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TESTING THE RANDOM WALK HYPOTHESIS IN THE STOCK MARKET PRICES: EVIDENCE FROM SOUTH AFRICA'S STOCK EXCHANGE (2000-2011)

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A DISSERTATION SUBMITTED IN FULFILMENT OF THE REQUIREMENTS OF OBTAINING A MASTER OF COMMERCE DEGREE IN ECONOMICS

FACULTY OF MANAGEMENT AND COMMERCE

DEPARTMENT OF ECONOMICS

UNIVERSITY OF FORT HARE

2013

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To my late sister, Faith

You encouraged me to further my studies, providing moral and financial support. The words you told me, “study hard to show thyself approved”, will never be forgotten. I love you and l miss you.

ACKNOWLEDGEMENTS

The completion of this dissertation has not been done by solo means. Firstly, l would like to thank the Almighty for His word says,‘commit all your plans to the lord and they will prosper’. In addition l would like to thank God for a wonderful supervisor, Mr Andrew Maredza (and his family), who gave me priceless support, guidance and encouragement not only academically but also spiritually. Without God using him, this dissertation would not have been successful. The financial support of the Zimbabwean Presidential Scholarship and the Govan Mbeki cannot go unmentioned. I also want to thank my family and friends for moral and social support, specifically Faith who prayed with me throughout till she was taken. Lastly but not least, l want to thank Forward in Faith church members in the Eastern Cape Province for their prayers and the time we fellowshipped together and just like an iron sharpens an iron, you ironed me spiritually and even socially. God bless you all.

ABSTRACT

The Johannesburg Stock Exchange market was tested for the existence of the random walk hypothesis using All Share Index (ALSI) and time series data for the period between 2000 and 2011. The traditionally used methods, the unit root tests and autocorrelation test were employed first and they all confirmed that during the period under consideration, the JSE price index followed the random walk process. In addition, the ARIMA model was built and it was found that the ARIMA (1, 1, 1) was the model that best fitted the data in question. Furthermore, residual tests to help determine whether the residuals of the estimated equation show random walk process in the series were done. It was found that the ALSI resembles series that follow random walk hypothesis with strong evidence of RWH indicated in the conducted forecasting tests which showed vast variance between forecasted values and actual indicating little or no forecasting strength in the series. To further validate the findings in this research, the variance ratio test was conducted under heteroscedasticity and it also strongly corroborated that the existence of a random walk process cannot be rejected in the JSE. It was concluded that since the returns follow the random walk hypothesis, it can be said that JSE is efficient in the weak form level of the EMH and therefore opportunities of making excess returns based on out- performing the market is ruled out and is merely a game of chance. In other words, it will be of no use to choose stocks based on information about recent trends in stock prices.

Key words: Random walk hypothesis, ARIMA, JSE, Variance ratio test.

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LIST OF ACRONYMS

ACF	Autocorrelation Function
ALSI	All Share Index
ADF	Augmented Dickey Fuller
ALTX	Alternative Exchange
APT	Arbitrage Pricing Theory
AR	Autoregressive
ARIMA	Auto Regressive Integrated Moving Average
BESA	Bond Exchange of South Africa
BJ	Box Jenkins
BSE	Bahrain Stock Exchange
BSE	Budapest Stock Exchange
CAPM	Capital Assert Pricing Model
DCM	Development Capital Market
DSE	Dhaka Stock Exchange
EMH	Efficient Market Hypothesis
ETF	Exchange Traded Funds
FMCA	Financial Market Control Act
FSB	Financial Services Board
FTSE	Financial Times Stock Exchange
FX	Foreign Exchange Market
GGM	Gordon Growth Model
LMIL	London Market Information Link
JSE	Johannesburg Stock Exchange
MA	Moving Average
MAPE	Mean Absolute Percentage Error
PACF	Partial Autocorrelation Function
RWH	Random Walk Hypothesis
SA	South Africa
SAFEX	South Africa Futures Exchange
SARB	South African Reserve Bank
SECA	Stock Exchange Control Act
SENS	Stock Exchange News Service

SML	Securities Market Line
StatsSA	Statistics South Africa
WEF	World Economic Forum
VRT	Variance Ratio Test
VCM	Venture Capital Market

