (1995), Cheung and Ng (1998), Maysami and Koh (2000), McMillan (2001), Chaudhuri and Smiles (2004),

3.3.3 LITERATURE REVIEW: ARCH AND GARCH FRAMEWORK

In order to correctly and accurately forecast returns and their relationship with economic factors one needs a properly functioning and modern technique to fully utilize the model. The Least Squares (LS) methodology is generally used when analyzing multifactor models (Burmeister and Wall, 1986). This is based on the supposition of constant variance of residual terms. However, this supposition does not always hold in reality especially for financial returns which normally tend to be heteroscedastic (Gujarati, 2003). If the assumption of homoscedasticity does not hold this methodology (LS) is used for the analysis and estimation of regression coefficients, these will be inefficient and will not have minimum variance which is the purpose of Least Squares. They will also have overstated standard errors with very large confidence intervals meaning we cannot use data to make any accurate statistical inferences. Therefore, to ensure that we make correct statistical inferences, we need to use the right methodology to model the return generating process.

As a result, an econometric framework from the family of ARCH/GARCH models is used. This framework was chosen for its ability to deal with heteroscedasticity, non-normality, dependence and volatility clustering (Engle, 1982; Palm, 1996 and Engle, 2004). According to Dowd (2005), ARCH/GARCH family of models treats heteroscedasticity as a variance to be modeled and as a result corrects for what least squares methodology cannot and thereby avoid instances where incorrect inferences are made. The ARCH/GARCH family of models can accommodate kurtosis and are tailor made for financial time series, and volatility clustering which causes leptokurtosis (Dowd, 2005). It goes a step further by estimating the variance of individual terms and identifying a more robust depiction of the return generating process (Engle, 1982; Engle 2001). This makes the ARCH/GARCH family of models the closest to true "*random residuals after standardizing for conditional distributions*" (Engle, 1982).

Engle (1982) introduced the ARCH model in 1982 and Bollerslev (1986) generalized the ARCH model, GARCH. After this Engle and Bollerslev (1986) collaborated to produce the Integrated GARCH (IGARCH) model. Soon after a number of extensions followed suite, Engle *et al* (1987) ARCH-in-Mean (ARCH-M) and its generalization, GARCH-in-Mean (GARCH-M) model and Nelson's Exponential GARCH (EGARCH). A great number of further extensions and generalizations have been proposed to which Engle (2004) referred to as the *alphabet soup of ARCH models* (these include but not limited to; AARCH, APARCH,

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Moolman (2004), Gan et al. (2006), Nikkinen et al. (2006), Ratanapakorn and Sharma (2007), Humpe and MacMillan (2007), Gunsel and Cukur (2007), Paavola (2007), Olalere (2007), Ahmed (2008), Kilian and Park (2009), Bonga-Bonga and Makakbule (2010), Hancocks (2010), Connor and Korajczyk (2010) and Odhiambo (2011). The list however is too long that it cannot exhaustively be covered in this paper.

FI-GARCH, FIEGARCH, GED-ARCH, TARCH, MARCH, NARCH, SNPARCH, SQGARCH, CARCH and many more).

The ARCH models can be used for various functions and volatility forecasting is one of these. Xiao and Aydemire (2007) argue that volatility forecasting has grown in terms of importance in financial markets especially over the last decade. Akgiray (1989) proves that ARCH and GARCH models forecast volatility better than Historical Average and Exponentially Weighted Moving Average techniques. Engle (2004) states that, due to the assigning of optimal weights to parameters; these models make it possible to obtain forecasts of variance closest to those of the next period.

French *et al* (1987) used GARCH-in-Mean to prove that the daily returns of the S&P Composite index are positively related to the volatility of returns between January 1928 and December 1984. Chou (1988) posits that the ARCH/GARCH family of models is an effective tool when it comes to modeling the behavior of financial time series data.

The ARCH/GARCH framework allows the conditional variance to be modeled as a by-product of the conditional mean equation. This is helpful when looking at macroeconomic variables that do not seem to demonstrate any effect on the mean returns but influence volatility like gold prices and when looking at volatility spillovers from international markets. Morales (2008) argues that the most effect of gold on returns is through volatility spillovers and feedback. As demonstrated in the literature review, Mangani (2007) used a GARCH (1,1) model to show that gold prices influenced the volatilities of returns of the JSE. There is also a long list of researchers that have sought to use the ARCH/GARCH family of models to model returns on the JSE or to calculate volatility to be used in some analysis of JSE information.

3.3.4 CONCLUSION

This chapter reviewed the empirical work done in this field starting with work done in global markets, then proceeding to emerging markets before taking a look at South Africa. The empirical evidence we looked at shows that the APT model is robust and applicable across most (if not all) markets around the world. This was demonstrated by looking at the two different schools of thought used to test APT. We took a look at the statistical approach developed by Gehr (1978) and Roll and Ross (1980) and looked at the approach where macroeconomic variables are pre-specified. Multiple studies were done in developed markets utilizing the former technique ascertained that most markets are characterized by the APT model. However, it could not provide concrete answer on the number of factors as these proved to be different in different markets. This technique faced some criticism due to its inability to assign real economic variables to the factors derived.

The next methodology that was reviewed was that of pre-specifying macroeconomic variables and this showed that there is a strong link between stock returns and macroeconomic variables. This methodology has been widely used and favored in the field of finance due to its applicability to real life situations and benefits. Although the work of Chen *et al* (1986) is recognized as the base in this field, there still lacks the theoretical foundation on the selection of the appropriate variables. As a result, variables tend to differ across different countries with a wide range selected due to their applicability in that particular country. The empirical tests reviewed above showed a long list of priced factors in different markets namely; money supply, industrial production, interest rates, inflation rate, exchange rates, oil prices, gold prices, global factors, and many more. As with statistical procedures, literature fails to tell us how many factors are actually necessary for the APT model.

The APT model has also been subject to some analysis within the South African market with Van Rensburg (1996, 1997, 1999 and 2002), Page (1986), Jefferis and Okeahalam (2000), Moolman and Du Toit (2005), Olalere (2007), Mangani (2008a), Hancocks (2010), Gupta and Modise (2011) and Hsing (2011) among a few that have shown that the JSE is characterized by a multifactor model in the form of APT.

CHAPTER 4:
DATA PROPERTIES AND BEHAVIOUR

4.1. INTRODUCTION

After reviewing literature on models that are used to analyze the generating process of the APT, one hardly encounters instances where properties of underlying data are discussed. Most studies assume that the underlying data is normally, independently and identically distributed. These assumptions make the process of analyzing data much easier as it avoids having to take the steps to rectify and correct data for use in the analysis. However, Mangani (2007b, 2008b) argues the assumption that data on the JSE is independently and identically distributed and that it is multivariate normal showing that the GARCH (1,1) model is the best model suited for JSE data. He posits that out of all the ARCH family of models the GARCH (1,1) model presents the best fit for properties observed on the JSE. According to Engle (2001) the GARCH (1,1) is the simplest and most robust of the family of ARCH/GARCH models. Even in its simplest form it has proven very successful in giving parsimonious models that are easy to estimate (Engle, 2001). Bollerslev (1992) calls it easily the workhorse of all financial data analysis and handling. As a result, before we discuss the methodology used for this analysis, the first step that needs to be undertaken is to do an exploratory analysis of data used in this analysis to ascertain whether it fits the characteristics and properties of data that requires an ARCH/GARCH model.

The one glaring shortcoming of the studies of the adequacy of APT done by Chen *et al.* (1986) was their failure to give adequate attention to the properties of the stock returns in their analysis. This shortcoming may translate into even bigger issues as the failure to give due care to behavior and properties of data may lead to an incorrect econometric methodology being used to estimate the model. The use of an incorrect methodology may also lead to inaccurate conclusions and thus nullifying whatever result may have been observed (Gujarati, 2003). In most studies of this nature, researchers normally make an assumption about the supposed distribution, behavior and other characteristics of the data which do not always hold in reality. This chapter investigates the assumptions of normality, independence, volatility clustering and stationarity before deciding which framework best suits the discussed properties and behavior.

4.2. THE BEHAVIOUR AND PROPERTIES OF JSE SHARE RETURNS

The level of volatility and returns that can be achieved in emerging markets has been covered widely in literature (Harvey, 1995; Kim and Singal, 2000). The return generating process using the APT framework has also received a lot of attention as mentioned above but it is the properties and behavior of data that most hinders application of the correct econometric model.

4.2.1. THE DISTRIBUTION OF RETURNS

The starting point when it comes to data used in any analysis is to assume that it is normally distributed (Tsay, 2002). However, many empirical studies point otherwise especially since the work of Mandelbrot (1963) (Fama, 1965).
In reality, with properties of data, skewness measures symmetry around the mean while kurtosis measures how peaked the distribution of the data is, with leptokurtic data having kurtosis greater than 3 with fat fails whilst platykurtic data has a kurtosis of less than 3 and less data in the tails (Brooks, 2008).

In his analysis, Fama (1965) found a greater proportion of data to be centered around the mean with a great number of observations observed in the tails compared to that which is implied by the normal distribution. This means that the assumption of normality is not an accurate standpoint for data. Praetz (1972) along tested properties of stock returns and concluded that, along with most studies, financial time series data is not normal but characterized by excess kurtosis.

According to Arditti (1967), an investor will always be reluctant to accept an investment with negative skewness, because it has a limited upside relative to the much larger loss that may be experienced. Simkowitz and Beedles (1980) further expand on the work of Arditti (1967) on skewness and posit that asymmetry is very prevalent that data cannot be expected to be normal.

As a result of these studies, rather than assume a normal distribution for our data, we will conduct our analysis of normality using the Jarque-Bera statistic. This will be shown in the chapter six and the selection of an appropriate econometric model for the data chosen.

4.2.2. INDEPENDENCE OF RETURNS (AUTOCORRELATION)

The APT framework requires that data used in the analysis of the return generative process be unpredictable. The general assumption in literature is that there is no major direct dependence in stock returns (Cont, 2001). This is based on the work of the weak-form EMH, which says an investor cannot use previous day's returns to predict future returns. EMH posits that returns should be independent of one another because economic news come into the market in a random, independent form and stock prices adjust to this information without there being any correlation to past moves (Reilly and Brown, 2012:152-153). This means that the independence of returns supports EMH and points to it as being valid (Cont, 2001). Autocorrelation is deemed to be present if returns at t are either positively or negatively correlated to returns at time $t-1$, $t-2$, etc. In the assumption of no correlation;

$$(\tau) = corr(r(t), r(r + \Delta t)) = 0\ ) \tag{4.1}$$

According to Campbell *et al.* (1997), if equation 4.1 is correct then financial time series can be assumed to have no autocorrelation and consequently independent.

Akgiray (1989) rejects the assumption of independence using Ljung-Box Q statistics saying that financial returns are dependent. Lo and MacKinlay (1988) using weekly NYSE data found evidence of first order serial correlation in indices and aggregate portfolio returns while they found no evidence in individual stocks.

4.2.3. STATIONARITY

One of the properties of returns that has received a lot of attention and has been investigated thoroughly is that of stationarity. This is when time series of return is assumed to be identically distributed leading to both mean and variance remaining constant over time (Gibbons and Hess, 1981). This means that the properties of data from sample to sample do not produce different qualities (Mandelbrot, 1967). Non-stationary data has far reaching implications for any analysis as it often lead to incorrect inferences, meaning that a sample cannot be used to statistically make an inference about the whole population. As a result, given the fact that most economic indicators tend to have an upward trend, one cannot simply apply simple regression methods as this will encounter false correlations (Michailidis, 2008).

Although there is still debate on the non-stationarity of the mean, scholars are in agreement on the variance differing over different time periods. The widely used test for stationarity is the Augmented Dickey-Fuller (ADF) test of Dickey and Fuller (1979). Time series data has unit root if its data has a negative or positive trend to it in any given time (Brooks, 2008). One way of correcting for no-stationary data is first differencing or rate of change which is normally applied to economic data. The method of rate of change is the method that will be applied to non-stationary data in this paper and with it a possibility of spurious regression should be remote (Chinzara and Aziakpono, 2009).

4.3. VOLATILITY AND VOLATILITY CLUSTERING

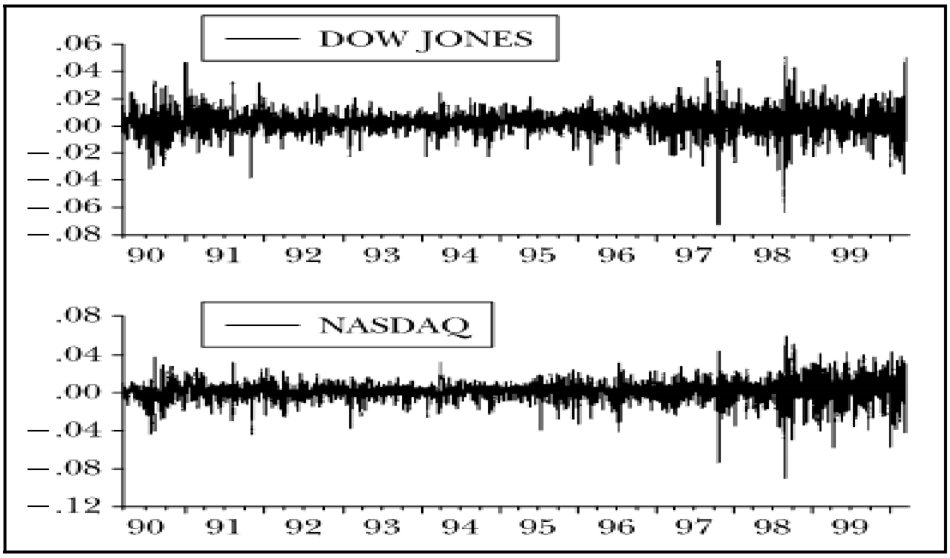
Volatility is defined as the measure of price variation over time resulting in a spread of all possible outcomes of any uncertain variable being observed (Poon, 2005). The study and measure of volatility has long been an interest of financial participants but there is still no theoretical basis on how volatility comes into existence in the first place, although some point to it being affected by the microstructure of the market (Roll, 1984). The shape and spread of the distribution is of utmost importance to financial market participants for a various number of reasons. As indicated above, the shape of the distribution informs, for instance, risk averse investors whether they want to be exposed to a certain security. Investors in financial markets define volatility of data as risk, as a result, they factor this in their investing decisions as it guides portfolio construction, is chief in option pricing and risk management. Some of the reasons why volatility matters to financial market participants;

i. the issue of portfolio diversification as defined by Markowitz (1962), centers around risk as defined by volatility,
ii. the greater the volatility the wider the range of possible outcomes and as a result if a certain cash flow is required from an investment for certain reasons (this includes retirement savings, funding, investment or payment), the greater the possibility of a shortfall arising and;
iii. it is a parameter in the Black-Scholes model and thus is crucial for option pricing.

As a result of this, an analysis of risk in any economic or financial data is important as it gives a picture into the behavior of data and its distribution.

4.3.1. VOLATILITY CLUSTERING

Volatility clustering in finance is a phenomenon when periods of high (low) volatility in returns are followed by periods of high (low) volatility. This means that volatility fluctuation is a dependent function over time meaning that alternate periods of high volatility and calmness are grouped together and characterize data (Chan and Cryer, 2008). This means that contrary to Black Scholes equation's assumption of constant volatility, variance changes with time as modelled in Bruno Dupire's Local Volatility, Poisson Process and Heston model of stochastic volatility where volatility moves to new levels or increases over time, respectively (Jacobsen & Dannenburg, 2003). Returns are not correlated but absolute returns, $|r(t)|$, or their squares display a positive or decaying autocorrelation function (Kirman & Teyssiere, 2005). Engle (2001) notes that volatility clustering is evident when one looks at time series data of financial prices (see figure 4.1).



Source: Engle (2001)

Figure 4.1: Time series plot of DJIA and NASDAQ returns

Figure 4.1 shows plots of the Dow Jones Industrial Average and NASDAQ illustrating Engle's (2001) of observable volatility clustering in returns. They show that the amplitude of returns is of a time-varying nature. They illustrate what is known as the ARCH effect which leads to the deviation of the data distribution from normal often leading to excess kurtosis (Engle, 2001). Defined in terms of risk, this means that some periods in markets are riskier than others and this is not by chance but connected in some order (Engle, 2001).

Samouilhan (2007), Louw (2008) and Niyitegeka and Tewari (2013), investigated and found presence of volatility clustering in JSE returns.

The observation of this nature has led to the use of the ARCH/GARCH family of models for model analysis, volatility forecasting and pricing of derivatives as these models are able to account for effect of clustering in their analysis (Engle, 1982 and Bollerslev, 1986).

4.5. CONCLUSION

The distribution of stock returns is assumed to be normal, which is not always a true reflection of reality. Returns in reality tend to deviate from this assumed normal and are characterized by excess kurtosis, fat tails and skewness. Returns appear to be dependent and literature has shown that where they appear to be independent it is only for a short while. They do however demonstrate volatility clustering which has necessitated the introduction of ARCH/GARCH models. Some studies have indicated presence of volatility clustering and deviation from normality for JSE data. Although this study is yet to determine whether our data is characterized by a violation of these assumptions, literature in general calls for an econometric model that accounts for these violations. This ensures that the inferences made are statistically accurate. This is the reason this paper has chosen to use the ARCH/GARCH model for this analysis and the methodology will be discussed in the next chapter.

CHAPTER 5:

ECONOMETRIC ANALYSIS: JSE, DATA AND METHODOLOGY

5.0 INTRODUCTION

This chapter sets to discuss the data used and identify the econometric methodology used for the analysis and achieve the objectives set out in chapter one. The main aim is to demonstrate advantages of using the econometric framework chosen to achieve objectives set out in chapter one. After this the chapter includes the process followed to choose the macroeconomic variables to use as candidates risk factors in our model. As demonstrated in the literature we reviewed, the main aim of this step is to demonstrate the link between every macroeconomic variable chosen as a factor and stock market returns.

As discussed in the previous chapter financial time series data is not well behaved and according to Mangani (2007b, 2008b) JSE returns are neither independent nor identically distributed but are characterized by non-normality, clustering and heteroscedasticity. He proceeded to show that of all the complex alternatives in the ARCH family of volatility models, the GARCH (1,1) model is a more suitable description of JSE returns (Mangani, 2009:49). As a result, I have chosen to use a GARCH (1,1) model, in accordance with Mangani (2009), to model the returns of the JSE with the aim of identifying the macroeconomic variables that are priced in the return generating process with a special focus on beta of the precious metal factor.

5.1 SELECTION OF VARIABLES AND DATA

The analysis in this study focuses on aggregate index data of the FTSE/JSE. However, instead of the widely used FTSE/JSE All Share Index which has +/- 164 shares, this study uses a truncated index. The reasons for this decision will be explained below, this created index consists of the Top 100 shares listed on the JSE as measured by free-float market capitalization and is called FTSE/JSE ALSI Top 100 Index. Nine macroeconomic variables were chosen as shown in table 5.1 below, namely: South African (SA) industrial production[5], OECD industrial production, SA money supply, SA consumer price index, SA 10-year government bond yield, USD/ZAR nominal exchange rate, Morgan Stanley Capital Index: All Country World Index (USD) (henceforth MSCI ACWI), USD precious metal index (gold and platinum price) and USD oil prices. These chosen variables have been selected due to their perceived importance as

[5] This is used as a proxy for South African GDP because the GDP data is released on a quarterly basis and industrial production is a good proxy as it measures the real economic activity.

determinants of stock market behavior and thus influencing returns. Also these variables have been chosen as guided by the literature review as they featured prominently in a number of studies of a similar fold done on the JSE (Jefferis and Okeahalam, 2000; Moolman and du Toit, 2005). The data used for this study is for the period 31 July 2002 to 30 April 2013, sourced from various sources as shown in the table below.

Table 5.1 Variable Description and Source Summary

Variable Code	Name Description	Source	Log Transformation	UNIT
ALSI100	**FTSE/JSE Top 100**	JSE/Barra/Own Research (VBA)	YES	PRICE INDEX
INDPROSA	**Industrial Production of South Africa**	Bloomberg/SARB	YES	INDEX (2010 = 100)
INDPROOECD	**Industrial Production of OECD Countries**	Bloomberg/World Bank	YES	INDEX (2010 = 100)
MONEYSUP	**M3 Money Supply**	Bloomberg/SARB	YES	R MILLIONS
SACPI	**Consumer Price Index**	Statistics SA/INET	YES	INDEX (2012 = 100)
SAGB10	**SA 10-year Government Bond Yield**	JSE/INET	NO	PERCENTAGE
GMC1*	**Alexander Forbes Money Market Index**	INET	NO	PERCENTAGE
ZARUSD	**Nominal Exchange Rate**	INET	YES	RANDS/DOLLAR
CRUDE	**Price of Brent Crude Oil**	INET	YES	USD PER BARREL
GLD5PLAT	**Precious Metal Index (50% Gold Price (USD) + 50%Platinum Price (USD))**	INET	YES	USD PER OUNCE
GOLD$	**Gold Price (USD)**	INET	YES	USD PER OUNCE
PLAT$	**Platinum Price (USD)**	INET	YES	USD PER OUNCE
MSCIACWI$	**MSCI ACWI (USD)**	Thomson Reuters Datastream	YES	PRICE INDEX

*Created by foremost asset consultants in Ginsburg, Malan and Carsens as a risk-free index before selling their asset consulting business which is formally known as A Forbes today

All the variables are in monthly frequency and as indicated above some data has been logarithmically transformed using the natural log. This means that the returns used in this study are of a natural logarithm nature such that the return of variable *i* at time *t* is given by

$$r_{it} = \ln S_{it} - \ln S_{it-1} \qquad (5.1)$$

where r_{it} is the total return on the variable, S_{it} is the index level at time *t* and S_{it-1} is the index level at *t-1*. The transformation to logarithmic form is due to the fact that time series data normally display a trend over time so transforming them to log levels removes the trend. However, even after removing the trend these returns are normally non-stationary due to the fact that volatilities and correlations change over time and thus need an appropriate model for the analysis. In keeping with Berry *et al.,* (1988), the returns used are total returns with dividends and income added back into price of the variable. Also the focus is on the underlying variables' ability to explain the excess returns achieved in the South African market. As a result excess returns of the FTSE/JSE Top 100 were used in the final analysis. The excess returns were calculated by using the Ginsburg, Malan and Carsons (GMC1) Alexander Forbes Risk Free Money Market Index and subtracting this from the returns of the ALSI Top 100 as described in equation (5.1). The arbitrary start period is based on availability of the underlying constituent data obtained from the JSE which was required for the construction of the ALSI Top 100 Index. The creation and reasons for the creation of this index are explained below.