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

The concept of market efficiency has dominated the financial literature due to the scarcity of financial resources, as such, how stock market prices behave plays a vital role in the allocation of the scarce financial resources. Market efficiency is used to explain the relationship that exists between information and share price in capital markets, following whether or not returns in a market follow a random walk process. Regulators now and again try to improve the condition of the Johannesburg Stock Exchange (JSE) by imposing different rules and regulations because price trends are important to investors and/or companies when deciding on diversifying their sources of investment capital and spreading risk. Stock prices also provide a benchmark against which returns on investments projects can be judged (Green et al., 2005). Equity is appropriately priced and no distortions in pricing of capital and risk if the market is informationally efficient.

Following the developments in the JSE, it is necessary to add to the existing literature concerning the randomness of the All Share Index (ALSI) using current information and see if the results have changed or not. Over the years, it has become a major interest to financial analysts to come up with theories and models that explain how stock market prices behave or how they can be determined. One such model is the Random Walk Hypothesis (RWH), which is a financial theory that stipulates that stock market prices evolve according to a random walk and thus the prices of the stock market cannot be predicted. Viney (2007; 309) defines random walk hypothesis as a theory that contends that each observation in a time series such as share prices is dependent on the previous observation. Put differently, the hypothesis states that price series do not exhibit predictive patterns over time but can best be described through a random walk. According to the RWH the actual lack of correlation between thepast and present can be easily seen hence if a stock goes up one day, no stock market participant can accurately predict that it will go up again the next day (Fama, 1965).

In order to understand the RWH, it is vital to understand the theories that describe how one can be able to predict the stock market price. There are basically two approaches to predicting stock prices that are common to market professionals which are chartist or technical theories and the theory of fundamental or intrinsic value analysis (Fama, 1965). The chartist theories hinges on the basic assumption that history repeats itself and thus the way to predict stock prices and increase one's potential gains is to become familiar with past patterns of price behaviour and recognise situations of likely repetition. This means that successive price changes in individual securities are dependent.

The fundamental or intrinsic analysts on the other hand, hold the assumption that at any point in time individual security has an intrinsic value or an equilibrium price which depends on the earnings potential of that security. Earnings potential in turn depends on fundamental factors such as quality of management, outlook of the industry and the economy, to name but a few. What this then means is that, an investor can through a careful study of these fundamental factors, be able to determine whether actual price is above or below its intrinsic value. If actual prices of stocks tend to move towards intrinsic values, an attempt to determine the intrinsic value is the same as making predictions of future price and this is the heart of the predictive procedure implied by the fundamental analysis (Mishkin, 2010).

In contrast, the RWH starts from the grounds that the market for securities is a good example of an efficient market and in an efficient market, rational profit-maximisers actively compete with each other and try to predict future prices. This competition leads to a situation where actual prices reflect all information and will be good estimates of the intrinsic value of the security. According to the RWH, the actions of the many participants will cause the actual price of a security to wander randomly around its intrinsic value. In the case that the variance between actual prices and intrinsic values are systematic rather than random in nature, knowledge of this should help intellectual market participants to better forecast the path by which actual prices will move toward intrinsic values. Whilst many intelligent traders try to take advantage of this knowledge, they tend to counteract such systematic behaviour in price series and even though uncertainty concerning intrinsic values will remain, actual prices of securities will stroll randomly about their intrinsic values (Fama, 1965).

The independence assumption of the random-walk model is valid as long as knowledge of the past behaviour of the series of price changes cannot be used to increase expected gains. The implication for investment purposes is that the independence assumption is an adequate description of reality if actual degree of dependence in series of price changes is not sufficient to make more profits of greater than the expected profits under a naive buy-and-hold policy (Brooks, 2008).

The main concern of this research is to test the random walk hypothesis in the JSE. ln other words the research aims at testing the hypothesis that successive price changes are independent. Since stock markets are important, the government, industry and even central or reserve banks of countries keep a close watch on the happenings of the stock market particularly the stock market price index. The stock market price changes now and again and sometimes a market's rise can be attributed to pure speculation or to changes in the economic variables. Hence at times trying to anticipate stock market movements by analysing traditional economic and financial indicators can lead to incorrect forecasts. Put differently, the idea or assumption of price dependency or serially independent price increments is supported by the act of different investors competing in the market. If there were correlation between different prices in different periods, clever investors could bet on it and beat the market (arbitrage). In their process of trying to outperform the market, they would then destroy the basis of their own investment strategy, and drive the correlations they utilised back to zero. As a result the (geometric) random walk model assumes that at a given moment it is impossible to estimate where in the business cycle the economy is, and utilise such knowledge for investment purposes (Fama, 1970). As noted by Ko and Lee (1991), if the random walk hypothesis holds, the weak form efficiency holds, but not vice versa. This then means that the evidence supporting the random walk hypothesis can be used to also support evidence of market efficiency, however, it must be noted that violation of the hypothesis of random walk need not be evidence of market inefficiency in the weak form.

It is against this background that this research looks at the behaviour of South Africa’s stock prices and more precisely the independence of the South African stock market prices. The random walk hypothesis states that stock price changes have the same distribution and are independent of each other, so a past movement or trend of a stock price or market cannot be used to predict its future movement.

1.2 Statement of the problem

On a typical day millions of shares exchange hands on the stock exchange. For any economy, the financial sector is the back bone of the economy and hence its functioning is of paramount importance to the well-being of that particular country, particularly how prices behave as prices are the measure of the wellbeing of the market. Hence there is concern over the pricing of stocks in the market since it affects all those who invest in it and the country as a whole. Distribution of the ownership of the economy's capital stock, which represents the chief role of the capital market, is ideally satisfied if the market follows the random walk hypothesis as prices from such a market provide accurate signals for resource allocation (Fama 1970 & 1991). According to Mishkin, (2010; 147), stock market performance (closing price) form part of the chief items in everyday news, because the stock market is the most important source of funds for businesses. The market for stocks is without doubt the financial market that receives the most concentration and scrutiny because of the role it plays in the economy and also because it is a summary measure of the performance of the economy.

A market following the random walk hypothesis indicates that past history of stock price movements and the history of stock trading volume do not contain information that will allow the investor to outperform the market using their knowledge of past price information. Rejection of this hypothesis has important implications on investors as this would mean the possibility to earn profits from forecasting prices will be little. Since random walk has important implications on portfolio management, it becomes apparent to test the hypothesis for South Africa's stock exchange.

Given that the authorities thrive now and again to improve the stock market, particularly in the areas of efficiency as an efficient stock market attracts even international investors, it becomes apparent to seek evidence for or against the random walk hypothesis of the JSE so as to determine whether it is efficient in terms of behaviour and forecastability of the stock prices. Having understood how the ALSI behaves, policy makers and regulators of the JSE may have a better understanding of the factors that may drive in the much needed capital from both local and international investors into the financial system.

1.3 Objectives of the study

The broad objective of this study is to examine whether the price index of the JSE, (All Share Index) follows a random walk. This main objective is explored through the following sub-objectives:

- To examine the trends of the ALSI (All Share Index).
- To investigate whether prices in the JSE follow a random walk process as required by market efficiency.

- To make policy recommendations concerning the stock markets based on empirical results.

1.4 Hypothesis

The study will test the following overall hypothesis

H_0: The JSE market does not follow a random walk process

H_1: The JSE market follows a random walk process.

1.5 Significance of the study

Financial time series, especially stock market prices and exchange rates are continually brought to attention through daily news reports in newspapers, television and radio informing us of the latest stock market index values (Mishkin, 2010). The capital market is a vital branch of the economy as it facilitates economic development, however, investors will only be motivated to save and invest in the market if their securities in that market are appropriately priced. Testing the market efficiency or rather in this case, testing the behaviour of the weighted index of the JSE (overall price of listed shares), is significant for investors and policymakers. It therefore becomes desirable to observe price behaviour and to understand the feasible development of the prices in the future. Private and corporate investors, businessmen and the public, including the brokers and analysts who advise shareholders can all benefit from a deeper understanding of price behaviour. As postulated by Ko and Lee (1991), numerous traders deal with the risks associated with changes in prices, these risks can normally be summarised by the variances of future returns, directly, or by their relationship with relevant covariances in a portfolio.