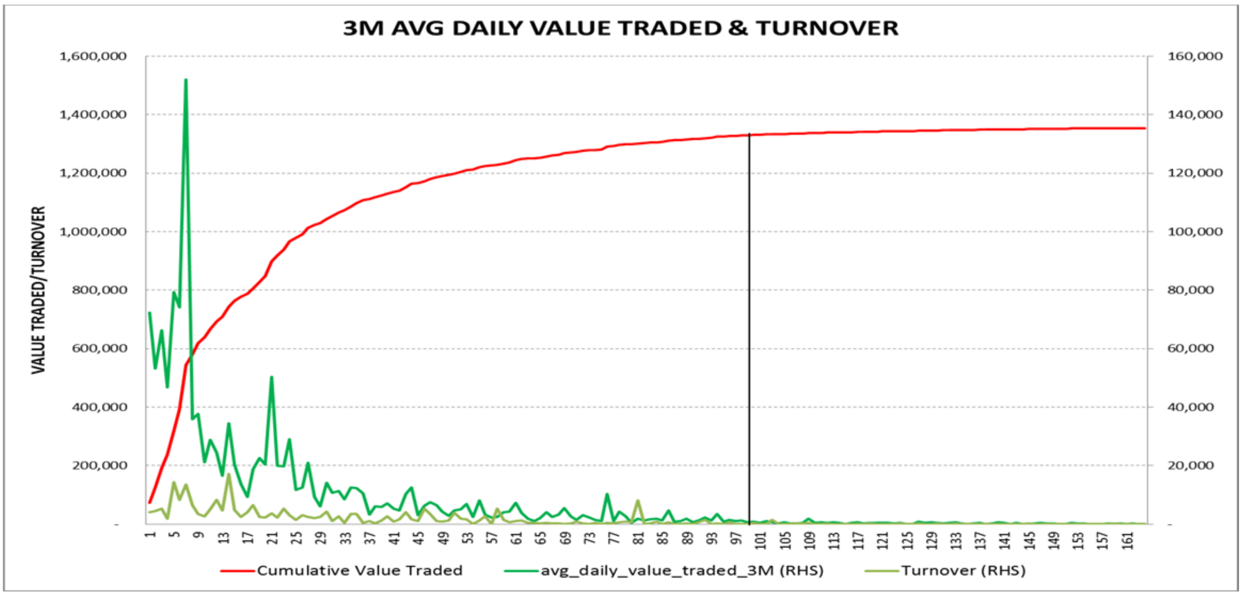
5.1.1 FTSE/JSE TOP 100 CREATION

There is a problem with asynchronous observations of stock price and betas due to the fact that frequently traded securities are biased upwards or downwards depending on the direction of market movement. At the same time thin traded securities are biased downward opposite to frequently traded securities. Levhan and Levy (1977) show that beta is very reliant on the return measurement interval with returns measured in discrete time. They continue to say that infrequently traded stocks present a significant delay in price adjustment and this has a significant effect on the stock's beta. Diacogiannis and Makri (2008) also show that a portfolio of infrequently traded stocks will have a very time sensitive beta compared to that of a portfolio of large frequently traded stocks.

According to Luoma, Martikainen and Perttunen (1993) on a thin traded market, systematic risk measures are affected by friction in the trading process. This is due to the fact that betas of infrequently traded stocks are biased downwards. This is caused by the fact that the true price of an infrequently traded stock does not reflect true changes instantaneously and will always need to be approximated with some previous price at last trade. As all these studies have shown, estimates of systematic risk i.e. beta coefficients are highly affected by thin/infrequent trading. This is why in their study of the applicability of the APT framework using UK data Beenstock and Chan (1986) imposed a tradability restriction of at least one trade per month on data to avoid estimation problems due to non-trading. Their data was more biased towards large capped stocks and they concluded that smaller capitalized firms (Small Caps) are less likely to trade than their large capitalized counterparts.

Due to reasons and observations made above, the FTSE/JSE All Index was truncated from the 164 stocks to the 100 most liquid stocks and this so happens to correspond to the Large and Mid-capped indices. The decision was made due to the fact that the approximation of the APT model in a country with finite stocks results in an inaccurate approximation due to the lack of near perfect diversification required in eliminating idiosyncratic risk (Shukla, 1997). It is this study's belief that sufficient diversification should be comfortably achieved with 100 shares in a portfolio. The FTSE/JSE Top 40 index contains 42 stocks due to dual listed Investec (INL & INP) and Mondi (MND & MNP) and makes up about 85% of the ALSI. The mid cap index is made up of the next 60 stocks with the rest forming the small cap index. The shares from 43 to 164 make up about 15%, as result the ALSI has a very long tails. As indicated above, some of these shares trade infrequently and as a result carry stale prices either from the previous month or earlier in the current month (Bradfield, 2003). This does not give a fair representation of the movement of the ALSI and thus has an effect or may cause some drag in the model. Another reason for the decision to use only the top 100 shares is based on the graph shown below.

Figure 5.1 Average daily value traded and Turnover



Source: Author Research & Bloomberg

Figure 5.1 shows that total cumulative amount traded on the JSE, using the average of daily value traded over the previous three months and turnover (volume of shares that change hands), reaches a plateau and turnover flattens out around about share 100 demonstrated by the vertical line drawn in the figure. As a result of the literature we have reviewed above, using any of the shares in positions above 100 will bias results due to thin trading.

Before expanding further on the reasons for creating an index exclusive and appropriate for this analysis the index creation methodology needs to be explained.

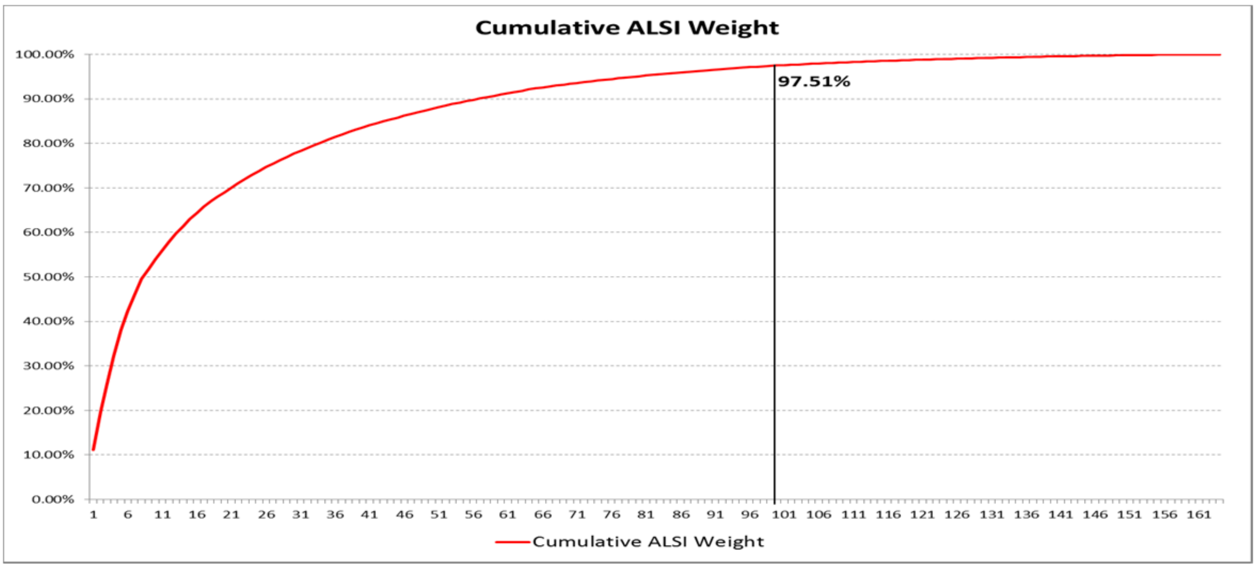
An algorithm was created and applied to ALSI data using JSE archived data from when constituents were available in soft copy. This dates back to July 2002, the algorithm sorts the shares and orders them from largest to smallest by weight in the ALSI in each month from July 2002 to April 2013. Thereafter, the algorithm (code in Appendix III) selects the top 100 stocks and creates usable files for each month (these files are available on request). Thereafter Barra is used to calculate the return of the new index FTSE/JSE ALSI Top 100 on a monthly basis assuming a buy and hold strategy discussed in Grinold and Khan (2000). The index construction methodology and calculation of returns follow the FTSE index creation methodology as described in the JSE Ground Rules. This makes use of free-float shares, which means each share's weight in the index is based only on the number of shares that are available for trading to the general public excluding any strategic holdings.

The index is rebalanced on a monthly basis. Therefore between two rebalancing dates index constituents remain fixed as well as the number of shares with the exception of when a company is delisted or suspended or during quarterly rebalancing of indices by the JSE. This means when the number of shares changes as a result of free-float factor, this may move the company out or into the top 100 depending on the movement of shares due to the rebalancing.

In all instances mentioned above the assumption used is that the share is sold at the last available valid month end price and the proceeds are immediately invested into another share that is next biggest at the end of that particular month i.e. share number 100, then 101, then 102, etc depending on the number of shares entering or exiting the index. Dividends, special cash payments of any kind, share splits are immediately reinvested or accounted for, respectively to ensure that the index is on a total return basis.

After this index has been created it is important to do some backtesting to ensure that the essence of the performance of the ALSI is not lost. The Ground Rules for Management of the FTSE/JSE Africa Index Series document states that the FTSE/JSE All Share Index is designed to represent performance of all South African companies listed on the Johannesburg Stock Exchange; as a result the backtest needs to show that this has not been altered in any way. The backtest results are shown and discussed below (for backtest purposes the created FTSE/JSE Top 100 is referred to as ALSI100 in all the graphs and tests). All the figures and data were created and calculated by the author of this paper.

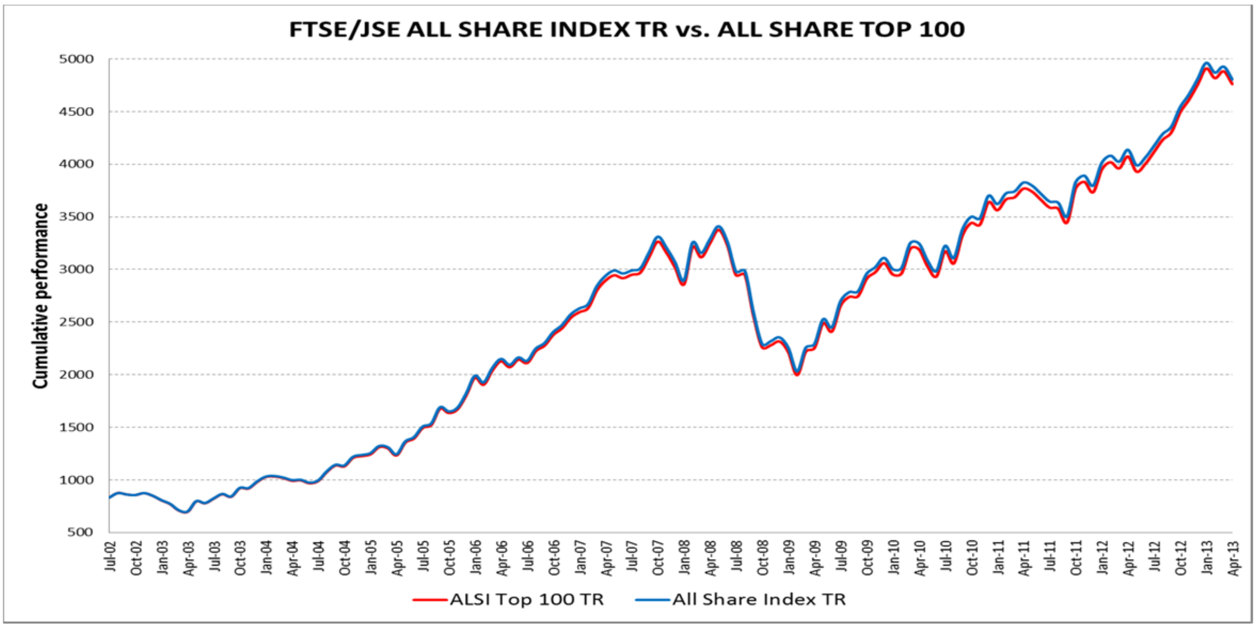
Figure 5.2 Cumulative ALSI Weight



Source: Author Research

As discussed above, the shares from 43 to 164 make up about 15% of the shares in the ALSI, this figure 5.2 shows that the top 100 shares make up about 98% capturing almost the whole market.

Figure 5.3 Cumulative Total Return Performances

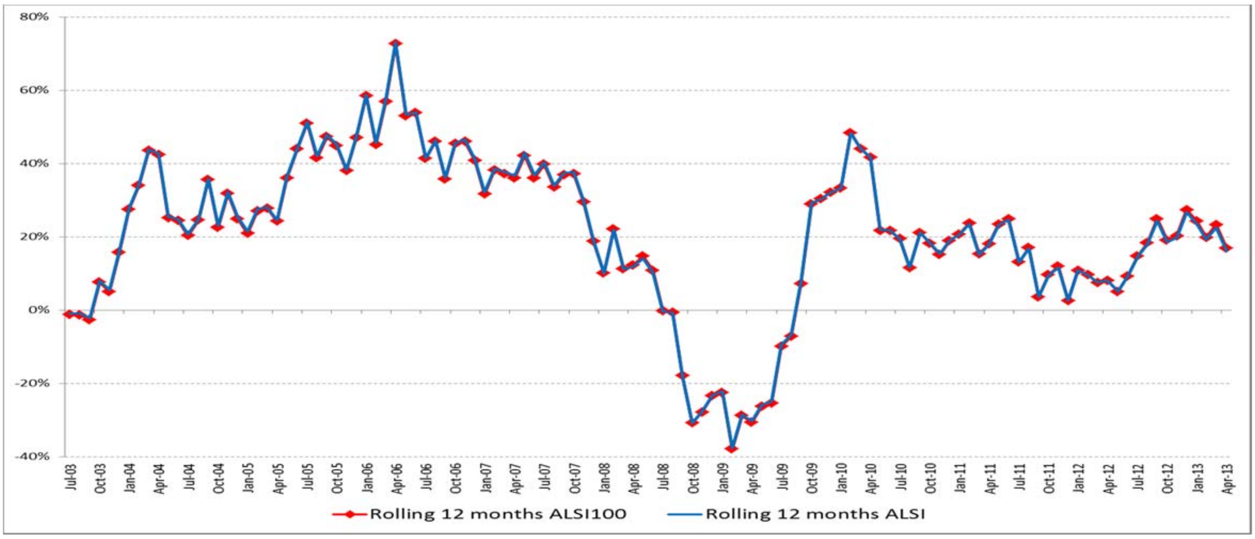


Source: Author Research

Graph 5.3 shows the cumulative performance of the ALSI versus our created index over the study period (the original ALSI is represented by a blue line while the created index is the red line) and as can be seen at the performance of these is nothing short of identical indicating that our created index is able to replicate the performance and thus be representative of the performance of the shares listed on the JSE. The performance trend and movement is maintained perfectly.

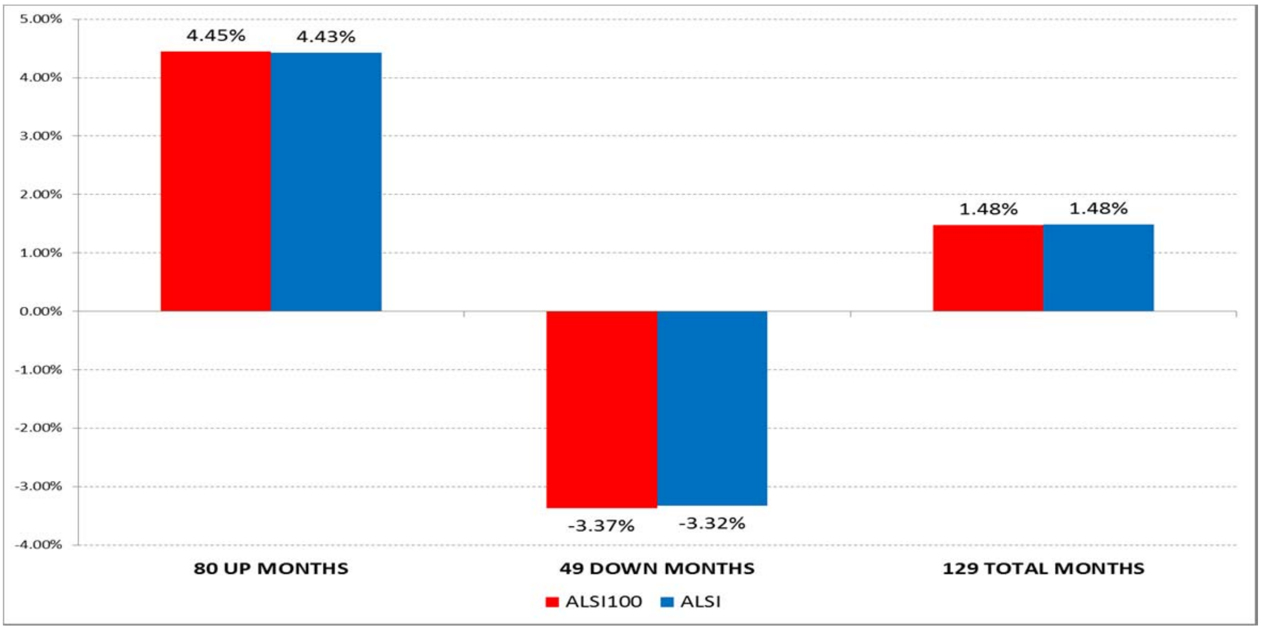
The rolling 12-month performance of these two indices is exactly identical with the charts moving on top of each other such that you cannot distinguish which line is which, without the markers making it discernible.

Figure 5.4 12-month rolling performance



The next graph looks at the return contribution of the two graphs against each other in up and down markets to ascertain that ALSI100 index is not biased downwards or upwards when compared to the original index which may cause problems for the tests.

Figure 5.5 Average Up and Down months



Our study period ranges from July 2002 to April 2013 representing 129 months of return data. However, as market participants know performance in any index is hardly ever in a straight line but characterized by up or down months. Breaking the market (ALSI) into those periods and looking at average monthly returns when the ALSI is up and down and matching those same months with those of the ALSI100 produces the graph as shown in figure 5.5. This performance is then averaged over the entire period to look at the average monthly period over this entire test period. The differences in up and down months between the two indices prove Bradfield's (2003) assertion that infrequently traded shares bias the market downwards in up periods and upwards in down periods. This means that our new index is appropriate as it eliminates some of the nags discussed above. To complete the backtest of these two indices a statistical test of similarity is performed. To do this we used a paired two sample for means t-test. The null and the alternative hypothesis for the test are listed below

H_0: $\mu_{ALSI} = \mu_{ALSI100:}$ The means of the two populations are identical

H_1: $\mu_{ALSI} \neq \mu_{ALSI100:}$ The means of the two populations are not identical

This is a two-tailed test given that the means can be different either way. The results are shown in table 5.2 below and as indicated in the up and down months, means (average monthly performance) over the study period are 1.48% and the p-values are highlighted in yellow. The p-values (one-tailed and two-tailed) are both above 5% and as a result show that there is insufficient evidence to reject the null hypothesis in favor of the alternative hypothesis. As result, this shows that we can use the created index as a representative of the performance of South African companies as listed on the JSE.

Table 5.2 Paired Two Sample for Means

t-Test: Paired Two Sample for Means

	ALSI100	*ALSI*
Mean	0.0148	0.0148
Variance	0.0024	0.0024
Observations	129.0000	129.0000
Pearson Correlation	0.9999	
Hypothesized Mean Difference	0.0000	
df	128.0000	
t Stat	-0.7144	
P(T<=t) one-tail	0.2381	
t Critical one-tail	1.6568	
P(T<=t) two-tail	0.4763	
t Critical two-tail	1.9787	

5.1.2 SELECTION OF MACROECONOMIC VARIABLES

Chen, Roll and Ross (1986) were pioneers in the field of using prespecified macroeconomic factors as candidates for risk factors using the APT framework as the underlying basis for their factor model. Their work is of such importance that it has gone on to be cited in over 2000 papers as researchers seek to replicate this work in various markets across the world. The literature review in chapter three gave us a wide range of possible variables that can be used as macroeconomic factors. The number of variables that characterize the return generating process of the APT model ranges between two and 20 (Beenstock and Chan, 1986).

The first step on the analysis of the APT framework done in this paper is to select the macroeconomic variables as candidate risk factors (Altay, 2003). The selection of these variables is somewhat of an arbitrary process, given that there is no science that guides the process guidance is taken from previous empirical work (Bilson *et al*., 2001). The logic applied by Chen *et al.* (1986) in their selection of variables to use as candidate risk factors is used as the base for this study. However, local conditions mean that there may be a need to use slightly different variables due to the fact that different markets react differently to factors (Berry *et al.,* 1986 and Poon & Tayler, 1991). As discussed in chapter three, the macroeconomic variables selected as candidate risk factors include industrial production growth rates, interest rates, inflation rate, gold price, oil price, international factors, money supply and exchange rates.

In this section these factors are introduced and discussed, including the base model behind the selection of these variables as guided.

5.1.2.1 *DIVIDEND DISCOUNT MODEL AS A BASE FOR VARIABLE SELECTION*

Equation 5.2 represents the dividend discount model, the basis upon which Chen *et al.,* (1986) relied upon in choosing the variables used their study. They used the formula to infer the linkages between macroeconomic factors and market returns as discussed in chapter three. This formula is shown below;

$$P_{i,t} = \sum_{n=1}^{\infty} \frac{E(D_{i,t+n})}{(1+k_i)^n} \tag{5.2}$$

where P_i is the is the price of share i at time t, $D_{i,t+n}$ represents the future dividend payments and $(1+k_i)^n$ is the discount factor to be used to discount dividends to present value with k as the discount rate. This equation shows that stock prices are a function of future cash flows in the form of dividend payments discounted to the present using an applicable discount rate (Chen *et al.,* 1986; Poon & Taylor, 1991; Clare and Thomas, 1994). As a result, putting the above assumptions together with Shukla's (1997) and Roll & Ross's (1980) argument of diversification that effectively eliminates idiosyncratic factors, the equation means that all the systematic factors that have or may have an effect on the cash flows and/or the discount factor influence the stock price and consequently its return (Clare & Thomas, 1994).

Using equation 5.2, the discount factor can be assumed to be the prevailing interest rates over the period of the study. So any changes in either short or long-term interest rates will affect the discount factor and cause a change in stock prices. The future dividend payments on the other hand are cash flows which are affected by company performance and in turn by underlying economic conditions. As a result, any variable that can cause a change in cash flows or the discount rate will cause a change in returns.

Chen *et al.,* (1986) believed that this could be even investment opportunities available to firms that may affect payout ratios. Chen (1983) believed that without theory of which factors to choose or how to choose those factors, one can rely on elaborating the logic and selection criteria for each variable included in the return generating process.

5.1.2.2 *THE SELECTION OF SYSTEMATIC RISK FACTORS*

In keeping with literature and Chen (1983), candidate risk factors are explained in this section. Given the wide range of possible risk factors that can be incorporated into the return generating process, not all factors will be discussed at length. The literature review has provided enough background on these and this section will only focus on the core factors and will be brief. As a result, this group of factors that will be discussed should not be treated as an exhaustive list of all possible factors that could affect returns but indicative.

5.1.2.3 *Aggregate Market indices*

Market indices have always been central to asset pricing given the work done by Sharpe (1963) with CAPM using the market index as its only pricing factor. This is often evident in the market when analysis is needed to provide guidance on the performance of stocks managers normally do this analysis on indices (Kwon and Young, 2008). This suggests that a market index provides invaluable information about the performance of shares. This is part of the reason the analysis on this report was based on the aggregate index rather than individual stocks. Unlike individual stocks that are affected by public news, aggregate indices returns move in accordance with macroeconomic factors and thus capture the shocks of these factors (Hamao, 1988). They are able to capture information that may have been missed by macroeconomic factors as per Chen *et al.*'s (1986) study.

In a world that is fully integrated by globalization it is prudent to assume that there is interconnectedness in the general operations of countries' economies. As a result, international equity indices can be assumed to capture the information set of international macroeconomic variables (Clare and Priestley, 1998). In a world characterized by stock markets that operate 24 hours a day from east to west and west to east, one has come to expect the interconnectedness in performance of stocks on a global scale. More often than not, traders in South Africa wake up and are mindful of US stock market performance overnight and the prevailing performance of Japanese and east Asia markets in their start of day trading. This serves as a guide of the general risk levels in the market as well as the possible direction of the market.
As a result of this, international stock indices have become instrumental in pricing of shares the world over. It was for this reason that Clare and Priestley (1998) relied up the MSCI World Index

to isolate the performance attributable to international influences on the performance of the Malaysian stock exchange. Van Rensburg (1996, 2000) uses the Dow Jones Industrial Average within the South African market model to show the influence of international markets on the JSE. As indicated in the literature review Fifield, Power and Sinclair (2002), looked at world factors that affect returns in 13 emerging countries and world market return was included as one of the factors they believed captures the performance of international stocks. This study uses the MSCI All Country World Index to capture the international macroeconomic innovations that influence returns on the JSE. The difference between using the index used by Clare and Priestley (1998) and this one is due to the fact that the former is only representative of developed markets and this omits a crucial part of the world stock markets contributed by emerging markets.