Stock markets have a welfare effect on the economy and therefore investors would want to understand how the prices are determined as it affects their financial outlook. Though often, the decision to invest in the market is independent of share prices, and merely risky, it still remains apparent to investors to understand whether the current price is independent of the last period’s price or not.

The important consideration for an investor is that if the random walk process does describe the movements of the JSE stock price, the history of previous movements of the share prices contains no valuable information about the likely future price movements. If the random walk theory is valid and if securities are efficient markets, then stock prices at any point in time will represent good estimates of intrinsic value or fundamental values. Thus addition fundamental analysis is of value only when the analyst or investor has new information which was not fully considered in forming current market prices. If not then the investor should forget about fundamental analysis and choose securities by some random selection procedure. In short the significance of this study is that if indeed the JSE follows RWH, then investors will know that they cannot make profits through determining the share's trading behaviour on the basis of historic price data.

Recent developments (in information dissemination) in the (JSE) suggest that information dissemination systems on the market have improved vastly ever since the 2007/2008 global financial crisis, raising concern on whether the developments have aided the efficiency of the market particularly in terms of the randomness of the stock prices (JSE, 2012). It is significant to study the stock market of a country and see if it follows random walk behaviour as this will help in making financial decisions that will at the end affect the whole economy since the stock market is a summary measure of the performance of the economy. Random walk has implications also on the actions of investors as chief players in the security market.

Stock prices are reflective of what is happening in the economy, and they affect confidence, that is, it can be a discouraging factor to know that prices in the current period have fallen given that they affect future prices.The study is also significant to policy makers because it can aid in the allocation of financial resources more efficiently. Understanding how the JSE price behaves makes policy implications easy to understood thereby helping in policy making. Moreover an efficient stock market can attract foreign portfolio investment, encourage domestic savings and improving the mobility of capital and financial resources.

In contrast to the random walk hypothesis are some economists and investors who believe that the market is predictable to some degree. These people believe that prices may move in trends and that the study of past prices can be used to forecast future price direction. There have been some economic studies that support this view, and try to prove the random walk hypothesis wrong and are called the non-random walk hypothesis. This study seeks to add to the existing debate by examining whether the Johannesburg Stock Exchange follows random or non-random walk.

Once the behaviour of the stock price is determined, one can better comprehend the market and the economy and the variable could be used for forecasting if the prices are dependent on each other, and hence one can make forecasts using past prices. On the contrary, if the prices do follow random walk, then one cannot systematically generate abnormal returns because making accurate forecast about prices using past price information will be impossible and the market is said to be efficient in the weak-form. Furthermore, if the market follows a random walk process, for any company the price of its security reflects the true picture of that company which will be good news. This will provide confidence and reduce the level of risk and hence, result in better decision making for decision-makers. On the other hand if the market is found not to follow the random walk, it may indicate that the JSE and/ or companies listed on the JSE need to consider making moves to improve their valuation of shares so as to make them efficient.

The study is also important in that the results of the study will offer useful insights that can help in managing investments in South Africa, which will in turn boost the economy as a whole.

1.6 Organisation of the study

The research is organised as follows, Chapter 1introduces the study by providing a background to the study, objectives, hypotheses and the significance of the study among other things.Chapter 2 provides an overview of the JSE, and Chapter 3 reviews both the theoretical and empirical literature relating to stock market behaviour. Chapter 4 discusses the methodology and sources of data. Chapter 5 presents estimated regression models, the results obtained and their interpretation. Chapter 6 presents a brief conclusion of the study, policy recommendations, limitations of the study and possible areas for further research.

CHAPTER TWO

OVERVIEW OF THE JSE

2.1 Introduction

This chapter provides an overview of the financial system and that of Johannesburg Stock Exchange (JSE), covering the history of the JSE, structure of the JSE market, as well as the recent developments in the JSE. Also presented here, are trends of the ALSI for the period beginning January 2000 to December 2011. Furthermore, the liquidity, market capitalisation, and the regulation framework within which the JSE operatesis outlined. Lastly, a discussion of the unique characteristics of stock markets that make them more likely to follow a random walk is presented.

2.2 An overview of the financial system

Financial systems or financial markets (bond and stock markets) generally have the basic function of ensuring the movement of funds from those who have a surplus (or those who want to save now) to those who have a shortage (Mishkin, 2010). A well functioning financial market channels funds from households, firms and governments that have saved surplus funds to those who need it. This market is essential for producing an efficient allocation of financial capital which contributes to higher production and efficiency for the overall economy. The financial market can be broadly divided into two parts namely the primary and the secondary market (Bodie, et al., 2003).

2.2.1 Primary and secondary financial market

The selling of securities can be done in either of the two markets namely primary and secondary markets. The primary market is a market in which the selling or issuing of new securities is done to initial buyers by a corporation or a government agent borrowing the funds (Faure, 2005). This market is not well known to the public because a transaction often takes place behind closed doors. The primary market, in other words, provides direct finance to savings-deficit economic units and for starting new organisations (Faure, 2005). In South Africa, securities are issued by the National Treasure, public corporations (for example ESKOM), public utilities (for example Telkom), local authorities and private sector when they need to finance their activities (JSE, 2012). The primary market facilitates the raising of new funds for the issuer or new issues of shares into the markets.

The secondary market on the other hand is a financial market in which securities that have been previously issued can be resold. The secondary market makes it easier and quicker to sell these instruments and it also determines the price of the security that the issuing firm sells in the primary market. The conditions in the secondary market are the most relevant to corporations issuing securities, as a result, it is the secondary market that receives the most attention and focus (Mishkin, 2010). The secondary market has many more benefits (in addition to facilitating the primary market), which includes the fact that it acts as a signal to the performance of the firm and it indicates the receptiveness of the market as a whole. The activities that take place in the secondary market of a financial market have strong determining influence on the undertakings of the primary market as liquidity, tradability, market rates, and scale of demand, (to name but a few), of instruments are all reflected in this market.

2.3 The South African stock exchange market

2.3.1 History and development of JSE

There are a number of stock exchanges in Africa, most of which are very small by world standards. The Johannesburg Stock Exchange (JSE) is the largest and most developed bourse in the continent (JSE, 2012).South Africa has only one stock exchange in operation, which is the JSE established in 1987 in order to raise finance for emerging gold mining ventures. A need for a stock exchange rose after the discovery of gold on the Witwatersrand in the 1880s which led to many mining and financial companies opening. Since the JSE is South Africa's only full service securities exchange, it connects buyers and sellers in four different financial markets, namely equities, equity derivatives, commodities derivatives and interest rate instruments. JSE Ltd offers the investor a first world trading atmosphere, with world class technology, surveillance and settlement in an emerging market framework, and is amongst the top 20 largest equity exchanges in terms of market capitalisation in the world (JSE, 2012).

JSEis a full service, modern securities exchange providing fully electronic trading, clearing and settlement in equities, derivatives (equity and commodities), and interest rate products and associated instruments. The JSE is also a major provider of financial informationproducts. Its main lines of business are listings, trading, clearing and settlement services, technology and related services, and information product sales. The JSE is licensed as anstock exchange market under the Securities Services Act of 2004. It is governed by an

Act of Parliament, the Securities Services Act, 2004, as well as its own rules and directives (which include requirements concerning listings, trading and disputes to name but a few) (Correia, et al., 2011). From amid the cuffs in 1887 to between markets and across continents in 2008, the JSE has become the financial link between investors, issuers and analysts (JSE, 2012). The Johannesburg Stock Exchange (JSE) is the prescribed market for listed shares that enables raising share capital by borrowers in the primary market and the trading of these shares in the secondary share market by investors. This market offers investors the access to an equities market, including stocks from the Main Board and the alternative exchange (ALTX). In line with the major stock exchange, the Johannesburg Stock Exchange runs an active financial derivatives market and an agricultural products market as well (JSE, 2012),

According to the World Economic Forum (WEF) Global Competitiveness report, South Africa is ranked first of the 142 countries in the regulation of its securities exchange in the year 2011 (JSE, 2012). This report suggests that the South Africa's stock exchange is a sound environment in which to invest. The report further states that the South African standards of corporate governance are highly ranked since the country achieved first place for strength in accounting and auditing standards (in 2011), and its credibility as an investment destination is also boosted strongly by the soundness of its banks. Overall South Africa moves up by four places to attain fiftieth position in 2012, remaining the highest-ranked country in sub-Saharan Africa and the second placed among the BRICS economies after China (JSE, 2012).