5.1.2.4 *Consumer Price Index or Inflation*

According to Chen *et al.,* (1986) the change in inflation has an effect on the cash flows as well as the discount rate in the Dividend Discount Model (DDM), equation 5.2. They suggest that inflation has an effect on sales, revenue and as a result nominal earnings and cash flows (Gunsel and Cukur, 2007). The issue on inflation is very relevant for South Africa given the fact that the South Africa Reserve Bank (SARB) has an inflation targeting policy which uses short-term interest rates to control the level of inflation. As a result of this, an outlook that shows higher inflation on the horizon will lead to the SARB increasing interest rates whilst a horizon of low inflation will lead to the SARB decreasing interest rates. This feeds into the DDM model for example high inflation expectation leading to high short-term interest rates translating to lower cash flows as the interest rates impose a higher cost of borrowing on corporates and also a higher discount rate (van der Merwe, 2004; Mishkin, 1995). Stocks are however affected differently by inflation rate and interest rates (Coetzee, 2002). Inflation numbers through the consumer price index need to be measure through the change in prices and costs in an economy post the end of any given month to get the full effect of the change and as a result these numbers are always released well into the new month. Due to this, markets respond to these innovations with a lag rather than at the precise period and as a result this study uses a lagged change in the consumer price index to get the full relationship between stock market returns and a change in the consumer price index.

5.1.2.5 *Economic Activity*

Gross Domestic Product (GDP) is the aggregate measure of production and/or economic output in a country. It can be surmised as a measure of overall real performance of an economy. Given the fact that the stock market is supposed to be the measure of performance of companies in an economy, assuming that the stock market represents all the companies in an economy one would expect a close correlation between the performance of an economy and the stock market. The GDP is measured quarterly whilst this analysis uses monthly data; as a result of this, the study uses a suitable proxy as a measure of economic activity. Using literature in this field as a guide, this topic seems to have been covered widely and the study has chosen to use the growth rate of industrial production as a measure of real economic activity.

Expected cash flows in a firm are expected to change with the change in economic activity as proxied by industrial production and this feeds into the DDM equation and thus means industrial production has a positive effect on stock returns (Elton *et al.*, 2003). However, industrial production numbers are released with a lag of about a month into the market. This means that the market will react to the industrial production number with a lag, it is for this reason that Chen (1991) used lagged industrial production growth as a measure of the underlying economy. It is for this reason that this study has chosen to use industrial production growth with a one month lag. Due to the effects of globalization and the interconnectedness in the global economic landscape, it means that the fortunes of one country are likely to be affected by activities taking place the world over. As a result of this we witnessed with the sweeping recession of 2008-2009 that as soon as countries' trading partners went into a recession they also followed suit as the market for their goods shrank, with this in mind an extra variable has been added to capture the effect of this on stock market returns. The industrial production of OECD countries has been added to capture the effect of globalization on stock returns with a one month lag.

5.1.2.6 *Interest rates*

The dividend discount model tells us that the price of any stock is determined by two factors, the present value of future cash flows and the discount factor. This means that a decrease in the stock price could be a result of a decrease in cash flows or an increase in interest rates which is the base DDM equation 5.2. Interest rates can also influence the cash flows through the cost of borrowing and the debt structure of the firm that may affect the earnings and consequently cash flows (Tobin and Brainard, 1977).

Given the fact that the APT was envisaged to be a model to look at effects over the short-run period the study has chosen not to use long term rates. Instead, monthly change in the yield of the

10-year RSA government bond is used and a negative relationship is hypothesized.

5.1.2.7 ***Oil prices and exchange rates***

Oil prices have increasingly played a bigger role in almost all the economies as the global economy has come to depend on oil as one of the main energy sources. This has been seen through the effect of oil trade on the geopolitical landscape as the world and different nations jostle for limited resources. This in turn has resulted in oil being seen as an important commodity in world economy and stock markets (Jones and Kaul, 1996). Combining this with the effect of globalization and the fact that almost every country participates in international trade makes these two variables very applicable in the return generating process. A country like South Africa which is a net importer of oil for mostly fuel purposes is affected across the spectrum by the prevailing price of oil as well as the underlying exchange rates. The South African department of energy says this on the determination of the petrol (fuel) price;

> *"This means that the domestic prices of fuels are influenced by (a) international crude oil prices, (b) international supply and demand balances for petroleum products and (c) the Rand/US Dollar exchange rate."*

In their study Nandha and Faff (2008) suggest that changes in oil prices have an effect on the general economy through the changes in the prices of production The effect of a change in oil price varies across countries and industries depending on whether an they use oil in their import process or a producer of oil (e.g. Sasol).

For a country like South Africa where, according to the SARB, over 30% of the consumption basket is imported, it makes exchange rates very pertinent in the determination of the return generating process. They have an effect on the overall performance of companies that are either heavy exports or importers of goods. The depreciation of currency has adverse effects on an import dominated economy whilst the appreciation has opposite effects (Nkoro and Uko, 2013). The exchange rate has suddenly become very important on South African stock market companies given the growing range of companies with foreign operations. The need to convert their offshore earnings back into rands means that these could be positively or negatively affected given the performance of the rand against various currencies. This means that the movement in the exchange rate has an effect on the cash flows in the dividend discount model. Moolman and du Toit (2005) found a significant relationship between the rand/dollar exchange rate and the returns on South African stocks. Their results were similar to those of Barr, Kantor and Holdsworth (2006) where they showed that the returns of the top 40 stocks on the JSE are affected by the exchange rate to varying degrees. This study uses the US dollar price of Brent crude per barrel while the exchange rate is the number of rands per US dollar (USDZAR rate).

5.1.2.8 *Monetary policy*

Money policy is seen as playing a crucial role in almost every economic policy that follows economic theory. Beenstock and Chan (1988) found money supply to be a significant variable in the pricing of stocks using UK data, the same conclusion was reached by Clare and Thomas (1994) in the same market, Cheng (1995) and Groenewold (1997). Changes in money supply are interpreted by the market as policy communication about future inflation direction, with increased money supply pointing to higher future inflation and vice versa (Mookerjee and Yu, 1997). Money supply's close relationship with GDP also indicates that changes in money supply impact economic activity and therefore has an effect on stock returns (Kandir, 2008). Financial markets have been affected by monetary policy that has been at play post the 2008-2009 financial crisis.

5.1.2.9 *Gold (precious metal) prices*

Gold is the world's oldest international currency and has played a significant role in most countries' currency system especially during the gold standard. When fiat money was first introduced, it was redeemable for gold. Gold is still viewed as the purest currency and considered as a safe haven asset and a hedge against stocks during a period of turmoil (Draper, Faff and Hillier, 2003).

A lot of empirical work has been done to look at the gold price's effect on the market return but not so much of other precious metals. According to Clare and Thomas (1994) the gold price has an effect on returns through its effect on the outlook of interest rates. Faff and Chan (1998) investigated the gold price effect on Australian stocks using data from the period the gold price was freely allowed to trade in 1975 to 1994 and found a significant relationship between excess stock returns and the gold price. Moolman and du Toit (2005) investigated the effect of gold price on South African stock returns within a structural model and found that there was a significant short-run relationship between stocks returns and gold price.

In our study the precious metal variable is captured with new variable created which has a 50% exposure to the gold price and a 50% exposure to the platinum price. This is due to the fact that these two metals have taken off in response to the uncertainties taking place in the global landscape. The two metals have exchange traded funds (ETF) that track the price changes and open up an avenue for investors to freely invest in these precious metals (see figure 7.3).

5.2 *ECONOMETRIC MODELLING FRAMEWORK: ARCH AND GARCH*

The aim of this study is to investigate the return generating process of South African stock returns within the APT model with a special focus on the precious metal beta. As discussed previously an appropriate econometric framework is needed to estimate the model. The previous chapter looked at the returns of the JSE and showed that financial market returns are seldom well-behaved with Mangani (2009) suggesting that they deviate from normality and instead have excess kurtosis, skewness and are dependent. Niyitegeka and Tewari (2013) and Louw (2008) showed that JSE data is characterized by volatility clustering. The studies above also showed that JSE data has ARCH effect and heteroscedasticity. These properties of returns and volatility need an econometric methodology designed to account and handle these type of characteristics. (For a more extensive review of the background of the ARCH/GARCH family of models please refer to the literature review section 3.3.3)

Chou (1988) posits that the ARCH/GARCH family of models is very robust for analyzing financial time series data. After using the GARCH (1,1) model to study time series behavior of 24 national market indices, Roll (1992) believes it is a robust analysis methodology and its modeling power eliminates the potential for misleading inferences.

The ability of ARCH/GARCH to model conditional variance as a by-product of the mean equation is helpful when looking at macroeconomic variables that do not seem to demonstrate any effect on the mean returns but influence volatility like oil prices and gold prices. Morales (2008) argues that the most effect of gold and oil prices on returns is through volatility spillovers and feedback. As demonstrated in the literature review, Mangani (2007) uses a GARCH (1,1) model to show that the gold prices influenced the volatilities of returns of the JSE. There is also a long list of researchers that have sought to use the ARCH/GARCH family of models to model returns on the JSE or to calculate volatility to be used in some analysis of JSE information.

Below a few characteristics of the models that will be used in the analysis are discussed.

5.2.1 *ARCH and GARCH MODELS*

To be able to model variance within ARCH, the framework adopts restrictive assumptions of data and treats moments of the mean as independent and identically distributed variables, z_t, in the form of {μ:σ} $\longrightarrow$ {0,1}, defined by standard deviation $\sqrt{ht}$, (Xiao and Aydemir, 2007):

$$\varepsilon_t = \sqrt{h_t} z_t, \quad z_t \sim i.i.d(0,1) \tag{5.3}$$

According to ARCH/GARCH family of models variance is described in terms of historical moments and residual term, ε_t, is defined as a "factor" in the mean equation (Xiao & Aydemir, 2007). As demonstrated previously, the return generating process is defined by the expected return and the residual and Engle *et al.* (2008) believes that this can be reduced to:

$$r_{it} = \mu_t + \varepsilon_t, \quad \varepsilon_t = \sqrt{h_t} z_t \tag{5.4}$$

where r_{it} is the return on stock *i* at time *t,* μ_t is the mean and ε_t is the innovation in the mean. Similar to $E(R_t)$ in chapter two serves as the expected value of the return and is referred to as the mean value of the equation. According to the APT framework, the conditional mean portion in equation 5.4 can be characterized by equation 5.5 below:

$$r_{it} = \mu_t + \sum \beta x_t + \varepsilon_t \tag{5.5}$$

where, $\sum \beta x_t$ is a vector of candidate risk factors. This equation means that the returns are a function of the vector of systematic risk factors, the conditional mean and a residual term. While the second portion of equation 5.4 can be assumed to be the conditional variance given by the equation below and is modeled within the mean equation:

$$h_t = \psi(\Omega_t, x_t) \tag{5.6}$$

where

h_t is the conditional variance,

Ω,is the information set at time t and

x_t is a set of risk factors.

This means that the conditional variance is determined and is a function of historical information and a set of risk factors. The definitive conditional variance equation is determined by the ARCH or GARCH model that is being used at any particular time thus allowing the model to describe and ascertain causes of variance in the investigated variable (Engle, 2001). This is important given our literature review where we have ascertained that some variables may not influence the returns of stocks but have an effect on the volatility. This means that to fully describe returns within the ARCH/GARCH model we need not only model the mean equation but also need to model the conditional variance.

This advantage and flexibility which is introduced by ARCH/GARCH models allows us to capture different characteristics of returns as described in chapter four. The ability to capture conditional variance makes the modeling process of returns much more accurate with a much higher degree of statistical applicability.

5.2.2. *ARCH and GARCH models*

These have been discussed above and will only be touched on briefly in this section. As discussed, this family of models was first introduced by Engle (1982) with the introduction of the ARCH model and this was followed by Bollerslev's (1986) generalization of ARCH, the GARCH model.

5.2.2.1 *ARCH*

The first model of the framework is the ARCH model of Engle (1982) who looked for a model where past variance was an important factor for calculating present and future variance. The ARCH model assumes a linear relationship between the dependent variable's mean and the chosen risk factors while variance is defined by the ARCH (*p*) model (Engle, 1982):

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \tag{5.7}$$

where h_t is the conditional variance with it being a function of past residual terms squared, ε^2_{t-1}, where $\omega > 0$ & $\alpha_i \geq 0$ such that the conditional variance is always positive. The (*p*) describing number of ARCH terms in the model. Since the only variable available is the return of the variable, the best way to estimate the conditional variance is to use maximum likelihood methodology by substituting h_t for σ^2, in the normal likelihood and then maximizing for the other parameters in the equation (Engle, 2001). Engle (2001) admits that this could be a daunting process which could take a considerable amount of time and skill and could be onerous, instead he suggests a use of software which is capable of handling such a process. He recommends use of EViews, SAS, GAUSS, TSP, Matlab or RATS. In this study we have chosen to use EViews and all result outputs other than those calculated using excel have been worked in this software.

5.2.2.2 *GARCH*

The one glaring deficiency of the ARCH (*p*) models is the fact that their conditional variance has high frequency fluctuations with massive volatility coming in short spurts (Bollerslev, 1986). In contrast the generalization of ARCH (GARCH) on the other hand allows for a wider range of behavior resulting in more consistent variance, this was the essence of Bollerslev's (1986) generalization of the original ARCH model. The GARCH model takes the form of GARCH (*p,*q) and is represented by the equation:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{5.8}$$

In this equation *q* represents the order of historic conditional variance where a very high β_j represents a persistence of volatility which requires a long period to adjust (Dowd, 2005). The most common form of this equation in the field of finance is that where both *p* and *q* take the form of one resulting in a GARCH (1,1) model. This means that there is one ARCH term and one GARCH term in the model. There are other various forms of this equation where more than one lag of the conditional variance and error terms are required (Engle, 2001).

Another condition of the above equation is for $\alpha_i + \beta_j < 1$, this means that unconditional variance is finite leading to a mean reverting process (Engle, 2001; Alexander 2008:136). According to Bollerslev, Chou and Kroner (1992) the GARCH model is more robust at the same time being easier than a relative ARCH model. They believe that a GARCH model with parameters of $p \leq 2$ and $q \leq 2$ is sufficient and more efficient to work financial data than an ARCH model of a higher order.

The GARCH (1,1) model is considered a workhorse of financial market data (Bollerslev, 1992) and has been used in many a study of a relationship between stock market returns and macroeconomic variables. Sadorsky and Henriques (2001) demonstrated that the ARCH/GARCH framework is a better alternative to the OLS methodology in modeling a return generating process by using a GARCH (1,1) in their study of the return generating process of the Canadian paper and forest industry returns. As a result, this study uses the GARCH (1,1) model for the analysis as this has been deemed to be the best suited model for South African stocks (Mangani, 2007b; Mangani, 2008b).

5.1.2.9 *Conclusion*

In this chapter, the data to be used in the analysis was discussed along with the creation of a substitute index, the FTSE/JSE ALSI Top 100 Index which was demonstrated to be a perfect substitute of the ALSI. The theoretical and empirical framework behind the selection of macroeconomic variables to be used in the analysis was discussed and the variables identified. Nine (eleven, when counting the exploratory gold and platinum variables) macroeconomic variables were chosen, namely: South African (SA) industrial production, OECD Industrial production, SA broad money supply (M3), SA consumer price index, SA 10-year government bond yield, USD/ZAR nominal exchange rate, Morgan Stanley Capital Index: All Country World Index (USD) (henceforth MSCI ACWI Index), USD precious metal index and USD oil prices.

The list of possible candidate risk factor is rather big but we have focused on those factors that may have a possible effect on the South African stock market returns.

The chapter also looked at the methodology chosen for this analysis, the ARCH/GARCH framework which was shown to have wide range of applicability within the field of finance. The reason for choosing this framework was based on the fact that returns have been shown to deviate from normality with excess kurtosis and skewness as well as showing some heteroscedastic behavior. The flexibility of this framework makes it much easier to handle the deviation from normality of the data. The objective of this study of investigating the return generating process of the South African stock market within the APT framework with a special focus on the precious metal beta has made choosing this framework somewhat of a no-brainer. This is due to the fact that this econometric framework is very robust for financial market data and the GARCH (1,1) has been proven to be well suited to South African return data. However, it remains to be determined whether our data manifests the departure from normality that has been discussed above and thus requiring the use of the ARCH/GARCH framework for the model estimation.

As a result, after setting the background, the theory and empirical review of the return generating process, the next chapter is dedicated to the empirical analysis of the return data and properties.

CHAPTER 6:
EMPIRICAL RESULTS

6.0 INTRODUCTION

In Chapter 1, the following objectives were set: investigate the return generating process within the Johannesburg Stock Exchange (JSE) framed with the APT with a special focus on the precious metal beta both on the mean and variance equation of the ARCH/GARCH model. However, before performing the analysis on the return generating process of the South African stock market returns using the APT framework, some preliminary analysis on the data needs to be done. This is done on the return series to ascertain the data characteristics and properties of its distribution to ascertain the appropriateness of using the ARCH/GARCH framework for the analysis. A normality test is performed using the Jarque-Bera test, for a normal distribution the data is characterized by a kurtosis of three and skewness coefficient of 0. Outliers tend to bias the test and may lead to a rejection of normality; as a result, Turkey's (1977) box plots are used along with Iglewicz and Hoaglin's (1993) modified Z-Score, a robust test for multiple outliers to ascertain which values are outliers. Thereafter, unit root testing for stationarity is done using both the Augmented Dickey-Fuller and Phillips-Peron tests, and then we look at the descriptive statistics and correlation matrix to examine the characteristics of data and test for multicollinarity. Finally an ARCH test is conducted on the data to ascertain whether the GARCH model is the appropriate econometric model for testing our set of data.

6.1 Preliminary Analysis of Data

6.1.1 Outliers

Observed variables sometimes contain outliers; these are unusually large or small variables in a data set. These unusually large or small numbers may be caused by various reasons; they could be erroneous entries in the data set or represent irregular or rare events. As mentioned above, outliers have a negative effect on the analysis of data as they tend to lead to erroneous conclusions due to their bias effect on tests.

For the purposes of this paper we use the informal tests to ascertain whether data contains any outliers. The two methods chosen for testing for outliers are Iglewicz and Hoaglin's robust test (which utilizes the modified Z-Score) and Turkey's boxplots. These tests are used to identify outliers and after identifying these, a form of winsorisation procedure is applied on these observations to bring them in line with the rest of the data set and eliminate their negative bias effect.

The two identification methods were chosen due to the fact that they make no assumption about the underlying distribution of the data nor do they rely on the mean and standard deviation. The other reason for using Iglewicz and Hoaglin's robust test is its ability to identify multiple outliers and thus not suffer from the swamping and masking effect. These are phenomena where observations swamp or mask each other and thus prevent each other from being identified as an outlier due to the presence or failure to eliminate one or the other observation (Acuna and Rodriguez, 2004).

The other important reason is that outliers tend to have an effect on the mean and consequently, the standard deviation of data. One popular method for identifying outliers is the Z-Score, which assumes that analysis data is normally distributed. The two estimators in this method are the sample mean and sample standard deviation, which are easily affected by outliers. To circumvent this problem, Iglewicz and Hoaglin's robust test for multiple outliers uses the modified Z-Score which utilizes the median and the median of the absolute deviation of the median (MAD) instead of the mean and standard deviation of the sample, respectively (Iglewicz and Hoaglin, 1993).

The Z-Score calculated using the formula:

$$Z_i = \frac{x_i - \bar{x}}{sd}$$

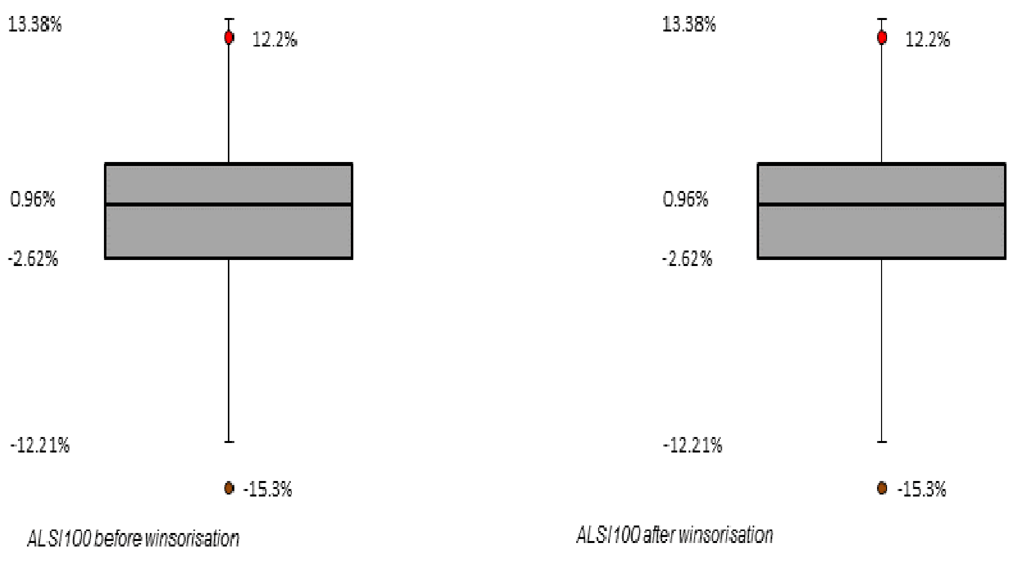
where; $\bar{x}$ and *sd* represent the sample mean and sample standard deviation, respectively. This assumes that the Z follows a normal distribution and Z-scores that exceed 3 in absolute terms are considered to be outliers. For the modified Z-Score the formula relies on median and median absolute deviation in the formula:

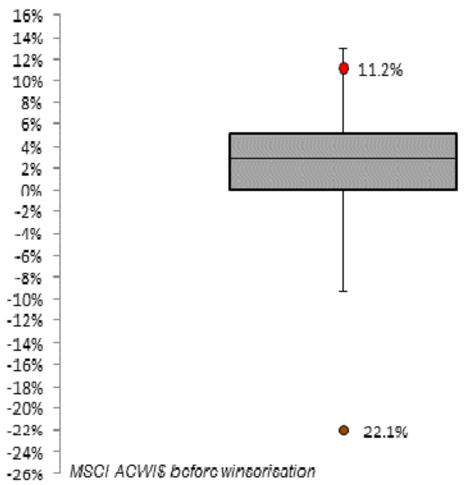
$$M_i = \frac{0.6745(x_i - \tilde{x})}{MAD}, \quad MAD = median\{|x_i - \tilde{x}|\}.$$

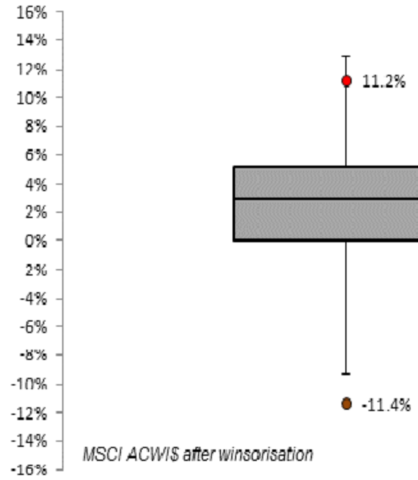
Iglewicz and Hoaglin (1993) propose that any data with $|M_i|>3.5$ should be labeled an outlier. The use of a median for the modified Z-Score avoids it being affected by presence of outliers. However, before calculating and using the Z-Score, Turkey's (1977) boxplot method was used on all the variables to identify possible outliers.

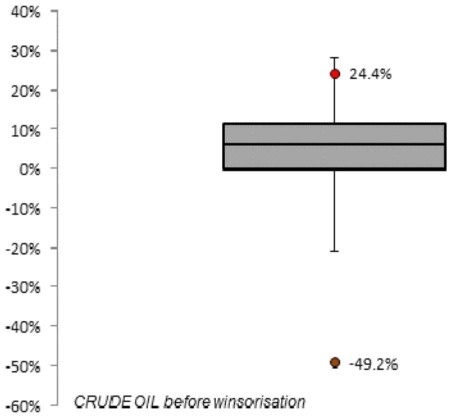
The boxplot method is a graphical display of continuous univariate information which shows lower, upper quartiles and the median (Seo, 2002). It then shows the lower and upper whiskers which are sometimes referred to as inner fences. It uses quartiles and an inter quartile range (IQR) which makes it less sensitive to extreme values as quartiles and IQR are somewhat resistant to these extreme values (Seo, 2002). The IQR is the distance between the upper (Q3) and lower (Q1) quartile. The inner fences are calculated by measuring 1.5 x IQR, below Q1 and above Q3 and the outer fences are 3 x IQR, below and above Q1 and Q3, respectively. A value that lies between inner and outer fences is a possible outlier and needs to be subjected to further testing, while a value beyond outer fences is a probable outlier. Once a boxplot has been used to identify possible outliers, Iglewicz and Hoaglin's robust test for multiple outliers is used to ascertain which data points are outliers. Thereafter a value identified as an outlier is excluded from the data set and a new median and median absolute deviation (MAD) calculated using the remaining observations. The excluded data points are then added back into the data set, however, these are first winsorised to the $|M_i|$ = 3.5 limit. This ensures that we retain all data points without subjecting data to outliers. The boxplots for the variables before and after outliers were identified and removed are shown below and in Appendix I. Some data sets did not present any outliers (e.g. ALSI100) and therefore no changes were made. The boxplots also show the maximum and minimum values before and after winsorisaiton.

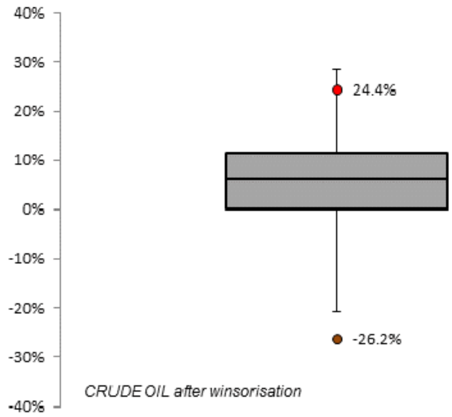
Figure 6.1: Boxplots











The graphical representation above shows winsorisation at work. The orange dot at the bottom shows the minimum value whilst the red dot at the top represents the maximum value for the data set. There were no outliers identified in the excess returns of the ALSI100 so the before and after graphs look identical. However, for the MSCI ACWI$ and CRUDE OIL variables the minimum data point looks to be too far from the lower whisker (on the graphs on the left). After these points were winsorised, the boxplots on the right show these points are much closer to the bottom whisker. The same process was performed for ZARUSD exchange rate, CPI, Money Supply, SA Industrial Production, OECD Industrial Production, SA Government 10-year bond yield, Gold and Platinum Prices and the 50/50 Index (the rest of the box and whisker plots are shown in Appendix I). All the following testing and analysis is done on the new data which has been cleaned and adjusted for outliers.

6.2.1 Data Properties

The data in table 6.1 indicates widespread deviation from normality for the variables used in this study in the form of skewness (mostly negative) and excess kurtosis. As expected for financial return data, the ALSI100 shows leptokurtic data suggesting that the distribution is characterized by peakedness and fat-tails (Tsay, 2002 and Patton, 2007). The rest of the variables also show excess kurtosis along with skewness which deviates from zero indicating departure from normality and asymmetry for data. The descriptive statistics were calculated after the process of winsorisation so there is no issue of outliers effecting skewness.

Table 6.1: Data Distributional Properties

	ALSI100	CRUDE	GLD5PLAT	GOLD$	INDPROOECD	INDPROSA	MONEYSUP	MSCIACWI$	PLAT$	SACPI	SAGB10	ZARUSD
Mean	0.66	1.09	1.06	1.23	0.08	0.10	1.00	0.69	0.81	0.46	8.55	-0.10
Median	0.96	2.43	1.28	1.56	0.21	0.10	0.86	1.39	1.90	0.43	-0.47	-0.58
Maximum	12.23	24.41	13.87	12.09	1.44	6.21	3.70	11.24	22.01	1.85	10.01	17.02
Minimum	-15.25	-26.22	-16.05	-15.56	-1.96	-6.21	-0.75	-11.40	-15.41	-0.67	-11.01	-12.64
Std. Dev.	4.90	9.64	5.43	5.20	0.82	2.20	1.03	4.97	7.13	0.46	1.00	5.09
Skewness	-0.30	-1.40	-0.81	-0.48	-2.18	-0.30	0.90	-1.15	-1.64	0.57	0.57	0.60
Kurtosis	3.50	8.05	4.83	3.85	11.02	3.88	4.37	6.05	10.09	4.08	3.55	3.54
Jarque-Bera	3.36	179.52	32.12	8.73	447.66	6.04	27.67	78.39	328.32	13.30	8.65	9.44
p-value	0.19	0.00	0.00	0.01	0.00	0.05	0.00	0.00	0.00	0.00	0.01	0.01
Observations	129	129	129	129	129	129	129	129	129	129	129	129

Akgiray (1989) notes that presence of excess kurtosis in our data points to the possibility of non-stationarity and dependence. The hypothesis of independence can be examined through the serial correlation model:

$$\rho_\tau = \frac{\text{cov}(R_{it}, R_{it-\tau})}{\text{var}(R_{it})} \qquad (6.1)$$

where ρ_τ denotes the correlation coefficient, while τ the lag order and R_{it} represents time series return of *i* at time *t*. Another model that can be used to investigate independence is Ljung-Box Q-statistics which tests whether the serial correlation coefficients are mutually equal to zero to a particular lag (Gujarati, 2003). The Q-statistics takes the form of:

$$LB = n(n+2)\sum_{k=1}^{m}\left(\frac{p_\tau}{n-k}\right) \qquad (6.2)$$

where *n* is the sample size and *m* is the lag length.

6.2.1 Test for Stationarity

Although the tests above can be useful in testing for independence, the more formal tests used to test whether the stochastic process underlying the time series is invariant over time in this study are the Augmented Dickey Fuller and the Phillips Peron tests. The test for stationarity examines whether the mean and variance of the time series is constant over time. If the mean and variance are constant over time then the time series is said to be stationary, if they are not constant over time then the time series is said to be non-stationary.

The Augmented Dickey Fuller (ADF) test is given by (Mishra and Sethi, 2008):

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \delta_2 \Delta Y_{t-2} + \ldots \ldots + \delta_p \Delta Y_{t-p} + \varepsilon_t \tag{6.3}$$

H_0: $\boldsymbol{\gamma} = 0$

H_1: $\boldsymbol{\gamma} > 1$

The ADF test is the basic test for stationarity which is widely used; however, it sometimes behaves poorly in the presence of autocorrelation. To tackle this major problem of the ADF test Phillips and Peron (1988) developed a more comprehensive theory of unit root on stationarity. Their theory is similar to that of ADF, but it incorporates an automatic correction of the Dickey Fuller procedure to enable for autocorrelation residuals. As a result, the Phillips and Peron (PP) tests perform better than or equally as well as the ADF tests in terms of comparative power due to the fact that serial correlation does not affect the asymptotic distribution of the statistic (Cashin and McDermott, 2003). It thus yields tighter confidence intervals as they use consistent estimators of variance (Cashin and McDermott, 2003; Sarris and Hallam, 2006).

The Phillips Peron test is based on the formula:

$$X_t = \eta + \beta_t + \pi X_{t-1} + \psi_t . \tag{6.4}$$

H_0: $\boldsymbol{\pi} = 0$

H_1: $|\boldsymbol{\pi}| < 1$

According to Davidson and MacKinnon (2004), the Phillips Peron test struggles to give the best results when it is used on finite data sets compared to the ADF test. As a result, both tests will be used for unit root testing given the fact that they complement each other's weaknesses.

The null hypothesis for both tests is that variable *x* contains unit root (i.e. the series is not stationary).

Table 6.2: Results from Unit Root Tests (ADF & PP)

VARIABLE	LEVELS			
	Augmeneted Dickey-Fuller		Phillips-Perron	
	Constant	Trend & Intercept	Constant	Trend & Intercept
ALSI100	-0.993	-1.371	-1.001	-1.629
CRUDE	-1.845	-2.807	-1.869	-2.676
GLD5PLAT	-1.646	-2.357	-1.633	-2.497
GOLD$	-1.333	-2.931	-1.225	-2.859
INDPROOECD	-2.509	-2.611	-1.997	-2.002
INDPROSA	-1.953	-1.947	-2.367	-2.532
MONEYSUP	-3.310	0.373	-2.737	0.096
MSCIACWI$	-1.693	-2.119	-1.685	-2.142
PLAT$	-2.159	-2.877	-2.205	-2.689
SACPI	1.089	-1.739	0.646	-1.515
SAGB10	-2.163	-2.627	-2.225	-2.724
ZARUSD	-2.567	-3.111	-2.638	-3.089
Critical Values	Constant		Trend & Intercept	
	1%	-3.482	**1%**	-4.031
	5%	-2.884	**5%**	-3.445
	10%	-2.579	**10%**	-3.147

VARIABLE	FIRST DIFFERENCED			
	Augmeneted Dickey-Fuller		Phillips-Perron	
	Constant	Trend & Intercept	Constant	Trend & Intercept
ALSI100	-11.298	-11.271	-11.430	-11.402
CRUDE	-8.926	-8.917	-8.932	-8.921
GLD5PLAT	-10.603	-10.644	-10.612	-10.639
GOLD$	-13.575	-13.584	-13.693	-13.715
INDPROOECD	-4.086	-4.077	-6.331	-6.320
INDPROSA	-6.166	-6.148	-18.094	-18.036
MONEYSUP	-6.145	-10.773	-10.573	-10.988
MSCIACWI$	-9.016	-8.989	-9.123	-9.090
PLAT$	-8.843	-8.869	-8.850	-8.868
SACPI	-8.035	-8.163	-8.071	-8.156
SAGB10	-10.465	-10.430	-10.443	-10.406
ZARUSD	-11.534	-11.746	-11.532	-11.752
Critical Values	Constant		Trend & Intercept	
	1%	-3.482	**1%**	-4.031
	5%	-2.884	**5%**	-3.445
	10%	-2.579	**10%**	-3.148

Table 6.2 shows results of unit root testing[6] where both the constant and trend & intercept were tested both using the levels and first differenced variables. Testing the constant and trend & intercept ensures that we correctly reject or accept the null hypothesis. The critical values for both tests are similar so it enables data to be graphically demonstrated without much redundancy. The table above shows that we cannot reject the null hypothesis at all critical values when the variables are in levels, however, we can reject the null hypothesis after first differencing. The results indicated that all variables are I(1) which means that they are intergrated at order 1. The non-stationarity of variables at levels indicates that there is series autocorrelation with the mean and variance not constant over time. The unit root tests were done using Eviews 6.0.

6.2.3 Testing for Multicollinearity

Multicollineariy refers to the occurrence where there is either a perfect or near perfect linear

[6] See Appendix II for ADF and PP results

relationship between the explanatory variables (Gujarati, 2003). This means that one independent variable can be linearly predicted by another resulting in inflated standard errors of the regression coefficients making them erratic to small changes of data. This may lead to inaccurate estimates. As a result of this, it is imperative that a test for multicollinearity is conducted to ensure that there is no bias or effect to the final analysis caused by this phenomenon. To test for multicollinearity pairwise correlation matrices for independent variables are estimated to ascertain whether any two variables demonstrate a high degree of correlation. According to Suzuki *et al.* (2008), the rule of thumb to test whether variables are highly correlated is |r|>0.7.

Table 6.3: Correlation Matrix of Independent Variables

	LINDPROSA	*LINDPROOECD*	*LMONEYSUP*	*LSACPI*	*SAGB10*	*ZARUSD*	*CRUDE*	*GOLD$*	*PLAT$*	*GLD5PLAT*	*MSCIACWI$*
LINDPROSA	100%										
LINDPROOECD	19.2%	100%									
LMONEYSUP	-19.6%	-0.5%	100%								
LSACPI	7.7%	-11.9%	2.1%	100%							
SAGB10	10.7%	5.2%	3.9%	1.9%	100%						
ZARUSD	-6.3%	-5.0%	-3.1%	0.5%	40.5%	100%					
CRUDE	12.5%	21.0%	18.3%	-8.3%	25.3%	-19.3%	100%				
GOLD$	-5.8%	-0.2%	11.2%	-14.0%	-20.6%	-26.8%	27.5%	100%			
PLAT$	2.9%	7.3%	7.7%	-11.9%	-0.7%	-21.6%	46.0%	64.6%	100%		
GLD5PLAT	0.3%	6.9%	10.6%	-13.4%	-9.3%	-28.0%	42.7%	85.2%	93.6%	100%	
MSCIACWI$	6.4%	20.8%	6.6%	-3.3%	-30.2%	-57.1%	23.1%	12.3%	34.6%	29.7%	100%

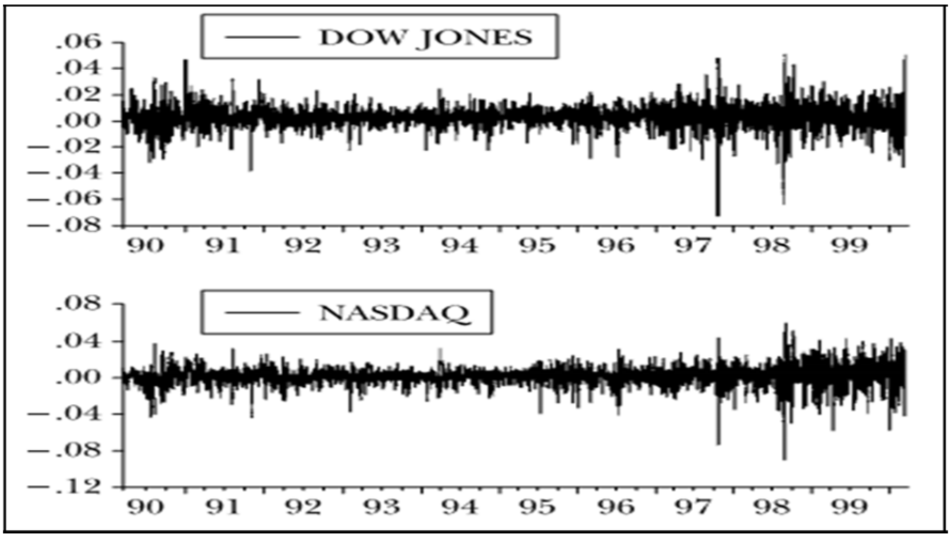
Pair-wise correlation of the macroeconomic variables

Table 6.3 shows pairwise correlation of independent variables. It has been colour-coded to detect whether any variables show a high degree of correlation between them. The blue colour indicates positive correlations which are below 60%, well below 70% threshold, while green indicates those variables that are negatively correlated but still above -70% threshold. As shown in the table above, dangerous territory is indicated by orange and red colours. The table shows that the only highly correlated variables are Gold$, Plat$ and GLD5PLAT (50% gold and 50% platinum price), these variables are interchangeable and will never be used together in the model. In fact, it bodes well that they demonstrate a high degree of correlation especially with the newly created variable (GLD5PLAT). Aside from these, the highest correlation between variables is -57.1% between the Rand/dollar exchange rate and the MSCI All Country World Index. This means that the independent variables do not have a multicollinearity problem and as a result we can proceed with all independent variables without making adjustments.

6.3 Testing for ARCH Effects

After testing the attributes and properties of data it can be surmised that the stage is set to test the econometric model discussed above and analyzing the relationship between the dependent variable and independent variables. However, the data has shown some attributes that show that it deviates from normality and according to Mangani (2009) JSE data is suited to a GARCH (1,1) econometric model. Chapter 4 and 5 have also demonstrated attributes that need to be presented by the data before a GARCH-type model can be estimated. According to Brooks (2008), it is imperative to perform Engle's (1982) ARCH test to ensure that the ARCH/GARCH class of models is suitable model for the time series. Before performing the ARCH test, Engle (2001) advises checking the time series for volatility clustering as this is a visual method that shows the presence of ARCH effects in your data. He does this by taking a look at the residuals of daily returns of the Dow Jones Industrial Index and NASDAQ. These are shown below and volatility clustering (prolonged periods of calmness followed by prolonged periods of increased volatility) can be clearly identified.

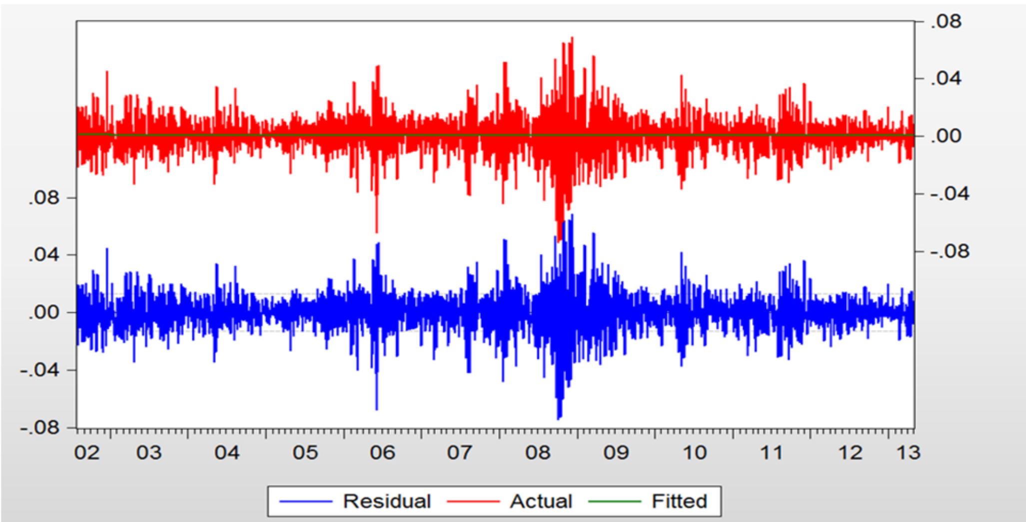
Figure 6.2: Dow Jones and NASDAQ Volatility Clustering



Source: Engle, 2001

A similar test was performed using our newly created ALSI100 index to ascertain whether it displays similar results to those of Engle (2001). This is shown in figure 6.3 below.

Figure 6.3: ALSI100 Volatility Clustering (daily returns)



Source: Author Research

As expected given the fact that literature has indicated that the JSE contains ARCH effects and suitable to ARCH/GARCH-type models, the graph above shows volatility clustering when using daily returns. Ordinary Least Squares (OLS) test is based on the assumption of homoscedasticity, whereas volatility clustering means there is heteroscedasticity present. The presence of clustering means that the time series data is suited for ARCH/GARCH-type models. However, this was performed using daily returns whereas all analysis in this study is based on monthly data. Therefore, the graph below shows the residuals of ALSI100 variable based on monthly return series data.

Figure 6.4: ALSI100 Volatility Clustering (monthly returns)

Source: Author Research

Monthly returns are a lot smoother with less volatility relative to daily returns and this is evident in the figure 6.4 above. The graph still shows volatility clustering in series data, even though it is not as pronounced it is more relevant that it can still be detected on monthly return series where one would expect these to have been smoothed out. This alone though is not enough to convince us to proceed with the ARCH/GARCH-type model analysis. The important test that needs to be conducted to ascertain presence of ARCH effects is the heteroscedasticity test or ARCH test.

Figure 6.5 below shows the results of the ARCH Test where the null hypothesis assumes that the coefficients on residual terms are jointly equal to zero and there are therefore no ARCH effects in the residuals. This means that volatility at time *t* is not predicted by volatility at time *t-1*.

H_0: $\alpha_1 = \alpha_2 = \alpha_3 = \ldots\ldots= \alpha_m = 0$ (6.5)

whereas the alternative hypothesis is given by:

H_a: $\alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \ldots\ldots\neq \alpha_m \neq 0$ (6.6)

In equation 6.5 and 6.6 (α) represents the coefficients of squared residual terms while *m* indicates the order of lags. As discussed above, OLS is based on the assumption of time constant variance whereas ARCH/GARCH models are based on the breakdown of that assumption of homoscedasticity where the error term is not constant over but time-varying. This is indicated by the alternative hypothesis equation. The figure below (an output from EViews 6) shows that the *p*-value of the ARCH test is 1.29% indicating statistical significance at the 5% level of significance. As a result, the null hypothesis of no ARCH effect in our data is rejected in favour of the alternative hypothesis.

Table 6.4: ARCH Effect Test

Heteroskedasticity Test: ARCH

F-statistic	6.364677	Prob. F(1,126)	0.0129
Obs*R-squared	6.154804	Prob. Chi-Square(1)	0.0131

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 09/05/14 Time: 02:04
Sample (adjusted): 2002M09 2013M04
Included observations: 128 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000529	0.000103	5.134241	0.0000
RESID^2(-1)	0.219048	0.086826	2.522831	0.0129

R-squared	0.048084	Mean dependent var	0.000676
Adjusted R-squared	0.040530	S.D. dependent var	0.000984
S.E. of regression	0.000964	Akaike info criterion	-11.03607
Sum squared resid	0.000117	Schwarz criterion	-10.99151
Log likelihood	708.3084	Hannan-Quinn criter.	-11.01796
F-statistic	6.364677	Durbin-Watson stat	1.885806
Prob(F-statistic)	0.012886		

The discussions above indicate that the ARCH/GARCH type econometric model is suited and appropriate for modeling returns of the FTSE/JSE ALSI100 Index. Table 6.1 shows that our data deviates from normality, figure 6.3 and 6.4 demonstrate that there exists volatility clustering in data whilst table 6.4 is a formal test which leads to the conclusion that both returns and residuals have properties which indicate that the ARCH/GARCH econometric model is appropriate for the South African market (Mangani, 2007b; Mangani, 2009; Hsing, 2011).

6.3 Model Specification and A priori Expectations

In chapter 5.1 data variables were discussed and theoretical as well as empirical reasons for selecting variables explored. This was based on the evidence that macroeconomic variables cause changes in stock market prices (Hancocks, 2010). As a result, the variables used in this study have been shown in table 6.5 below.

Table 6.5: Variables and A Priori Expectations

Variable Code	Name Description	Expected Sign	Lagged
ALSI100	FTSE/JSE Top 100 Index		NO
INDPROSA	Industrial Production of South Africa	+	YES
INDPROOECD	Industrial Production of OECD Countries	+	YES
MONEYSUP	M3 Money Supply	+	YES
SACPI	Consumer Price Index	-	YES
SAGB10	SA 10-year Government Bond Yield	-	NO
ZARUSD	Nominal Exchange Rate	+	NO
CRUDE	Price of Brent Crude Oil	+	NO
GLD5PLAT	Precious Metal Index (50% Gold Price (USD) + 50%Platinum Price (USD))	+	NO
GOLD$	Gold Price (USD)	+	NO
PLAT$	Platinum Price (USD)	+	NO
MSCIACWI$	MSCI ACWI (USD)	+	NO

The reasons for the expectations were discussed in chapter five. SA Industrial Production, OECD Industrial Production, Money Supply and South African Consumer Price Index have been lagged by a month. This data is only available post month end compared to variables like bond yields, exchange rates, MSCI ACWI, oil, gold and platinum prices which are readily available as these are traded on a daily basis and as a result investors can make informed decisions on the go without having to wait for data to be published. For instance, October’s inflation rate is only announced in November meaning that the market can only react to this number a month later.

Incorporating the priori expectations above, the resultant equation which is expected to result from the analysis, showing the result of the relationship between each variable and ALSI100 is:

$$\boldsymbol{R_{ALSI100}} = \boldsymbol{C} + \boldsymbol{\beta}_{INDPROSA} + \boldsymbol{\beta}_{INDRPROOECD} + \boldsymbol{\beta}_{MONEYSUP} - \boldsymbol{\beta}_{SACPI} - \boldsymbol{\beta}_{SAGB10} + \boldsymbol{\beta}_{ZARUSD} + \boldsymbol{\beta}_{CRUDE} + \boldsymbol{\beta}_{GLD5PLAT}\ (+\ \boldsymbol{\beta}_{GOLD\$};\ +\ \boldsymbol{\beta}_{PLAT\$}) + \boldsymbol{\beta}_{MSCIACWI\$} + \varepsilon_{ALSI100} \qquad (6.7)$$

6.4 Conclusion

In this chapter a preliminary analysis was performed on the set of data. All variables' time series data were found to be deviating from normal exhibiting excess kurtosis and skewness (see Table 6.1). After the ADF and PP stationarity tests were conducted on data, levels were found to be non-stationary while the differenced data revealed all series to be stationary (see Table 6.2). The independent variables were then tested for multicollinearity and discovered that all variables have pairwise correlations of less than the threshold of 0.7 (see Table 6.3) meaning that there will not be any effect on the standard errors of coefficients. The data was then tested for volatility clustering and ARCH effect (see figure 6.3 & 6.4 and table 6.4 & 6.5). This showed that our data contains ARCH effect and has some volatility clustering and thus meant that the ARCH/GARCH framework is an appropriate framework for modeling returns of the JSE. Finally in section 6.3 expectations of data were discussed. The results of the analysis are presented in the next chapter.