The JSE has been expanding and growing year after year, presenting opportunities for both local and foreign investors to take an interest in big companies operating in the African continent. It has plans to extend to all parts of Africa and is currently in the process of changing, upgrading and striving for new goals. The Johannesburg Stock Exchange has major entities as customers, such as South African Breweries (SAB), Anglo American and Anglo Plat, and provides its customers with a platform to clear equities, make use of electronic trading, settle equities and provide financial and agricultural derivatives. With millions of rands worth of exports, imports and industries such as agriculture, energy production, transportation and mining, to name a few, contributing to the economy of South Africa, the stock exchange is not slowing down for a second, with thousands of transactions passing through the JSE on a daily basis.

The JSE describes itself as the "engine room" of the South African economy, providing an orderly market for dealing in securities. Its main function can therefore be summarised as follows: to facilitate the raising of primary capital by re-channelling cash resources into productive economic activity, and building the economy while enhancing job opportunities and wealth creation. The JSE also provides an effective price determination facility and price risk management mechanism. It is privately owned and funded, and governed by a Board of Directors.

In 2001 the JSE introduced the South African Futures Exchange (SAFEX) which is a market that facilitates the trading of derivatives such as futures and options. The SAFEX division of the JSE enables hedging of underlying positions and the volumes on SAFEX significantly exceeds the volumes on the Main Board. In the year 2009 the JSE also introduced another important division; the Bond Exchange of South Africa (BESA) which is also referred to as JSE interest rate market.It is a market for the listing of debt securities issued by government, municipalities, parastatals (for example Eskom) and corporate bonds issued by banks and large companies. The BESA has been able to provide an effective and efficient market for the trading of government and corporate bonds (Correia, et al., 2011).Also important to note about the JSE is its partnership with the FTSE (Financial Times Stock Exchange) of 2002. The JSE Actuaries indices were replaced by the FTSE/JSE Africa Index Series on the 24th of June 2002 (JSE, 2012). FTSE and the JSE provided historic data of the indices. The JSE entered into an important partnership with FTSE, a global index provider to many international exchanges. This partnership enabled the JSE to provide enhanced, expanded and internationally recognised index products for the domestic, African and international markets. FTSE has built an enviable reputation of reliability and accuracy of indices and related data services.

The JSE, along with other stock exchange markets in Africa, has an essential role to play in the development of their individual countries as well as the entire continent. Owing to its size and development South Africa’s stock market the JSE plays a leading role in Africa. According to Correia, et al. (2011, p.13-4), it is important that the JSE ensures that there is a liquid market, offers protection to investors in the form of fair and equal treatment, and that there is proper and timely disclosure.The JSE offers investors an opportunity to take part in the equity market, debt market and a foreign exchange market to name but a few, and these are discussed below.

2.3.2 JSE's Debt market

One of the ways for firms and /or companies, of obtaining funds is by issuing debt instruments to investors. This happens as a contractual agreement by the borrower, which in this case is the firm, to pay the holder of the instrument a fixed amount of money at a regular interval until an agreed specified date or time. Debt instrument is like a loan taken and the firm has to pay regardless of it making a profit or not. The debt market is made up of two securities markets namely the capital and the money market which are differentiated by the term of maturity (Faure, 2005). The capital market is where the issuing and trading of securities (called bonds) with the maturity longer than one year. A money market on the other hand is the issue and trading of securities with maturities of less than a year. As postulated by Faure (2005), the money market brings together the demand for and supply of short-term funds whereas the bond market is an extension of the money market. In the South African market, the bond market is referred to as the Bond Exchange of South Africa (BESA) (JSE, 2012). The BESA operates as the only licensed exchange of bonds and is wholly owned by and is a subsidiary of the JSE Ltd. The compositions of the BESA are government sector bonds, parastatal bonds, corporate bonds, specific purpose vehicle (SPV) bonds and the foreign sector bonds (South Africa info, 2011). BESA is one of the most liquid bond market in the world (Reserve Bank, 2012).