CHAPTER 7:
RESULTS AND DISCUSSION

7.0 INTRODUCTION

As discussed in the previous chapter, the descriptive statistics of all variables show varying degrees of skewness and kurtosis leading to the conclusion that data deviates from normality. The results in the previous chapter also suggest that data exhibits heteroscedasticity and the ARCH/GARCH framework is a suitable model for capturing the presence of time-varying variance.

This chapter aims to bring together all the concepts and information developed through the study. This means that this chapter presents the multifactor APT discussed throughout the study and the results are discussed. This will be done using GARCH (1,1) model and by ascertaining which independent variables have a statistically significant relationship with the dependent variable (ALSI100) and direction of that relationship. The special interest of this study however, is to ascertain the beta or influence of precious metals on the returns of the JSE so this beta will be examined as well. This will be investigated by looking at both the mean and variance equation of the analysis.

7.1 ARCH/GARCH: PRESENTATION AND INTERPRETATION OF RESULTS

After identifying the set of possible macroeconomic factors for the model which have a pervasive effect on the systematic risk of the FTSE/JSE ALSI Top 100 Index a number of combinations were considered to investigate which factors will be included in the return generating process. A number of models were estimated and adjusted until the optimal model with the lowest Akaike Information Criterion (AIC) was identified. This approach is different to the normally employed approach of maximizing R^2; the reason for this is to identify the model with the best risk factors that explain the return generating process rather than achieving a high R^2 (Van Rensburg, 1996). As discussed in the preceding chapter the chosen specification to represent the multifactor model for the JSE return generating process is given by:

$$\boldsymbol{R_{ALSI100t}} = \boldsymbol{C} + \boldsymbol{\beta}_{INDPROSA}\text{INDPROSA}_{t-1} + \boldsymbol{\beta}_{INDRPROOECD}\text{INDPROOECD}_{t-1} + \boldsymbol{\beta}_{MONEYSUP}\text{MONEYSUP}_{t-1} - \boldsymbol{\beta}_{SACPI}\text{SACPI}_{t-1} - \boldsymbol{\beta}_{SAGB10}\text{SAGB10}_{t} + \boldsymbol{\beta}_{ZARUSD}\text{ZARUSD}_{t} + \boldsymbol{\beta}_{CRUDE}\text{CRUDE}_{t} + \boldsymbol{\beta}_{GLD5PLAT}\ \text{GLD5PLAT}_{t}\ \boldsymbol{(+\ \beta_{GOLD\$;}} + \boldsymbol{\beta_{PLAT\$})} + \boldsymbol{\beta}_{MSCIACWI\$}\text{MSCIACWI\$}_{t} + \varepsilon_{ALSI100t} \quad (7.1)$$

where $\boldsymbol{R_{ALSI100t}}$ is the return for the FTSE/JSE ALSI Top 100 Index at time t. The factors have been carefully chosen due to their relationship with the ALSI100. However, the factors in parentheses cannot be used in conjunction with the GLD5PLAT given that this factor has been derived from these factors. It is for this reason that they show a high correlation with this factor. The factor $GLD5PLAT_t$ represents the precious metal sector and according to the analysis later in this chapter the model that uses this factor rather than $GOLD\$_t$ and $PLAT\$_t$ is a better model selection according to the AIC. As discussed previously, each factor was carefully considered before being included into the model. For instance, $MSCIACWI\$_t$ was chosen as a proxy for world stock markets' performance (Clare & Priestley, 1996). The inclusion of this factor into the model goes to show the extent of global integration and the possibility that given the sheer size of global markets, South Africa and its economic policy may have very little impact on the performance of its stock market. In fact both the stock market and the movement of its currency may be affected by activities beyond SA's border. This may be one of the reasons there is a high level of correlation between MSCIACWI$ and ZARUSD (r=-57%). The fluctuations of stock markets on a global scale have sent reverberations into our stock market; as a result, it is important to check whether variance in these global markets has any statistically significant relationship with variance of the ALSI100. Given that the aim of this thesis is to investigate the relationship between the precious metal beta and the ALSI100, it is also important to test whether any variance in this factor leads to volatility in the ALSI100.

7.2 MODEL EVALUATION CRITERIA

In the previous chapter, the diagnostics of the residual term indicated that there are ARCH effects present and thus the ARCH/GARCH model is appropriate for the JSE return generating process. This model also allows for the testing of the conditional variance of MSCIACWI$ and GLD5PLAT versus ALSI100. As discussed above, the Akaike Information Criterion (Akaike, 1979 & 1987) is used given that it is the most relevant and famous comparison and selection criteria between models and is constructed on log likelihood. In choosing the best model using AIC, the minimization rule is used. This means that the model with the minimum AIC value indicates the best model. On the other hand the Schwartz/Bayesian Information Criterion (BIC) is less favourable to factor inclusion because it considers N and as a result, tends to underestimate the number of factors and thus biased against higher order models. According to Tu & Xu (2012), the order of model selection criteria should be AIC, followed by Hannan-Quinn Criteria (HQC) and then BIC. This is the same order which is applied in this study with the primary focus on using AIC.

In terms of R^2, although this normally gives an insight into how much of the variation in the dependent variable is explained by independent variables, this is not a good measure to use especially when dealing with a multifactor model. In the absence of AIC, the best measure to use would have been adjusted R^2. The conventional R^2 tends to give misleading results; this is due to the fact that it assumes that every factor that is added into the model helps in explaining the variation in the dependent variable. This means that it infers that the explained variation is as a result of all the independent variables in the model. It is for this reason that R^2 tends to increase with every added variable without there being any relationship between the added variable and the dependent variable. On the other hand the adjusted R^2 only tells us the percentage of the variation explained by the independent variables that actually affect the dependent variable. This will only be the variables with statistical significance. At the same time, it penalizes any added variable that does not belong in the model. This means that adding extra 'useless' variables into the model will serve to decrease this statistical measure. For that reason, the analysis will be interpreted using the adjusted R^2 rather than R^2.

7.3 MODEL SELECTION & RESULTS DISCUSSION

Table 7.1: ARCH/GARCH & OLS Models of FTSE/JSE ALSI Top 100 Index returns

VARIABLE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7
MEAN EQUATION							
Intercept	-0.009*	-0.010***	-0.011**	-0.007*	-0.009*	-0.008**	-0.009**
CRUDE	0.088**	0.095***	0.092***	0.066**	0.074**	0.089***	0.074**
GLD5PLAT	0.130**	0.104**	0.136***	0.120**	0.208***	0.141***	0.208***
INDPROSA	0.376***	0.362***	0.318***	0.339***	0.316**	0.319***	0.329***
MONEYSUP	0.844***	0.891***	0.835***	0.764***	0.794***	0.766***	0.791***
MSCIACWI$	0.915***	0.966***	0.984***	0.969***	0.868***	0.963***	0.874***
SACPI	-0.814	-0.928*	-0.914**	-0.955**	-0.503	-1.133**	-0.539
ZARUSD	0.418***	0.434***	0.415***	0.426***	0.393***	0.429***	0.397***
SAGB10	-0.118	-0.103					
INDPROOECD	0.345						
R^2	0.722	0.714	0.708	0.695	0.723	0.712	0.723
Adjusted R^2	0.701	0.695	0.691	0.677	0.707	0.695	0.707
AIC	-4.434	-4.471	-4.492	-4.424	-4.319	-4.457	-4.362
HQC	-4.29	-4.336	-4.366	-4.298	-4.202	-4.331	-4.291
BIC	-4.079	-4.138	-4.181	-4.113	-4.031	-4.147	-4.185
Durbin-Watson	2.238	2.225	2.173	2.087	2.238	2.216	2.38
VARIANCE EQUATION							
Intercept	0***	0***	0***	0***	0***	0***	
ARCH (1)	-0.105***	-0.142***	-0.180***	-0.132***	-0.007	-0.160***	
GARCH (1)	1.026***	1.012***	1.037***	1.003***	0.456**	1.025***	
MSCIACWI$	-0.003**	-0.004***	-0.003***	-0.003***	-0.005**	-0.003***	
GLD5PLAT	0.001	0	0.001**	0***	-0.001	0	
Econometric Model	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	OLS
DISTRIBUTION	GED	GED	GED	GED	NORMAL	Student t	NORMAL

Notes:

1. *** Indicates statistical significance at the 1 percent level of significance. ** Indicates statistical significance at the 5 percent level of significance. * Indicates statistical significance at the 10 percent level of significance.

The table above gives the results of the various models that were tested and analysed before the final model which is best for the JSE return generating process was selected. Using the adjusted R^2 measure it can be seen that all the proposed models above seem to provide a reasonable description of the return generating process of the JSE by explaining a sizeable variation of the FTSE/JSE ALSI Top 100 Index. The adjusted R^2 for Models 1 through to 7 ranges from 68% to 71% which points to the usefulness of the factors included in the model. Another pleasing statistic is that there is not much deviation between R^2 and adjusted R^2 meaning that there are no useless factors that have been included in the model that increase the R^2 measure while being penalized by adjusted R^2. Model 1 contains all the factors discussed in the previous chapter and included in equation 7.1. However, looking at variables, although adjusted R^2 is 70% the statistical insignificance of the OECD Industrial production and the South African Government 10-year Bond yield (SAGB10) (with bold values in table 7.1) means that there is still some scope to improve the model. Although it is mentioned above that BIC considers *N* in its measurement, the AIC measure is also improved by removing "useless" factors. The AIC statistic for Model 1 is -4.434. Removing the OECD Industrial Production factor improves the AIC statistic to -4.471 without penalizing the adjusted R^2 statistic, this remains at 69.5% meaning that this factor does not contribute much to the explanation of variation of returns of the JSE. The AIC statistic tells us that Model 2 is a better fit for the JSE return generating process.

After removing the SAGB10 factor due to its statistical insignificance we get Model 3. This is an unrestricted model with outliers corrected for using winsorisation procedure. This seems to be the best model given that it has the lowest AIC statistic compared to the previous two and any other model that was tested and analyzed. The AIC statistic is -4.492; this is the model that will be used as a point of reference for all the results of this analysis. The adjusted R^2 statistic is 69.1% compared to the 69.5% with SAGB10 factor and 70% with SAGB10 and INDPROOECD factors included meaning that the model does not lose much explanation power with the removal of these statistically insignificant factors. The other important fact about Model 3 is that all but one factors are statistically significant at the 1% confidence level which indicates the robustness of these factors within the model. The SACPI factor is still significant at the 5% significance level. All the factors in all models were tested for joint statistical significance using Wald's test of linear restrictions. This test is used to test the hypothesis on factors that have been estimated using maximum likelihood methodology. The null hypothesis has all coefficients restrained to zero:

$$H_0: c(1) = c(2) = c(3) = c(4) = c(5) = c(6) = c(7) = c(8) = 0 \qquad (7.2)$$

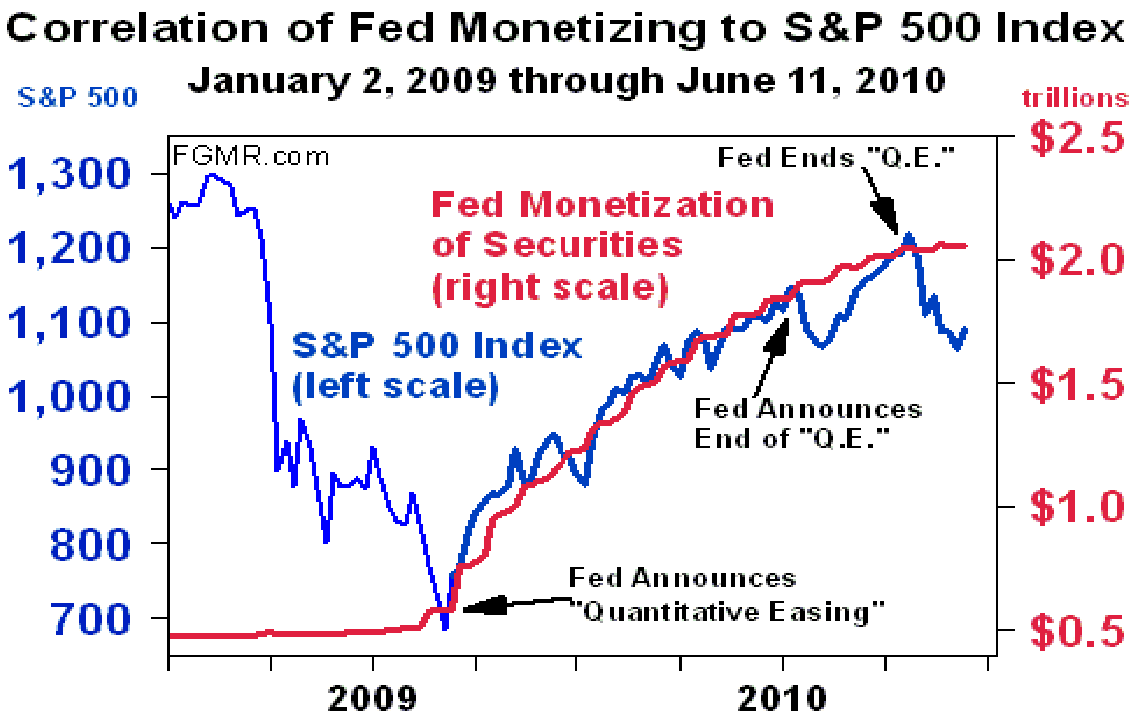
whereas the alternative hypothesis is given by:

H_a: $c(1) \neq c(2) \neq c(3) \neq c(4) \neq c(5) \neq c(6) \neq c(7) \neq c(8) \neq 0$

The resultant F-statistics for all the models reveal that the null hypothesis can be rejected at the 1% significance level indicating that the inclusion of all the factors in the model is statistically significant (Brooks, 2008).

Model 3 shows that excess returns of FTSE/JSE ALSI Top 100 Index are positively related to $CRUDE_t$, $GLD5PLAT_t$, $INDPROSA_{t-1}$, $MONEYSUP_{t-1}$, $MSCIACWI\$_t$ and $ZARUSD_t$ and negatively related to $SACPI_{t-1}$. This is in line with our priori expectations meaning that all the factors have behaved as expected. The magnitude of this relationship is of particular interest, with the MSCIACWI$ having the most influence on the movement of the ALSI100 returns. This is in line with the statement mentioned above about the onset of globalization and the interconnectedness of global stock markets and the era of 24 hour trading from Japan to the United States. The beta of this factor is 0.984, this means that for every 1% move in international markets (as proxied by MSCIACWI$) the ALSI100 is expected to move by 0.984% in the same direction, this is a common observation across all seven models analyzed. The observation should not come as a surprise given that most investors practice what is referred to as herd-mentality which means that they tend to be influenced and carried by current momentum in the market. This means that when momentum is moving one way in international markets South African investors and foreign investors investing in South Africa are expected to behave in a similar way given the flow of information. As alluded to previously, the efficient market hypothesis means that any mispricing in the market is quickly eliminated with the flow of information; there is also the issue of dual-listed stocks on the South African market with listings on the London Stock Exchange and ADRs on the American Stock Exchange. This means that as soon as these stocks trade on these markets, the information on their pricing quickly flows into the JSE and these trade accordingly.

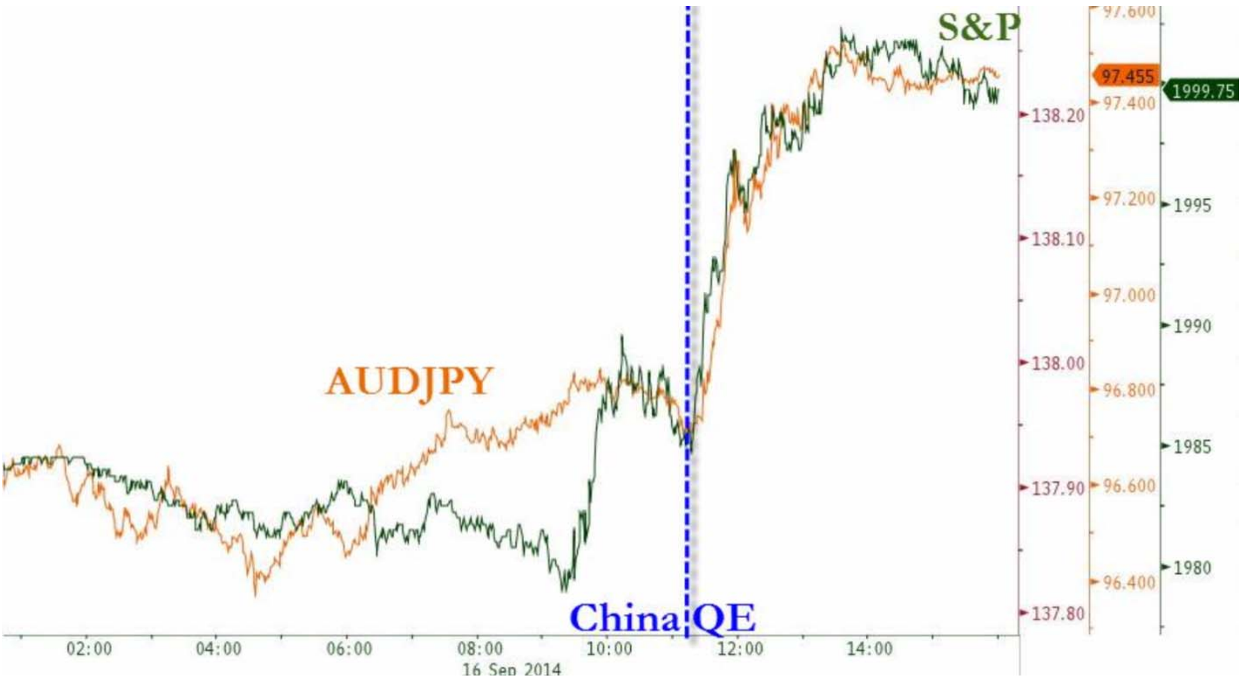
An interesting observation is that of the $MONEYSUP_{t-1}$ factor, it contributes massively to the movement of the ALSI100. A percentage point move in money supply (M3) results in a 0.835% move in the ALSI100 in the same direction. This is understandable given an increase in money supply leads to excess liquidity in the market and increase in money supply is normally associated with a decrease in real yields. This means that money available then searches for extra yield and is channeled to equities leading to an increase in nominal equity prices. Li (2012) found that, in his study of European markets, an increase in money supply leads to an increase in market capitalization of companies, this means that if shares in issue are assumed to be constant then this is as a result of an increase in prices. This is also evident in this age of quantitative easing (QE) where we have witnessed a surge in equity prices due to excess liquidity being pumped into the system. The graph below depicts this relationship clearly.



Source: Free Gold Money Report

The graph shows the near perfect correlation of the S&P 500 Index against the Federal Reserve's increase in money supply. The picture below shows a more immediate response to QE from China by the S&P 500 Index.

Figure 7.2: Effect of China QE on S&P 500 Index



Source: Author Research, Bloomberg

The most important part of money supply stems from the Dividend Discount Model formula:

$$P_{i,t} = \sum_{n=1}^{\infty} \frac{E(D_{i,t+n})}{(1+k_i)^n} \tag{7.3}$$

As mentioned above, the money supply has an inverse relationship with the discount rate. The price of stocks, according to formula 7.3, is determined by future cashflows discounted to the present and these are discounted using the discount rate. As result of an increase in money supply, the discount rate (depicted by *k* in formula 7.3) decreases, increasing the present value of future cashflows and thus the current stock price (Maskay, 2007). These results are consistent with those of Eita (2012) who discovered that there is a positive relationship between money supply and the Namibian Stock Exchange.

Using equation 7.3 and similar to the results of Linter (1975), Nelson (1976), Chen *et al.* (1986), Lee (1992) and Mukherjee & Naka (1995), inflation has a negative relationship with stock markets returns (Naka, Mukherjee and Tufte, 1998). Given South Africa's focus on inflation targeting by the South African Reserve Bank (SARB) monetary policy to control inflation levels in the economy through interest rates, the relationship is expected. The SARB has an inflation targeting band between 3 – 6%, this means that an increase in year-on-year inflation above this band results in the SARB increasing interest rates to combat demand-pull inflation and return this rate to below 6% and vice versa. Due to the fact that stock prices are inversely proportional to interest rates (relationship given by 7.3), and inflation rate is directly proportional to interest rates, a negative relationship between consumer prices and stock market returns is expected (Moolman and du Toit, 2005). This is in line with Hsing's (2011) finding of a negative relationship between the JSE and inflation rate as well as Alagidede & Panagiotidis (2010) who also found a negative relationship between JSE returns and inflation.

According to Priestley (1994), if returns for the dependent variable are expressed as excess returns the intercept, C (1), should be as close to zero as possible. This is due to the fact that there is no risk free asset otherwise if there was such an asset then the intercept should be zero. The intercept for all the models in table 7.1 do not show a big deviation from zero and this can be accepted.

As per the priori expectations, beta for the oil price shows a positive relationship with the returns of the ALSI100. This is expected given that some of the biggest holdings on the JSE have big stakes in the oil industry deriving a sizeable portion of their profits from this commodity. BHP Billiton the biggest diversified miner in the world (also the second biggest stock in the ALSI100 at 30 April 2013 while it was the biggest stock by far for 90% of the sample period) derives over 25% of its after tax profits from oil and gas operations according to their 2013 annual report. They also report that for every US$1/barrel move in the oil price, their after tax profit moves by US$50 million. Sasol on the other hand (7th largest stock in ALSI100 on 30 April 2013) generates 100% of their profits from oil and gas operations. This means that the oil price is a big factor in their profitability. As a result, this makes the price of crude an important component in the pricing of JSE stocks. Lately, the fortunes of the world economy have been clearly depicted in the price of oil with demand in the commodity firmly driven by performance or expected future performance of the global economy. This was evident in 2008 when the impending global recession drove the price of crude to US$40/barrel.

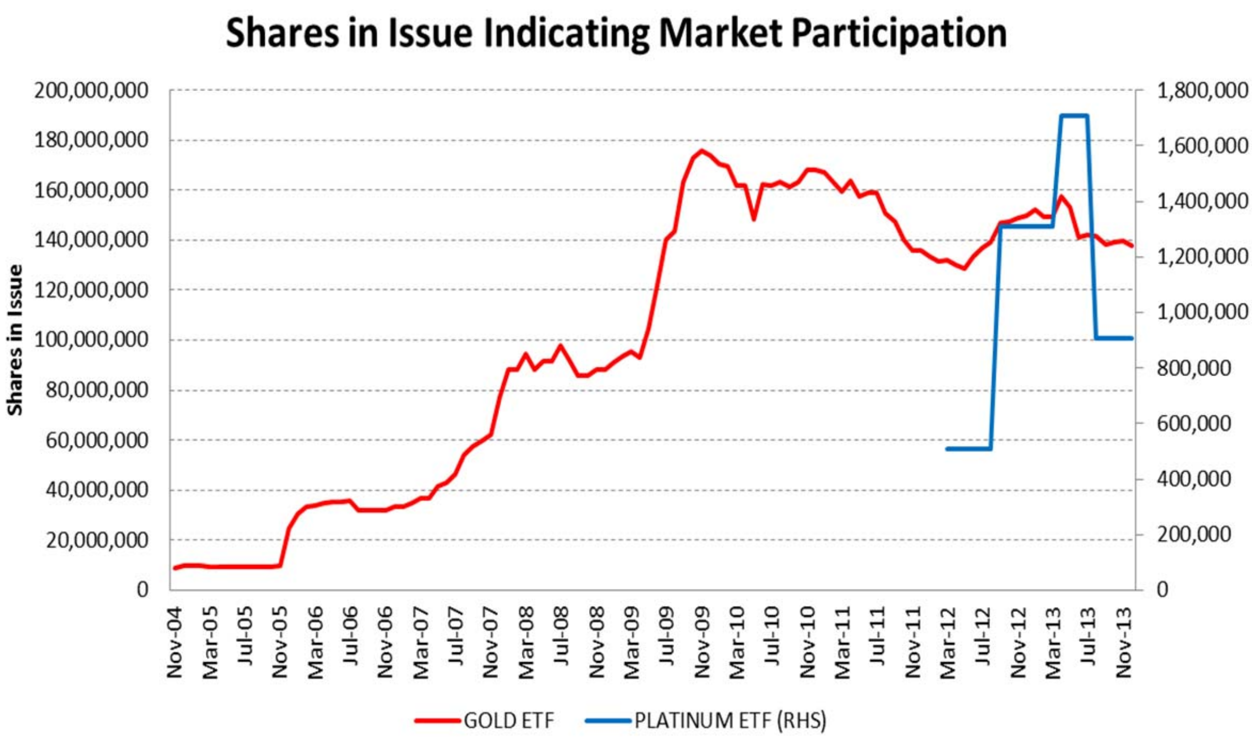
Stock prices are expected to be a leading indicator of economic performance; this means that a positive relationship between stocks and crude should be expected given that they both serve as economic indicators. The results of this study are similar to those of Sadorsky (2001), Arouri & Julien (2009) and Iqbal *et al.* (2012) whose studies show a positive relationship between oil and stock market returns.

Chinzara (2011) and Hsing (2011), found a positive relationship between the performance of the JSE and depreciation of the Rand versus US dollar. This is similar to the results derived by Barr & Kantor (2005) and Barr, Holdsworth & Kantor (2006) where they demonstrate that a depreciating exchange rate is beneficial for JSE stocks. This is based on the fact that the South African market is dominated by Rand hedge companies (companies with foreign based operations who sell into foreign markets) and Rand leverage companies (companies with SA based operations who sell into foreign markets). This means that these companies stand to benefit from a depreciating Rand either through returning dollar earnings or making their exports more competitive, respectively. Their conclusion was similar to that of Moolman & du Toit (2005) in their development of the South African stock market econometric model, they found a significant relationship between the devaluation (depreciation) of the currency and the South African stock market returns. This was based on Solnicks's (1987) theory of increased exports and consequently profits and stock prices as a result of a depreciating currency.

The results show that for a one unit movement in industrial production results in a 0.32% move in returns of ALSI100. According to Chen *et al.* (1986) and Gunsel & Cukur (2007), this is due to the fact that as the economy increases, it leads to an increase in aggregate consumption resulting in increased profitability for corporate companies. According to equation 7.3, increased profitability leads to an increase in dividends and thus share prices. The results of this study are similar to those of Moolman & du Toit (2005) and Hsing (2011) who all found a positive relationship between the South African stock market returns and the underlying economic activity.

According to Bernard *et al.* (2006) and Batten, Ciner & Lucey (2010), precious metals have an important economic function given that their price fluctuations impact both the viability and investment decisions of governments and corporations. These are even more severe for commodity producing and dependent countries like South Africa and Australia as these metals can often lead to economic or stock market booms or busts (Bhattacharyya & Williamson, 2009; Batten *et al.*, 2010). In the context of stock markets, precious metals have played a significant role as a balancing asset in the portfolio, assisting in asset allocation decisions as well as useful in risk reduction (Chow *et al.*, 1999; Abanomey and Mathur, 2001; Chan and Young, 2006). This means that precious metals are a useful form of investment especially during tough investment environments (Edwards & Caglayan, 2001). This is evident in the graph shown below in figure 7.3; it shows the investments into the Gold and Platinum ETFs on the JSE. Holdings of these metals increased during the times of market turmoil or increased volatility in 2009 and 2013 proving Edwards and Caglayan's (2001) observation.

Figure 7.3: GOLD & PLATINUM ETF Investment



The JSE having been founded on the back of precious metals' discovery and being mainly dominated by the mining shares in the gold and platinum industries until the 1980s responds positively to an increase of the gold price (Mangani, 2008b). The results of this study also confirm the same results as those above and those of Moolman and du Toit (2005) and Mangani (2009) about the positive relationship between precious metals and JSE returns. These results are also in line with those of Wang *et al.* (2010) who discovered a positive relationship between gold prices and the stock markets of Germany, Japan, Taiwan and China. Model 3 as well as all the other tested models indicate a reasonable contribution to return by this variable. The precious metal beta shows a positive relationship between the variable and ALSI100. This is the crux of our study and the results are in line with the expectations and all the studies that have been done in this field, especially in South Africa. Mangani (2009) focused on the FTSE/JSE Top 40 Index stocks and found a significant positive relationship between these stocks and the precious metal (gold). The results (Model 3) show that for every 1% move in our created precious metal index, the ALSI100 moves by approximately 0.14%. This shows that precious metals are still a factor on the JSE with beta of these metals showing significance and contributing to the return generating process of the JSE as defined within the APT framework.

7.3.1 MODEL SELECTION & COMPARISON: AIC, DW, Distribution and Econometric Model

As discussed in section 7.2 the AIC is the statistical measure of choice that was used to select the best performing model. In the previous section it was demonstrated that Model 3 has the lowest AIC statistic and given the minimization rule applied in model selection, it was deemed as the best performing model that best captures the return generating process for the FTSE/JSE ALSI Top 100 Index (Ericsson & Karlsson, 2004). Model 3 along with all other models in table 7.1 have undergone a winsorisation procedure except for Model 4. This is a procedure where outliers are moderated to Modified Absolute Deviation (MAD) of 3.5. Comparing Models 3 and 4 shows the benefits of dealing with and correcting outliers before doing any analysis, Model 3 is better on all measured statistics when compared to Model 4. The econometric model used (GARCH (1,1)) is still robust to outliers though, with all the factors still statistically significant, albeit with a varying degree, with almost the same beta coefficients as those in Model 3 with the signs remaining unchanged.

Models 5 and 6 use identical data as Model 3 but are analyzed with different assumptions about the underlying distribution of data. Model 5 assumes an underlying Normal Gaussian distribution while Model 6 assumes an underlying Student t distribution. The results show that Model 3, which assumes a Generalized Error distribution (GED), is a far superior and best performing model according to the various statistical metrics. The reason for this lies in our analysis of the FTSE/JSE ALSI Top 100 Index data in table 6.1, this showed that the JSE excess returns are leptokurtic with a kurtosis statistic greater than 3. This means that they exhibit a high peak and fatter tails. According to Nelson (1991) and Angelidis, Benos & Digiannakis (2003), Generalized Error Distribution (GED) is the fat tails distribution. They contend that Normal Gaussian does not generate ARCH/GARCH models accurately, in order to model adequately the thickness of tails, they believe that the GED works better followed by Student t (Angelidis, Benos & Degiannakis, 2003). They contend that GED works similarly or better than Normal Gaussian for financial market data, solving the hump problem due to the fact that it exhibits thicker tails than normal. On the other hand, they argue that the Student t distribution tends to overcorrect for thick tails rendering it less functional than GED. They concluded that using ARCH/GARCH with residuals modeled under GED yields an acceptable result which is never the case under Normal Gaussian distribution; as a result they assert that the Student t distribution works best for EGARCH models while GED is well suited for GARCH modeling (Angelidis, Benos & Degiannakis, 2003).

This is evident in the results as the GED distribution modeled analysis shows the lowest AIC statistic, followed by Student t and then Normal Gaussian. It is for this reason that all subsequent analysis is modeled under GED. In table 7.1 Model 7 is done using Ordinary Least Squares (OLS) and the results of this model are almost identical to those of Model 5 in every detail. The coefficients are similar, and the resultant statistics are the same as well. This means that for normally distributed data ARCH/GARCH econometric modeling can still be applied as long as this is modeled with the underlying distribution applied as Normal Gaussian.

After determining which model is most appropriate for the return generating process on the JSE by looking at the adjusted $R^2$and AIC statistic, the next step is to test for presence of autocorrelation in the residuals of the resultant model. The test for presence of autocorrelation was done using the Durbin-Watson statistic. If e_t is the residual at time $t,$ the test statistic is given by the formula:

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2}, \qquad (7.4)$$

where T is the number of observations. For large samples this formula can be approximated as DW ≈ 2 (1 – r (e_t, e_{t-1})), with r being the correlation coefficient. This means that the Durbin-Watson (DW) statistic will always fall between 0 and 4 i.e. for perfect positive correlation with r = 1; DW ≈ 2 (1 - 1) = 0, for perfect negative correlation with r = -1; DW ≈ 2 (1 – (-1))

= 4 and when there is zero correlation, r = 0; DW ≈ 2 (1 – 0) = 2. Therefore, the Durbin-Watson statistic near zero means that residuals have a strong positive correlation, a statistic near 2 means residuals have little or no positive or negative correlation, whilst a statistic near 4 indicates negative correlation. This means that there is always a choice between two possible tests, for positive autocorrelation or negative autocorrelation. The DW statistic has two critical values, d_l and d_u, the lower and upper critical value, respectively. They lie between 0 and 2, with $d_l < d_u$. However, due to two possible tests the testing spectrum from 0 to 4 is divided into five different regions, with each test being examined in three regions. The two tests are given below and for each test regions are explained below and shown in the graph below that:

For DW less than 2 (Test 1):

H_0: ρ = 0

H_a: ρ > 0

1. $0 \leq DW < d_l$: *reject the null hypothesis in favour of the alternative hypothesis and conclude that there is positive autocorrelation*
2. $d_l < DW < d_u$: *the test is inconclusive; we neither reject nor fail to reject the null hypothesis.*
3. $d_u < DW$: *fail to reject the null hypothesis and conclude that there is no positive autocorrelation*

For DW greater than 2 (Test 2):

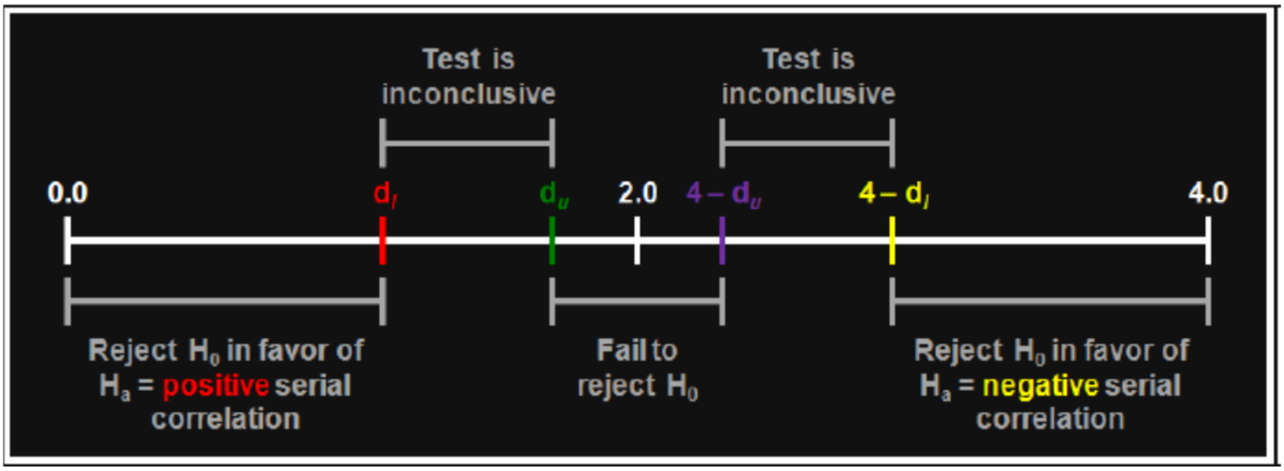
H_0: ρ = 0

H_a: ρ < 0

1. $DW < 4 - d_u$: *fail to reject the null hypothesis and conclude that there is no negative autocorrelation*
2. $4 - d_u < DW < 4 - d_l$: *the test is inconclusive; we neither reject nor fail to reject the null hypothesis.*
3. $4 - d_l < DW \leq 4$: *reject the null hypothesis in favour of the alternative hypothesis and conclude that there is negative autocorrelation*

Graphically both these test can be illustrated below in figure 7.4.

Figure 7.4: Durbin-Watson Test Regions



Source: Author Research

Model 3 has a DW statistic of 2.173 which means that we are testing for negative autocorrelation. The model has k = 7 (independent variables), n = 129 (observations) and significance level of 1%, using the Durbin-Watson significance tables, the values for d_l and d_u are 1.53 and 1.72, respectively. Since we are testing for negative autocorrelation, this means that the lower bound of the inconclusive region is $(4 – d_u)$ is 4 – 1.72 = 2.28 whilst the upper bound is $(4 – d_l)$ is 4 – 1.53 = 2.47. As a result, the 2.173 statistic falls in the first region of Test 2, meaning that we fail to reject the null hypothesis and conclude that there is no negative autocorrelation.

These findings (AIC statistic, ARCH/GARCH model and DW statistic) suggest that Model 3 is the most appropriate and suited for the return generating process on the JSE and works best for our objective.

7.3.2 CONDITIONAL VARAINCE: ARCH/GARCH Model

The variance equation is shown below for the models shown in table 7.1. Given their effect or expected effect on the ALSI 100 Index volatility, the MSCIACWI$ and GLD5PLAT variables have been added into the variance equation as regressors. The variance equation is given by equation 5.8, as illustrated below.

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \qquad (7.5)$$

However, with additional terms added to the equation, this becomes;

$$h_t = \omega + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1} + C_{12}\ MSCIACWI\$ + C_{13}\ GLD5PLT \qquad (7.6)$$

where h_t is the variance of the residual derived from the residual of the mean equation. It is the current month's volatility of ALSI100. ε^2_{t-1} is the previous month's squared residuals from the mean equation. This is also known as the previous month's ALSI100 information about volatility or the ARCH term. h_{t-1} this is a one month lag of h_t which is the previous month's residual volatility or the GARCH term. The results of the equation are given in 7.2 below.

Table 7.2: ARCH/GARCH Models of FTSE/JSE ALSI Top 100 Index: Conditional Variance

VARIABLE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
			VARIANCE EQUATION			
Intercept	0***	0***	0***	0***	0***	0***
ARCH (1)	-0.105***	-0.142***	-0.180***	-0.132***	-0.007	-0.160***
GARCH (1)	1.026***	1.012***	1.037***	1.003***	0.456**	1.025***
MSCIACWI$	-0.003**	-0.004***	-0.003***	-0.003***	-0.005**	-0.003***
GLD5PLAT	0.001	0	0.001**	0***	-0.001	0
Econometric Model	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)
DISTRIBUTION	GED	GED	GED	GED	NORMAL	Student t

Notes:

1. *** Indicates statistical significance at the 1 percent level of significance. ** Indicates statistical significance at the 5 percent level of significance. * Indicates statistical significance at the 10 percent level of significance.

Focusing on Model 3, the results show that both the ARCH and GARCH terms are individually and jointly statistically significant, providing evidence of the presence of ARCH/GARCH effect and volatility clustering of the returns on the JSE. This means that the conditional variance on FTSE/JSE ALSI100 is of a time-varying nature. According to Engle (2001), the ARCH/GARCH model only works if the sum of the coefficients of the ARCH and GARCH terms is less than one (i.e. $\alpha + \beta < 1$). These parameters measure the persistence of the volatility of returns and a number close to zero means volatility reverts to long term volatility with a higher speed; while a number closer to one means that volatility persists and only mean reverts ever so slowly (Engle, 2001). Otherwise a sum of these parameters which is over one means that the model implodes as the volatility is not mean-reverting (Adjasi, 2009).

The negative sign of the ARCH term is in contrast to the bulk of literature especially that of Engle (1982) and Bollerslev (1986) who accentuate the importance of a non-negative ARCH term. However, studies that followed revealed that a non-negative constraint on the ARCH term is too restrictive and they showed that a negative estimate can be obtained (Nelson & Cao, 1992; He & Terasvirta, 1999). According to Alshogeathri (2011), in the GARCH model the sign of the ARCH/GARCH term is of little to no relevance whereas the magnitude of the coefficients is the only factor that matters for conditional variance (Nkoro & Uko, 2013). The sum of the coefficients of the conditional variance equation for Model 3 is (-0.18 + 1.037) 0.86 which is less than one revealing that conditional variance is stationary. Since the sum is closer to one than zero, it means that this process only mean reverts slowly (Engle, 2001). The coefficient of the

GARCH term is higher than that of the ARCH term, meaning that the volatility of the ALSI100 is affected more by past volatility than it is by the economic news of the preceding month. The analysis further shows that the returns of the ALSI100 are influenced by the volatility of MSCIACWI$ and GLD5PLAT, albeit slightly. This is expected since the increased volatility in both of these variables is usually associated with increased volatility throughout the global financial markets landscape.

These results confirm that the ARCH/GARCH framework is the most appropriate framework for the return generating process on the JSE. The analysis of the results on table 7.2 also confirms that the GARCH (1,1) model is the most suited model for the ALSI100 returns and their volatility.

7.3.3 Alternative Risk Factors and Models

The multifactor model of the returns of the FTSE/JSE ALSI100 Index tells us that seven risk factors are responsible for the return generating process and these factors represent different risk categories at play within the JSE. The model chosen that best describes and is well suited for returns on the JSE is Model 3. However, for completeness of this study, table 7.3 below compares Model 3 with alternative models that either utilize a different risk factor for precious metals or by splitting the study period into sub periods (Chen *et al.,* 1986).

Table 7.3: Alternative ARCH/GARCH Models of FTSE/JSE ALSI Top 100 Index returns

VARIABLE	MODEL 3	MODEL 8	MODEL 9	MODEL 10^	MODEL 11#
MEAN EQUATION					
Intercept	**-0.011****	**-0.010***	**-0.009****	**-0.010***	**-0.013**
CRUDE	0.092***	0.090***	0.097***	0.082*	0.082
GLD5PLAT	**0.136*****			0.174**	0.181***
INDPROSA	0.318***	0.340***	0.246**	0.376***	0.131
MONEYSUP	0.835***	0.759***	0.809***	0.926***	0.745
MSCIACWI$	0.984***	0.918***	0.948***	0.935***	0.71***
SACPI	-0.914**	-0.51	-1.046**	-1.544**	0.969
ZARUSD	0.415***	0.428***	0.403***	0.446***	0.231**
GOLD$		**0.188*****			
PLAT$			0.078*		
R^2	0.708	0.72	0.692	0.702	0.742
Adjusted R^2	0.691	0.704	0.675	0.67	0.709
AIC	-4.492	-4.376	-4.396	-4.35	-4.283
HQC	-4.366	-4.25	-4.269	-4.165	-4.097
BIC	-4.181	-4.065	-4.085	-3.882	-3.811
Durbin-Watson	2.173	2.253	2.176	1.822	2.509
VARIANCE EQUATION					
Intercept	**0*****	**0*****	**0*****	**0*****	**0*****
ARCH (1)	-0.180***	0.01	-0.126***	-0.156	0.358
GARCH (1)	1.037***	0.458*	0.960***	0.67***	-0.09
MSCIACWI$	-0.003***	-0.005***	-0.003***	-0.003	-0.003
GLD5PLAT	0.001**			-0.003	-0.003
GOLD$		-0.002			
PLAT$			0		
Econometric Model	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)
DISTRIBUTION	GED	GED	GED	GED	GED

^ 31/07/2002 - 31/12/2007
# 31/12/2007 - 30/04/2013

Notes:

1. *** Indicates statistical significance at the 1 percent level of significance.
   ** Indicates statistical significance at the 5 percent level of significance.
   * Indicates statistical significance at the 10 percent level of significance.

It is possible that other risk factors explain returns of the ALSI100 better than the chosen ones. However, given our main objective of focusing on the precious metal factor, this section will only seek to explore other possible risk factors for this factor and leave others for a different study. Model 8 uses gold as a representative risk factor for precious metals. Gold as a factor is statistically significant within the model at the 1% level of significance. The rest of the other factors and their coefficients do not differ significantly from Model 3 with the exception of the SACPI factor which is not only very different but is also not statistically significant. ALSI100 also seems to be more responsive to a movement in gold than it is to our chosen factor with a one percent move in the metal resulting in a 0.188% move in the dependent variable compared to a movement of 0.136% for our chosen metal. R^2 and adjusted R^2 seem to be slightly higher for Model 8 but the statistic which has been used to select the

most appropriate model, AIC statistic, is lower for Model 3 compared to Model 8.
Model 9 uses platinum as a precious metal representative risk factor. The outcome of this model is very close to that of Model 3 in terms of both the coefficients of factors and their statistical significance. It results in a seven factor model compared to the six factor model for Model 8. Although R^2 and adjusted R^2 are the lowest of the three models (3, 8 and 9), the AIC statistic is lower than Model 8 (only just) whilst it is higher than Model 3 indicating that Model 3 is still the best suited and most appropriate model for the JSE return generating process. This also points to the selection (in this case built) of the representative risk factor for this category as being correct.

The study period spans over 129 months and this has been split into two (almost) identical periods. The first part is 65 months, spanning from 31/07/2002 to 31/12/2007, Model 10. The second part spans 64 months, from 31/12/2007 to 30/04/2013, Model 11. This seeks to explore whether the precious metal factor is only priced in one period or whether it influences the returns over the entire period. The

Model 10 does not seem to deviate much from Model 3 in terms of the number of factors with all seven risk factors statistically significant in this model. The coefficients do not show much deviation either; R^2 and adjusted R^2 also do not lag too far behind. The AIC statistic is still higher than that of Model 3 while the precious metal coefficient is slightly higher for Model 10 at 0.174. Model 11 though seems to have very different results; there are only 3 priced factors, precious metal, global markets and exchange rate. The coefficients are markedly different from those of Model 3 with the R^2 and adjusted R^2 slightly higher, with the AIC statistic much higher even an analysis which drops all the other statistically insignificant variables with the hope of improving AIC only results in it improving slightly to -4.35 from -4.28. As a result, these observations validate our selection of Model 3 as the best model for the return generating process of the JSE.

7.4 Conclusion

The main focus of this chapter was to present and apply the results of the analysis and APT framework, respectively. This was done successfully by presenting a model that best represents and is suited for the return generating process of JSE stock returns. Following the postulate of the APT framework factors were found to be pervasive and able to explain a big variation of the dependent variable.

The analysis showed that the returns of the JSE are well suited for the ARCH/GARCH econometric framework with underlying returns best suited to be modeled using the Generalized Error Distribution (GED) methodology. Returns are characterized by a GARCH (1,1) model. This was in keeping with the statistical properties discussed in the previous chapter about the behavior of the JSE returns shown in preliminary results as well as other studies that have shown that JSE returns are best suited for a GARCH(1,1) model.

The final model chosen was selected using the AIC statistic based on the minimization rule, Model 3 proved to be the most appropriate and well suited model for the JSE return generating process. This was on the face of many examinations against alternative strategies and models. The multifactor model selected is made up of seven risk factors and the diagnostics of the results using the Durbin-Watson test show that the ARCH/GARCH model corrects for autocorrelation previously present in our returns. The conditional variance model also shows that the precious metal factor also impacts the volatility of the dependent variable, albeit very small.

The next chapter concludes this thesis, the final summary of the study and the findings are reiterated with possible areas of further research identified.

CHAPTER 8:
CONCLUSION

8.0 SUMMARY OF THE STUDY AND CONCLUSIONS

The main aim of the study was to identify and extract the beta attributable to the precious metal factor within a JSE multifactor pricing model. This was done by first empirically testing the return generating process of the JSE and developing a wholly functioning model within the confines of APT multifactor model using ARCH/GARCH econometric framework. The model was built using macroeconomic variables as pre-specified risk factors with precious metal factor used as one of the factors. This was to ascertain whether precious metals, as they were instrumental in the formation of the JSE, still have a role to play within the market and the return formation. This purpose was outlined in Chapter 1.

The study started off by reviewing existing theoretical literature of asset pricing models and underlying theory on the relationship between the macroeconomic variables and stock prices in Chapter 2. In this section EMH was reviewed as it provides theory on investor behavior and the efficiency of markets as it leads to the elimination of arbitrage profits. The Dividend Discount Model was also touched on briefly as it provides a guide on the selection of macroeconomic factors. Thereafter, modern portfolio theory and its role as a basis for asset pricing models was explored. Furthermore CAPM as a pioneer of asset pricing models and APT were reviewed. Further to this development of APT from some of the failures of CAPM along with a distinction about different sources of risk.

Chapter 3 reviewed the empirical literature. This was divided into two parts; we took a look at the statistical approach developed by Roll and Ross (1980) and looked at the approach where macroeconomic variables are pre-specified. The empirical tests showed a long list of priced factors in different markets and these were chosen for our study: South African (SA) industrial production, OECD Industrial production, SA broad money supply (M3), SA consumer price index, SA 10-year government bond yield, USD/ZAR nominal exchange rate, Morgan Stanley Capital Index: All Country World Index (USD) (henceforth MSCI ACWI Index), USD precious metal index and USD oil prices.

Chapter 4 reviewed the properties of data and it was concluded that although the usual assumption is that data is normally distributed, it is seldom a case for financial market returns. They tend to be characterized by excess kurtosis, fat tails and skewness.

As a result, in Chapter 5 it was decided that the ARCH/GARCH econometric framework is the best suited model to use for our analysis as it better handles the properties of heteroscedasticity.

This was after discussing data, creation of a new index (ALSI100) and selecting factors to be used in the analysis and the reason for selecting those factors. In Chapter before proceeding with analyzing the data a few measures needed to be taken like correcting data for outliers using winsorisation, testing for unit root using ADF and PP and testing the properties of data. JSE data was discovered to deviate from normal characterized by excess kurtosis, skewness and volatility clustering. It was also discovered that it has ARCH effect in its residual.

In chapter 7, the results were presented and discussed. The hypothesized relationship between the JSE and macroeconomic variables was given by the equation below:

$$\boldsymbol{R_{ALSI100t}} = \boldsymbol{C} + \boldsymbol{\beta}_{INDPROSA}\mathrm{INDPROSA}_{t-1} + \boldsymbol{\beta}_{INDRPROOECD}\mathrm{INDPROOECD}_{t-1} + \boldsymbol{\beta}_{MONEYSUP}\mathrm{MONEYSUP}_{t-1} - \boldsymbol{\beta}_{SACPI}\mathrm{SACPI}_{t-1} - \boldsymbol{\beta}_{SAGB10}\mathrm{SAGB10}_{t} + \boldsymbol{\beta}_{ZARUSD}\mathrm{ZARUSD}_{t} + \boldsymbol{\beta}_{CRUDE}\mathrm{CRUDE}_{t} + \boldsymbol{\beta}_{GLD5PLAT}\ \mathrm{GLD5PLAT}_{t}\ (+\ \boldsymbol{\beta}_{GOLD\$;} + \boldsymbol{\beta}_{PLAT\$}) + \boldsymbol{\beta}_{MSCIACWI\$}\mathrm{MSCIACWI\$}_{t} + \varepsilon_{ALSI100t}$$

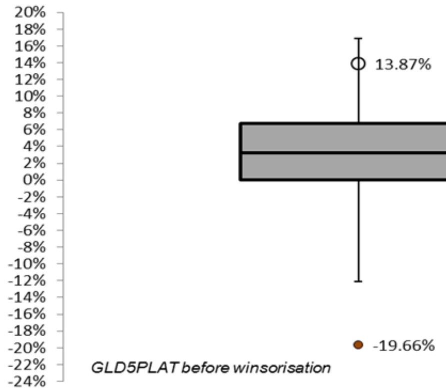
The results showed that all variables behaved as expected in terms of their relationship with the JSE. Results indicate that changes in South African (SA) industrial production, SA broad money supply (M3), SA consumer price index, USD/ZAR nominal exchange rate, Morgan Stanley Capital Index: All Country World Index (USD), USD precious metal index and USD oil prices significantly influence and explain the variation of FTSE/JSE ALSI Top 100 Index. While OECD Industrial production and SA 10-year government bond yield were found that they do not have a relationship with the market. Our results also showed that the hypothesis of a multifactor model within the JSE holds with Wald's test of significance proving this to be true.

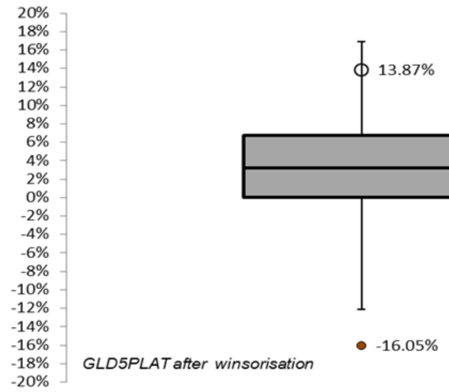
8.1 AREAS OF FURTHER RESEARCH

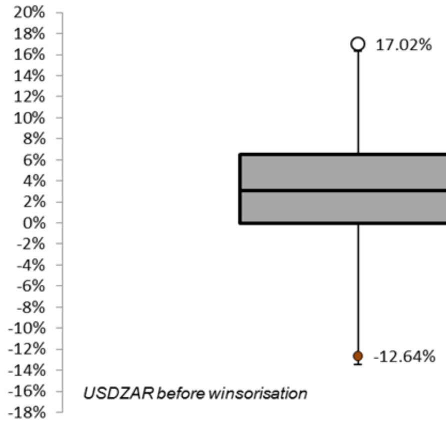
The findings of this study provide scope for areas of further research. Some of these areas could be to extend this study to the underlying sectors of the JSE and individual shares to ascertain how they respond to these factors especially the precious metal factor. The results of that could give some scope on whether precious metals influence cyclical or defensive stocks (sectors).

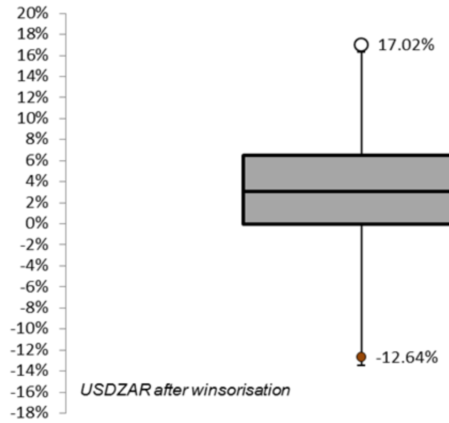
This could be done in conjunction with separating the precious metals and treating them as different risk factors and seeing how individual stocks and sectors react to gold and platinum as factors. These metals have historically had different uses with gold being used more as an investment while platinum has industrial uses in catalytic convertors of diesel cars and only recently started receiving attention as an investment (see figure 7.3). Another area could be to investigate further could be to use different variables as factors or possibly try the original variables used by Chen *et al.* (1986) to test whether they increase the robustness of the model.

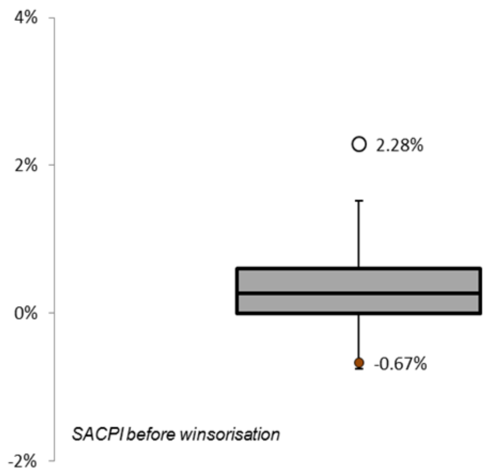
<u>**APPENDIX I: BOX PLOTS BEFORE AND AFTER WINSORISATION**</u>

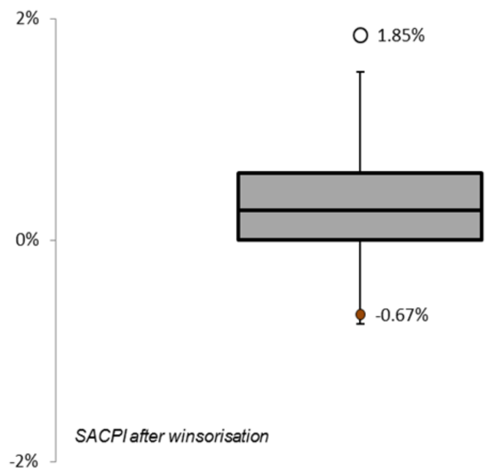


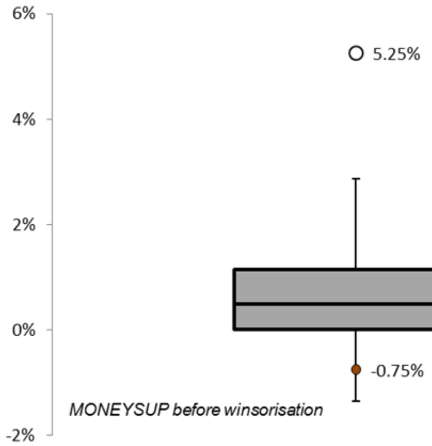











6%
4%
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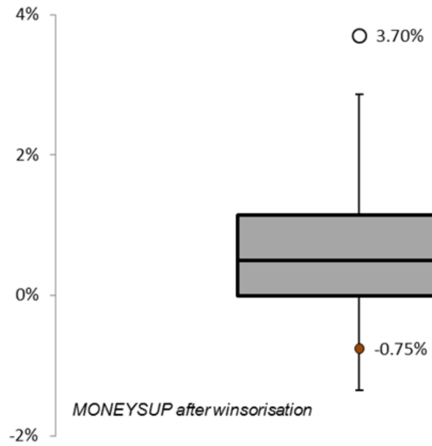
0%
-2%
5.25%
-0.75%
MONEYSUP before winsorisation


4%
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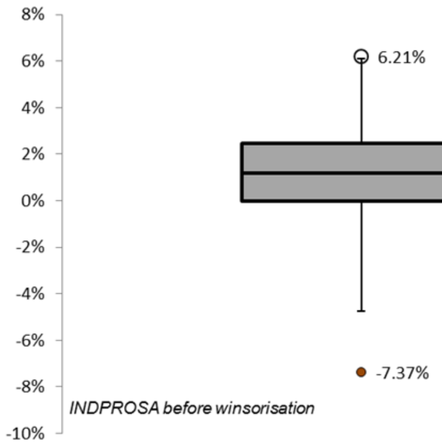
-2%
3.70%
-0.75%
MONEYSUP after winsorisation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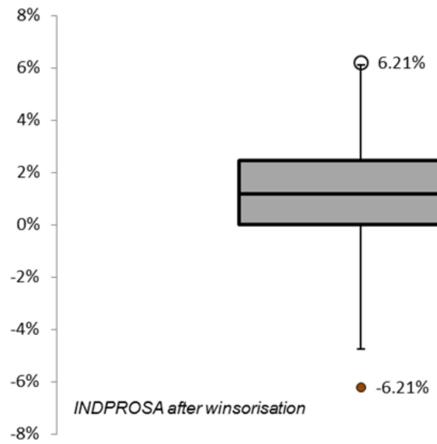
-8%
-10%
6.21%
-7.37%
INDPROSA before winsorisation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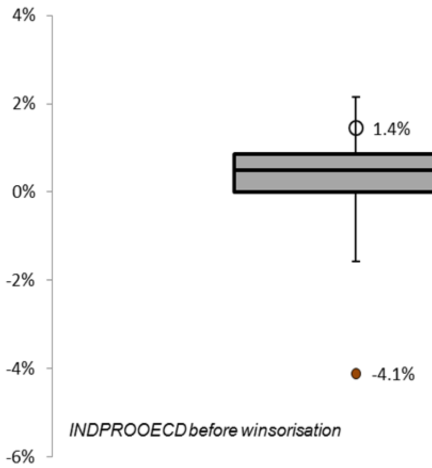
INDPROSA after winsorisation


4%
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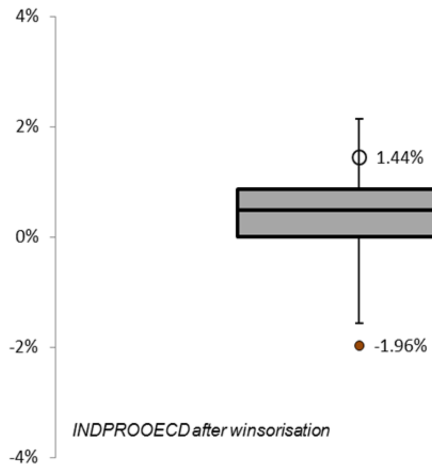
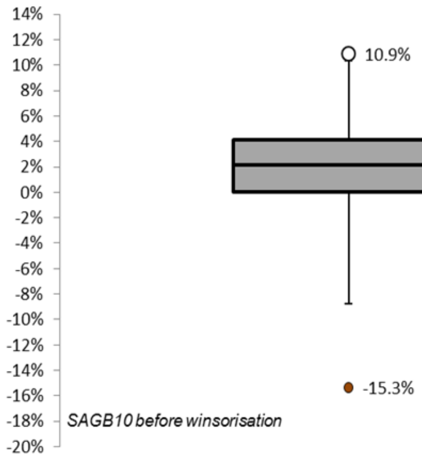
-4%
-6%
1.4%
-4.1%
INDPROOECD before winsorisation


4%
2%
0%
-2%
-4%
1.44%
-1.96%
INDPROOECD after winsorisation


14%
12%
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4%
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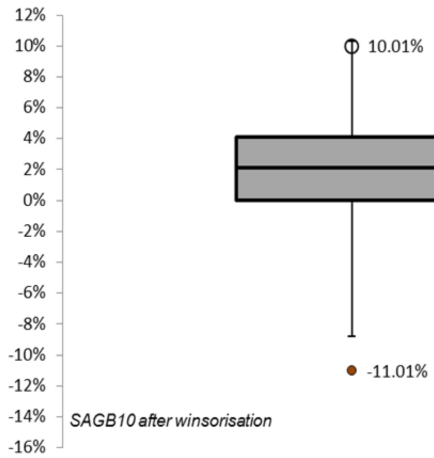
-2%
-4%
-6%
-8%
-10%
-12%
-14%
-16%
-18%
-20%
10.9%
-15.3%
SAGB10 before winsorisation


12%
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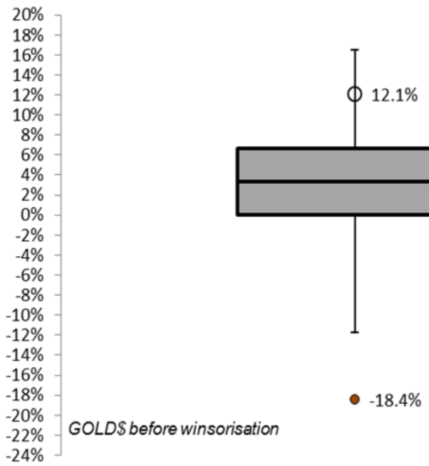
4%
2%
0%
-2%
-4%
-6%
-8%
-10%
-12%
-14%
-16%
10.01%
-11.01%
SAGB10 after winsorisation


20%
18%
16%
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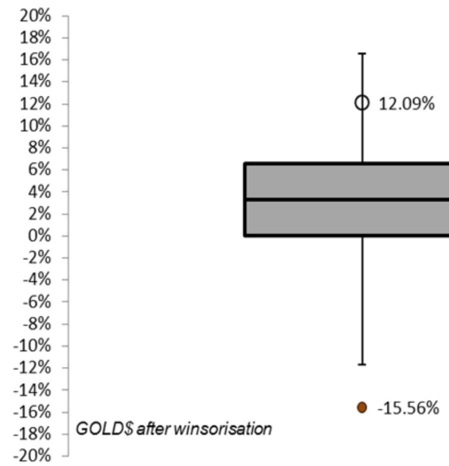
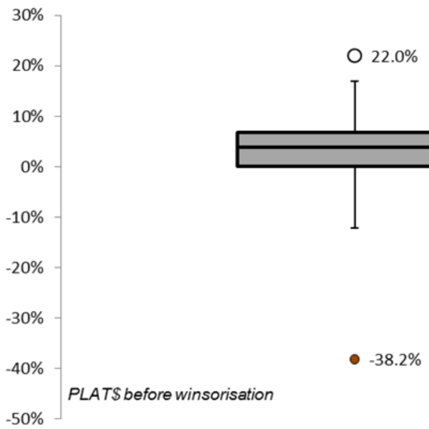
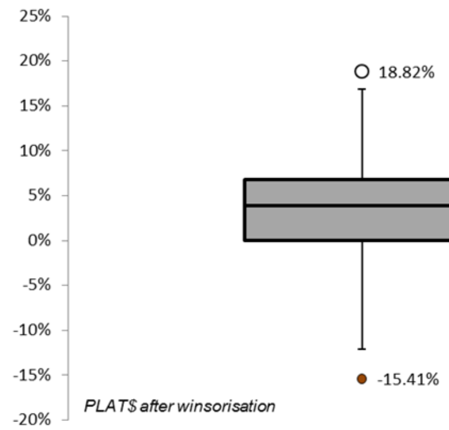
-6%
-8%
-10%
-12%
-14%
-16%
-18%
-20%
-22%
-24%
12.1%
-18.4%
GOLD$ before winsorisation

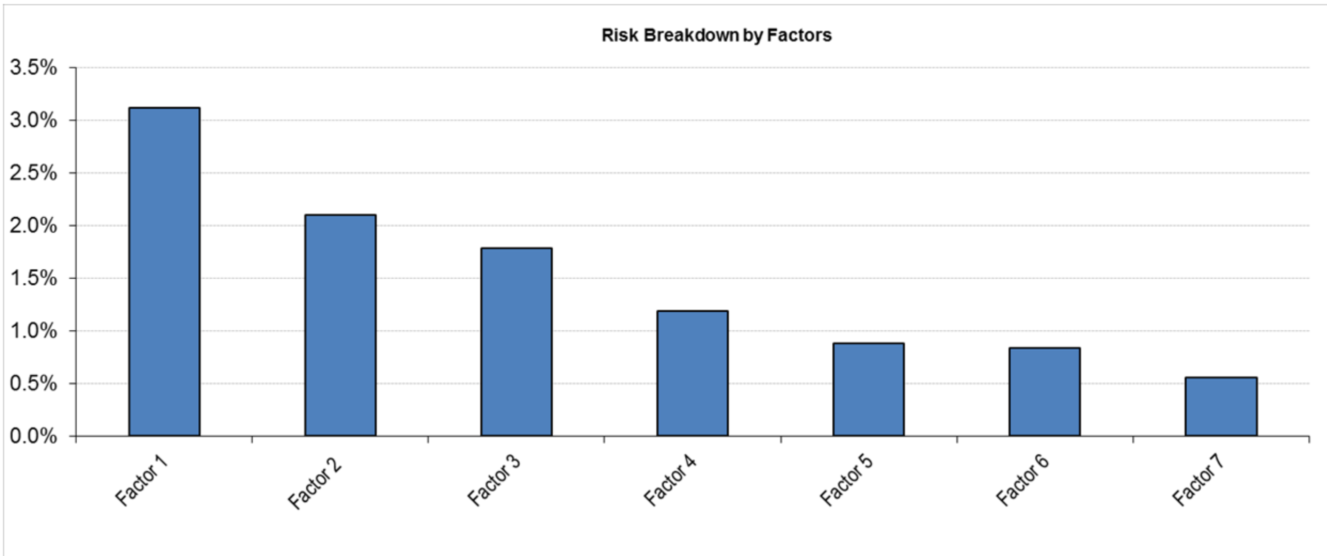

20%
18%
16%
14%
12%
10%
8%
6%
4%
2%
0%
-2%
-4%
-6%
-8%
-10%
-12%
-14%
-16%
-18%
-20%
12.09%
-15.56%
GOLD$ after winsorisation


30%
20%
10%
0%
-10%
-20%
-30%
-40%
-50%
22.0%
-38.2%
PLAT$ before winsorisation


25%
20%
15%
10%
5%
0%
-5%
-10%
-15%
-20%
18.82%
-15.41%
PLAT$ after winsorisation

APPENDIX II: PCA RESULTS, CHRIS HART TWEET

Risk Breakdown			
	Total	Systematic	Specific
FTSE/JSE ALSI Top 100 Index	12.75%	12.21%	3.69%



Source: EMA, Bloomberg and Author Research

The graphs above show the risk breakdown of the ALSI100 with the first graph showing that the index is not fully diversified with stock specific risk present. The second graph shows factors derived through principal components analysis. They show that the ALSI 100 is characterized by a seven factor (from 20 factors, 13 were discarded for low eigenvalues) model similar to our conclusion using macroeconomic factors. (Data for individual share returns was sourced from Bloomberg)

31 December 2013		
Code	**Name**	**% in JSE**
ANG	ANGLOGOLD ASHANTI	0.81
GFI	GOLDFIELDS	0.42
HAR	HARMONY	0.16
PAN	PAN AFRICAN RESOURCE	0.06
SGL	SIBANYE	0.15
DRD	DRDGOLD	0.01
RNG	RANDGOLD	0.00
Total		**1.60**

Source: JSE

Source: Chris Hart (Strategist at Investment Solutions) Tweet & Twitter

APPENDIX III: VBA CODE FOR ALSI TOP 100 FILES CREATION

```
Sub Best_Tester()

Dim i As Integer
Dim r As Integer
Dim k As Integer

i = 66

k = 9

    Do While Not IsEmpty(ActiveCell.FormulaR1C1 = Cells(i + 1, k))
    Range("D1").Select
    ActiveCell.FormulaR1C1 = Cells(i + 1, k)

    Application.Run "Research.xlsm!ALSI_TOP100BM_Creator"
    Range("D1").Select

    i = i + 1
    Loop

End Sub

Sub ALSI_TOP100BM_Creator()

    save_name = Cells(1, 4).Value

    Range("A4:B103").Select
    Selection.Copy
    Workbooks.Add
    Selection.PasteSpecial Paste:=xlPasteValues, Operation:=xlNone, SkipBlanks _
        :=False, Transpose:=False
    Columns("B:B").Select
    Selection.NumberFormat = "0"
```

```
    Selection.Insert Shift:=xlToRight, CopyOrigin:=xlFormatFromLeftOrAbove
    Range("B1").Select
    ActiveCell.FormulaR1C1 = "~"
    Selection.AutoFill Destination:=Range("B1:B100")
    Range("B1:B101").Select

    Sheets("Sheet2").Delete
    Sheets("Sheet3").Delete

    Range("A4").Select

    ActiveWorkbook.SaveAs Filename:= _
        "C:\Users\tmzobe\Desktop\School\Thesis\BMK\" & "ALSI" & "." & save_name & "",
FileFormat:= _
        xlCSV, CreateBackup:=False
    ActiveWorkbook.Save
    ActiveWorkbook.Close

End Sub
```

APPENDIX IV: FTSE/JSE ALL SHARE INDEX SHARES (31/07/2002)

Rank	Code	Name	Weight (%)	Size (Cap)
1	AGL	ANGLO AMERICAN PLC	15.01	Large Cap
2	BIL	BHP BILLITON PLC	9.59	Large Cap
3	CFR	FINANCIERE RICHEMONT-DEP REC	8.17	Large Cap
4	SAB	SABMILLER PLC	5.65	Large Cap
5	SOL	SASOL LTD	5.48	Large Cap
6	GFI	GOLD FIELDS LTD	4.13	Large Cap
7	OML	OLD MUTUAL PLC	3.92	Large Cap
8	SBK	STANDARD BANK GROUP LTD	3.02	Large Cap
9	AMS	ANGLO AMERICAN PLATINUM LTD	2.75	Large Cap
10	REM	REMGRO LTD	2.67	Large Cap
11	SAP	SAPPI LIMITED	2.37	Large Cap
12	FSR	FIRSTRAND LTD	2.21	Large Cap
13	LBT	LIBERTY INTERNATIONAL PLC	2.07	Large Cap
14	ANG	ANGLOGOLD ASHANTI LTD	1.98	Large Cap
15	IMP	IMPALA PLATINUM HOLDINGS LTD	1.71	Large Cap
16	SLM	SANLAM LTD	1.66	Large Cap
17	HAR	HARMONY GOLD MINING CO LTD	1.60	Large Cap
18	NED	NEDBANK GROUP LTD	1.16	Large Cap
19	BGA	BARCLAYS AFRICA GROUP LTD	1.10	Large Cap
20	BVT	BIDVEST GROUP LTD	1.08	Large Cap
21	BAW	BARLOWORLD LTD	1.04	Large Cap
22	EXX	EXXARO RESOURCES LTD	0.96	Large Cap
23	TBS	TIGER BRANDS LTD	0.91	Large Cap
24	INP	INVESTEC PLC	0.82	Large Cap
25	IPL	IMPERIAL HOLDINGS LTD	0.80	Large Cap
26	MTN	MTN GROUP LTD	0.72	Large Cap
27	RMH	RMB HOLDINGS LTD	0.69	Large Cap
28	VNF	VENFIN PTY LTD	0.65	Large Cap
29	LGL	LIBERTY GROUP LTD	0.60	Large Cap
30	ACL	ARCELORMITTAL SOUTH AFRICA	0.57	Large Cap
31	NPK	NAMPAK LTD	0.55	Large Cap
32	JNC	JOHNNIC HOLDINGS LTD	0.51	Large Cap
33	DRD	DRDGOLD LTD	0.47	Large Cap
34	DDT	DIMENSION DATA HOLDINGS PLC	0.45	Large Cap
35	INL	INVESTEC LTD	0.43	Large Cap
36	AFB	ALEXANDER FORBES	0.41	Large Cap
37	SHF	STEINHOFF INTL HOLDINGS LTD	0.40	Large Cap
38	AVI	AVI LTD	0.35	Mid Cap
39	NTC	NETCARE LTD	0.34	Mid Cap
40	SHP	SHOPRITE HOLDINGS LTD	0.31	Mid Cap
41	MOZ	METOZ HOLDINGS LTD	0.31	Mid Cap
42	RLO	REUNERT LTD	0.31	Mid Cap
43	WHL	WOOLWORTHS HOLDINGS LTD	0.30	Mid Cap
44	MMI	MMI HOLDINGS LTD	0.30	Mid Cap
45	CRN	CORONATION HOLDINGS LTD-N	0.28	Large Cap
46	AEG	AVENG LTD	0.26	Mid Cap
47	ARI	AFRICAN RAINBOW MINERALS LTD	0.26	Mid Cap
48	PIK	PICK N PAY STORES LTD	0.25	Large Cap
49	MUR	MURRAY & ROBERTS HOLDINGS	0.24	Mid Cap
50	ABL	AFRICAN BANK INVESTMENTS LTD	0.23	Mid Cap

51	NHM	NORTHAM PLATINUM LTD	0.23	Mid Cap
52	TRU	TRUWORTHS INTERNATIONAL LTD	0.22	Mid Cap
53	NPN	NASPERS LTD-N SHS	0.22	Mid Cap
54	APN	ASPEN PHARMACARE HOLDINGS LT	0.22	Mid Cap
55	ILV	ILLOVO SUGAR LTD	0.20	Mid Cap
56	TON	TONGAAT HULETT LTD	0.20	Mid Cap
57	AFE	AECI LTD	0.20	Mid Cap
58	SUI	SUN INTERNATIONAL LTD	0.19	Mid Cap
59	ECO	EDGARS CONSOLIDATED STORES	0.18	Mid Cap
60	WAR	GOLD FIELDS OPERATIONS LTD	0.18	Mid Cap
61	SPG	SUPER GROUP LTD	0.18	Mid Cap
62	AFX	AFRICAN OXYGEN LTD	0.18	Mid Cap
63	CLS	CLICKS GROUP LTD	0.18	Mid Cap
64	FPT	FOUNTAINHEAD PROPERTY TRUST	0.17	Mid Cap
65	BCX	BUSINESS CONNEXION GROUP	0.17	Mid Cap
66	MSM	MASSMART HOLDINGS LTD	0.17	Mid Cap
67	ABI	AMALGAMATED BEVERAGE INDS	0.16	Large Cap
68	JDG	JD GROUP LTD	0.16	Mid Cap
69	SNT	SANTAM LTD	0.15	Mid Cap
70	ENR	ENERGY AFRICA LTD	0.14	Mid Cap
71	AFR	AFGRI LTD	0.14	Mid Cap
72	TFG	THE FOSCHINI GROUP LTD	0.13	Mid Cap
73	PPC	PPC LTD	0.13	Mid Cap
74	DTC	DATATEC LTD	0.11	Mid Cap
75	MDC	MEDICLINIC INTERNATIONAL LTD	0.11	Mid Cap
76	AVG	AVGOLD LTD	0.11	Mid Cap
77	CPT	CAPITAL ALLIANCE HOLDINGS	0.11	Mid Cap
78	NIB	NEDCOR INVESTMENT BANK HLDGS	0.11	Large Cap
79	TSX	TRANS HEX GROUP LTD	0.10	Mid Cap
80	ELH	ELLERINE HOLDINGS LTD	0.09	Mid Cap
81	ALT	ALLIED TECHNOLOGIES LTD	0.09	Mid Cap
82	MLB	MALBAK LTD	0.09	Mid Cap
83	DTA	DELTA EMD LTD	0.09	Mid Cap
84	AFI	AFRICAN LIFE ASSURANCE CO	0.09	Mid Cap
85	MPC	MR PRICE GROUP LTD	0.09	Small Cap
86	SAC	SA CORPORATE REAL ESTATE FUN	0.09	Small Cap
87	AVS	AVIS SOUTHERN AFRICA LTD	0.08	Small Cap
88	MVL	MVELAPHANDA RESOURCES LTD	0.08	Mid Cap
89	BAT	BRAIT SE	0.08	Mid Cap
90	TDH	TRADEHOLD LTD	0.08	Small Cap
91	PEP	PEPKOR LIMITED	0.08	Small Cap
92	USV	UNITED SERVICE TECHNOLOGIES	0.07	Small Cap
93	NBC	NEW BOND CAPITAL LTD	0.07	Mid Cap
94	SIS	SUN INTL SOUTH AFRICA LTD	0.07	Mid Cap
95	CRH	CORONATION HOLDINGS LTD	0.06	Large Cap
96	DSY	DISCOVERY LTD	0.06	Mid Cap
97	AMB	AMB HOLDINGS LTD	0.06	Small Cap
98	PAM	PALABORA MINING CO LTD	0.06	Mid Cap
99	APL	NET 1 APPLIED TECH HOLDINGS	0.06	Small Cap
100	TIW	TIGER WHEELS LTD	0.05	Small Cap

101	MHH	MIH HOLDINGS PTY LTD	0.05	Mid Cap
102	OCE	OCEANA GROUP LTD	0.05	Mid Cap
103	PMN	PRIMEDIA LTD-'N' SHRS	0.05	Small Cap
104	PSG	PSG GROUP LTD	0.05	Small Cap
105	ELE	ELEMENTONE LTD	0.05	Mid Cap
106	UTR	UNITRANS LTD	0.05	Mid Cap
107	SLU	INVESTMENT SOLUTIONS HLDGS	0.05	Mid Cap
108	CHE	CHEMICAL SERVICES LTD	0.05	Small Cap
109	CAT	CAXTON AND CTP PUBLISHERS AN	0.05	Mid Cap
110	DLV	DORBYL LTD	0.04	Small Cap
111	MPL	METBOARD PROPERTIES LTD	0.04	Small Cap
112	RDF	REDEFINE PROPERTIES LTD	0.04	Small Cap
113	CRM	CERAMIC INDUSTRIES LTD	0.04	Small Cap
114	MFL	METROFILE HOLDINGS LTD	0.04	Small Cap
115	RAH	REAL AFRICA HOLDINGS LTD	0.04	Mid Cap
116	EHS	EVRAZ HIGHVELD STEEL AND VAN	0.04	Mid Cap
117	GMB	GLENRAND MIB LTD	0.04	Small Cap
118	CXT	CAXTON PUBLISHERS & PRINTERS	0.04	Mid Cap
119	CPA	CORPCAPITAL LTD	0.04	Small Cap
120	SGG	SAGE GROUP LTD	0.04	Mid Cap
121	GBL	GENBEL SOUTH AFRICA LIMITED	0.03	Small Cap
122	TRT	TOURISM INVESTMENT CORP LTD	0.03	Small Cap
123	MRF	MERAFE RESOURCES LTD	0.03	Small Cap
124	ADR	ADCORP HOLDINGS LTD	0.03	Small Cap
125	MST	MUSTEK LTD	0.03	Small Cap
126	CEN	CENTRECITY PROPERTY FUND	0.03	Small Cap
127	SFT	SOFTLINE LTD	0.03	Small Cap
128	GNN	GRINDROD LTD-N	0.03	Small Cap
129	OZZ	OZZ LTD	0.02	Small Cap
130	GRF	GROUP FIVE LTD	0.02	Small Cap
131	PGH	ABSA TRADING & INVESTMENT SO	0.02	Small Cap
132	WBO	WILSON BAYLY HOLMES-OVCON	0.02	Small Cap
133	BTG	BYTES TECHNOLOGY GROUP LTD	0.02	Small Cap
134	MBT	MB TECHNOLOGIES PTY LTD	0.02	Small Cap
135	AHV	AFRICAN HARVEST LTD	0.02	Small Cap
136	GNK	GRINTEK LTD	0.02	Small Cap
137	RCL	RCL FOODS LTD/SOUTH AFRICA	0.02	Small Cap
138	PGR	PEREGRINE HOLDINGS LTD	0.02	Small Cap
139	PON	PROFURN LIMITED	0.02	Small Cap
140	HDC	HUDACO INDUSTRIES LTD	0.02	Small Cap
141	BEL	BELL EQUIPMENT LTD	0.02	Small Cap
142	SRL	SA RETAIL PROPERTIES LTD	0.02	Small Cap
143	BPL	BARPLATS INVESTMENTS LTD	0.02	Small Cap
144	ACP	ACUCAP PROPERTIES LTD	0.02	Small Cap
145	GIJ	GIJIMA GROUP LTD	0.02	Small Cap
146	TSH	TSOGO SUN HOLDINGS LTD	0.01	Small Cap
147	AGI	AG INDUSTRIES LTD	0.01	Small Cap
148	WET	WETHERLYS INVESTMENT HLDGS	0.01	Small Cap
149	CLH	CITY LODGE HOTELS LTD	0.01	Small Cap
150	GLT	GLOBAL TECHNOLOGY LTD	0.01	Small Cap
151	PMA	PRIMEDIA LTD/SOUTH AFRICA	0.01	Small Cap
152	GND	GRINDROD LTD	0.01	Small Cap
153	COM	COMAIR LTD	0.01	Small Cap
154	CLI	CLIENTELE LTD	0.01	Small Cap
155	CDZ	CADIZ HOLDINGS LTD	0.01	Small Cap
156	WLN	WOOLTRU LTD-N SHS	0.00	Mid Cap
157	PBT	PBT GROUP LTD	0.00	Mid Cap
158	ITV	INTERVID LTD	0.00	Small Cap
159	CPI	CAPITEC BANK HOLDINGS LTD	0.00	Small Cap

APPENDIX IV (Continuted): FTSE/JSE ALL SHARE INDEX SHARES (30/04/2013)

Rank	Code	Name	Weight (%)	Size (Cap)
1	BIL	BHP BILLITON PLC	10.81	Large Cap
2	SAB	SABMILLER PLC	9.67	Large Cap
3	AGL	ANGLO AMERICAN PLC	5.85	Large Cap
4	CFR	FINANCIERE RICHEMONT-DEP REC	5.73	Large Cap
5	MTN	MTN GROUP LTD	5.51	Large Cap
6	NPN	NASPERS LTD-N SHS	4.77	Large Cap
7	SOL	SASOL LTD	4.31	Large Cap
8	SBK	STANDARD BANK GROUP LTD	2.74	Large Cap
9	OML	OLD MUTUAL PLC	2.71	Large Cap
10	BTI	BRITISH AMERICAN TOBACCO PLC	2.25	Large Cap
11	FSR	FIRSTRAND LTD	1.85	Large Cap
12	REM	REMGRO LTD	1.77	Large Cap
13	SLM	SANLAM LTD	1.77	Large Cap
14	SHP	SHOPRITE HOLDINGS LTD	1.50	Large Cap
15	APN	ASPEN PHARMACARE HOLDINGS LT	1.42	Large Cap
16	ANG	ANGLOGOLD ASHANTI LTD	1.30	Large Cap
17	IMP	IMPALA PLATINUM HOLDINGS LTD	1.29	Large Cap
18	BVT	BIDVEST GROUP LTD	1.27	Large Cap
19	WHL	WOOLWORTHS HOLDINGS LTD	1.03	Large Cap
20	GRT	GROWTHPOINT PROPERTIES LTD	0.97	Large Cap
21	BGA	BARCLAYS AFRICA GROUP LTD	0.97	Large Cap
22	GFI	GOLD FIELDS LTD	0.95	Large Cap
23	SHF	STEINHOFF INTL HOLDINGS LTD	0.89	Large Cap
24	MNP	MONDI PLC	0.89	Large Cap
25	TRU	TRUWORTHS INTERNATIONAL LTD	0.83	Large Cap
26	INP	INVESTEC PLC	0.78	Large Cap
27	NED	NEDBANK GROUP LTD	0.76	Large Cap
28	TBS	TIGER BRANDS LTD	0.75	Large Cap
29	REI	REINET INVESTMENTS SA-DR	0.72	Mid Cap
30	LHC	LIFE HEALTHCARE GROUP HOLDIN	0.71	Mid Cap
31	IPL	IMPERIAL HOLDINGS LTD	0.70	Large Cap
32	VOD	VODACOM GROUP LTD	0.70	Large Cap
33	KIO	KUMBA IRON ORE LTD	0.68	Large Cap
34	NTC	NETCARE LTD	0.60	Mid Cap
35	MPC	MR PRICE GROUP LTD	0.60	Mid Cap
36	RMH	ALEXANDER FORBES	0.59	Large Cap
37	ITU	INTU PROPERTIES PLC	0.59	Large Cap
38	RDF	REDEFINE PROPERTIES LTD	0.56	Mid Cap
39	MDC	MEDICLINIC INTERNATIONAL LTD	0.55	Large Cap
40	DSY	DISCOVERY LTD	0.49	Large Cap
41	MMI	MMI HOLDINGS LTD	0.47	Mid Cap
42	TFG	THE FOSCHINI GROUP LTD	0.45	Mid Cap
43	LON	LONMIN PLC	0.43	Mid Cap
44	SPP	SPAR GROUP LIMITED/THE	0.42	Mid Cap
45	NPK	NAMPAK LTD	0.41	Mid Cap
46	AMS	ANGLO AMERICAN PLATINUM LTD	0.41	Large Cap
47	MSM	MASSMART HOLDINGS LTD	0.41	Large Cap
48	EXX	EXXARO RESOURCES LTD	0.41	Large Cap
49	BAW	BARLOWORLD LTD	0.40	Mid Cap
50	ABL	AFRICAN BANK INVESTMENTS LTD	0.39	Mid Cap

51	AVI	AVI LTD	0.34	Mid Cap
52	RMI	RMI HOLDINGS	0.33	Mid Cap
53	HAR	HARMONY GOLD MINING CO LTD	0.33	Mid Cap
54	CPF	CAPITAL PROPERTY FUND	0.32	Mid Cap
55	PPC	PPC LTD	0.30	Mid Cap
56	SAP	SAPPI LIMITED	0.29	Mid Cap
57	CLS	CLICKS GROUP LTD	0.29	Mid Cap
58	MND	MONDI LTD	0.29	Large Cap
59	CML	CORONATION FUND MANAGERS LTD	0.29	Mid Cap
60	ARI	AFRICAN RAINBOW MINERALS LTD	0.28	Large Cap
61	RES	RESILIENT PROPERTY INCOME	0.27	Mid Cap
62	CPI	CAPITEC BANK HOLDINGS LTD	0.27	Mid Cap
63	INL	INVESTEC LTD	0.27	Large Cap
64	RLO	REUNERT LTD	0.26	Mid Cap
65	LBH	LIBERTY HOLDINGS LTD	0.25	Mid Cap
66	BAT	BRAIT SE	0.24	Mid Cap
67	HYP	HYPROP INVESTMENTS LTD-UTS	0.24	Mid Cap
68	AFE	AECI LTD	0.24	Mid Cap
69	AEG	AVENG LTD	0.23	Mid Cap
70	FPT	FOUNTAINHEAD PROPERTY TRUST	0.22	Mid Cap
71	TRE	TRENCOR LTD	0.21	Mid Cap
72	SUI	SUN INTERNATIONAL LTD	0.20	Mid Cap
73	PFG	PIONEER FOODS LTD	0.20	Mid Cap
74	ASR	ASSORE LTD	0.20	Large Cap
75	CCO	CAPITAL & COUNTIES PROPERTIE	0.20	Mid Cap
76	TON	TONGAAT HULETT LTD	0.20	Mid Cap
77	PIK	PICK N PAY STORES LTD	0.19	Mid Cap
78	AIP	ADCOCK INGRAM HOLDINGS LTD	0.18	Mid Cap
79	MUR	MURRAY & ROBERTS HOLDINGS	0.18	Mid Cap
80	OMN	OMNIA HOLDINGS LTD	0.18	Mid Cap
81	DTC	DATATEC LTD	0.18	Mid Cap
82	VKE	VUKILE PROPERTY FUND LTD	0.17	Mid Cap
83	GND	GRINDROD LTD	0.17	Mid Cap
84	ACP	ACUCAP PROPERTIES LTD	0.17	Mid Cap
85	SAC	SA CORPORATE REAL ESTATE FUN	0.17	Mid Cap
86	ILV	ILLOVO SUGAR LTD	0.16	Mid Cap
87	WBO	WILSON BAYLY HOLMES-OVCON	0.16	Mid Cap
88	NHM	NORTHAM PLATINUM LTD	0.15	Mid Cap
89	SPG	SUPER GROUP LTD	0.14	Small Cap
90	HCI	HOSKEN CONS INVESTMENTS LTD	0.14	Mid Cap
91	JSE	JSE LTD	0.14	Small Cap
92	NEP	NEW EUROPE PROPERTY INVEST	0.13	Small Cap
93	SGL	SIBANYE GOLD LTD	0.13	Mid Cap
94	SNT	SANTAM LTD	0.12	Mid Cap
95	EMI	EMIRA PROPERTY FUND	0.12	Mid Cap
96	FBR	FAMOUS BRANDS LTD	0.11	Small Cap
97	LEW	LEWIS GROUP LTD	0.11	Mid Cap
98	EOH	EOH HOLDINGS LTD	0.09	Small Cap
99	CLH	CITY LODGE HOTELS LTD	0.08	Small Cap
100	CVH	CAPEVIN HOLDINGS LTD	0.08	Small Cap

101	SYC	SYCOM PROPERTY FUND	0.08	Small Cap
102	TKG	TELKOM SA SOC LTD	0.08	Mid Cap
103	AEN	ALLIED ELECTRONICS CO-N SHRS	0.08	Mid Cap
104	OCE	OCEANA GROUP LTD	0.08	Mid Cap
105	MPT	MPACT LTD	0.08	Small Cap
106	ACL	ARCELORMITTAL SOUTH AFRICA	0.07	Mid Cap
107	ARL	ASTRAL FOODS LTD	0.07	Small Cap
108	JDG	JD GROUP LTD	0.07	Mid Cap
109	REB	REBOSIS PROPERTY FUND LTD	0.07	Small Cap
110	FFA	FORTRESS INCOME FUND LTD-A	0.06	Small Cap
111	AFP	ALEXANDER FORBES -PREFERENCE	0.06	Small Cap
112	MTA	METAIR INVESTMENTS LTD	0.06	Small Cap
113	PAN	PAN AFRICAN RESOURCES PLC	0.06	Small Cap
114	IVT	INVICTA HOLDINGS LTD	0.06	Small Cap
115	BLU	BLUE LABEL TELECOMS LTD	0.06	Small Cap
116	AFX	AFRICAN OXYGEN LTD	0.06	Mid Cap
117	CMP	CIPLA MEDPRO SOUTH AFRICA LT	0.06	Small Cap
118	KAP	KAP INDUSTRIAL HOLDINGS LTD	0.06	Mid Cap
119	RBP	ROYAL BAFOKENG PLATINUM LTD	0.05	Mid Cap
120	CSB	CASHBUILD LTD	0.05	Small Cap
121	ADR	ADCORP HOLDINGS LTD	0.05	Small Cap
122	IPF	INVESTEC PROPERTY FUND LTD	0.05	Small Cap
123	HDC	HUDACO INDUSTRIES LTD	0.05	Small Cap
124	GRF	GROUP FIVE LTD	0.05	Small Cap
125	SUR	SPUR CORP LTD	0.05	Small Cap
126	ADH	ADVTECH LTD	0.05	Small Cap
127	RCL	RCL FOODS LTD/SOUTH AFRICA	0.05	Mid Cap
128	PNC	PINNACLE HOLDINGS LTD	0.05	Small Cap
129	DRD	DRDGOLD LTD	0.05	Small Cap
130	EQS	EQSTRA HOLDINGS LTD	0.05	Small Cap
131	CLR	CLOVER INDUSTRIES LTD	0.05	Small Cap
132	PMM	PREMIUM PROPERTIES LTD-UTS	0.05	Small Cap
133	ZED	ZEDER INVESTMENTS LTD	0.04	Small Cap
134	HPA	HOSPITALITY PROPERTY FUND-A	0.04	Small Cap
135	BCX	BUSINESS CONNEXION GROUP	0.04	Small Cap
136	BRN	BRIMSTONE INVESTMENT - N SHS	0.04	Small Cap
137	OCT	OCTODEC INVESTMENTS LTD	0.04	Small Cap
138	TMG	TIMES MEDIA GROUP LTD	0.04	Small Cap
139	RIN	REDEFINE PROPERTIES INTERNAT	0.04	Small Cap
140	RBX	RAUBEX GROUP LTD	0.03	Small Cap
141	TCP	TRANSACTION CAPITAL	0.03	Small Cap
142	AFR	AFGRI LTD	0.03	Small Cap
143	PGR	PEREGRINE HOLDINGS LTD	0.03	Small Cap
144	ELI	ELLIES HOLDINGS LTD	0.03	Small Cap
145	AWA	ARROWHEAD-A	0.03	Small Cap
146	KGM	KAGISO MEDIA LTD	0.03	Small Cap
147	AWB	ARROWHEAD-B	0.03	Small Cap
148	PAM	PALABORA MINING CO LTD	0.03	Small Cap
149	MFL	METROFILE HOLDINGS LTD	0.02	Small Cap
150	HSP	HOLDSPORT LTD	0.02	Small Cap
151	PGL	PALLINGHURST RESOURCES LTD	0.02	Small Cap
152	DLT	DELTA PROPERTY FUND LTD	0.02	Small Cap
153	GPL	GRAND PARADE INVESTMENTS LTD	0.02	Small Cap
154	HWN	HOWDEN AFRICA HOLDINGS LTD	0.02	Small Cap
155	ALT	ALLIED TECHNOLOGIES LTD	0.02	Small Cap
156	MRF	MERAFE RESOURCES LTD	0.02	Small Cap
157	AEL	ALLIED ELECTRONICS COR-A SHR	0.02	Mid Cap
158	SSK	STEFANUTTI STOCKS HOLDINGS	0.02	Small Cap
159	BEL	BELL EQUIPMENT LTD	0.01	Small Cap
160	CIL	CONSOLIDATED INFRASTRUCTURE	0.01	Small Cap
161	PET	PETMIN LTD	0.01	Small Cap
162	LHG	LITHA HEALTHCARE GROUP LTD	0.01	Small Cap
163	YRK	YORK TIMBER HOLDINGS LTD	0.01	Small Cap
164	HPB	HOSPITALITY PROPERTY FUND-B	0.01	Small Cap
165	CZA	COAL OF AFRICA LTD	0.01	Small Cap
166	CMH	COMBINED MOTOR HOLDINGS LTD	0.01	Small Cap

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