2.3.3 JSE's Equity market

The second way of obtaining funds in a financial market is by issuing equity such as stock which is a claim to share in the net income and assets of a business and represents ownership by investors of productive assets of the firm. The equity market in South Africa represents the market for the issue and trading of equities which includes stocks from Main Board and Alternative Exchange and an interest rate market (JSE, 2012). The Equity Market provides investors with the opportunity to trade a multitude of listed securities including Equities, Exchange Traded Funds (ETF's) and Warrants. This market also provides companies with the opportunity to raise capital in a highly regulated environment through the Main Board. In line with the major stock exchange, the Johannesburg Stock Exchange runs an active financial derivatives market and an agricultural products market.

The local bourse makes use of a sophisticated automated trading system for its equities market, which is also used by the London Stock Exchange. Buyers and sellers enter their orders through their appointed JSE members, and the trading system matches those orders and this is referred to as the central order book. The settlement of transactions on the central order book is guaranteed by the JSE in that, if a buyer or seller is unable to settle their transaction and the member firm trading on behalf of that buyer or seller is unable to settle on their behalf, the JSE will take appropriate steps to protect the counterparty to the trade. In other words, the bourse manages the counterparty risk where a party to a central order book transaction might fail to fulfil its obligations. However, settlements of trades that occur outside the central order book are not guaranteed by the JSE (JSE, 2012).

2.3.4 Foreign exchange market

A foreign exchange market (forex, FX or currency market) is where the exchange of global decentralised trading of international currencies can determine the relative values of different currencies (Mishkin,2004). It assists international trade and investment by enabling currency conversion and enables direct speculation in the value of currencies and trade based on the interest rate differences between two currencies (Standard bank, 2010). In other words, the primary role of the South African's foreign exchange market is to assist international trade and capital movements in South Africa.To be able to participate in this market,by providing a market where different currencies can be exchanged for one another, banks have to be authorised by the Reserve bank first. It is in this market where market futures, options and swaps are traded. According to the Department of Justice 2001, the FX is the biggest in terms of turnover in the South African financial markets and given the fact that the South African economy is open, this market is vital.

2.4 Information dissemination developments

Information is vital to investors in a stock market because if they stay uninformed they will be outperformed by informed participants. In a bid to improve information flow, the JSE issued 'The Guidelines on the Dissemination of Price Sensitive Information' and subsequently introduced SENS in August 1997 (JSE, 2012). These guide lines were aimed at improving the dissemination of price sensitive information, helping companies manage price sensitive information; and giving the media, company advisors, institutional shareholders and analysts a greater understanding of the framework within which companies should disseminate such information.

Information dissemination is important when talking about random walk process which hinges on the fact that there is no information asymmetry resulting in prices being independent of each other. The financial sector in South Africa is relatively sophisticated and facilitates information flows in a way that one would expect of a developed stock market. There is good quality research on JSE listed companies and many financial institutions have substantial in-house research facilities (Rathborne&Grosch, 1997).

The JSE provides a Stock Exchange News Service (SENS) through which company news, including price-sensitive information, are distributed to the market.SENS (Securities Exchange News Service known then as Stock Exchange News Service), a real time news service for the dissemination of company announcements and price sensitive information, was introduced in 1997. SENS ensures early and wide dissemination of all information that may have an effect on the prices of securities that trade on the JSE.

After the successful implementation and running of SENS, the JSE introduced yet another information dissemination service called InfoWiz in May 2002. This ‘Live Data Delivery System’ transmits live data to subscribed information vendors, JSE members and financial institutions. InfoWiz broadcasts data on best bid and offer, mid-price, number and volume at best price, uncrossing price and volume, official closing price, trade report volume and price, start of day reference data as well as full market depth and indices values. SENS publications are also broadcast through InfoWiz. InfoWiz is highly standardised in fact InfoWiz is an equivalent of London Market Information Link (LMIL). It was implemented in partnership with the London Stock Exchange (LSE) and the actual system is still housed in London (JSE, 2012).Keane, (1983) states that the securities market is highly organised and is not only superior in terms of quality and quantity of information, but also in the speed with which the information is disseminated to market participants. All the securities markets therefore invest sizable amounts in their efforts to provide real time information to their members. Even though some markets also provide information to their participants, information provision is not as critical and as extensive as in the securities market.

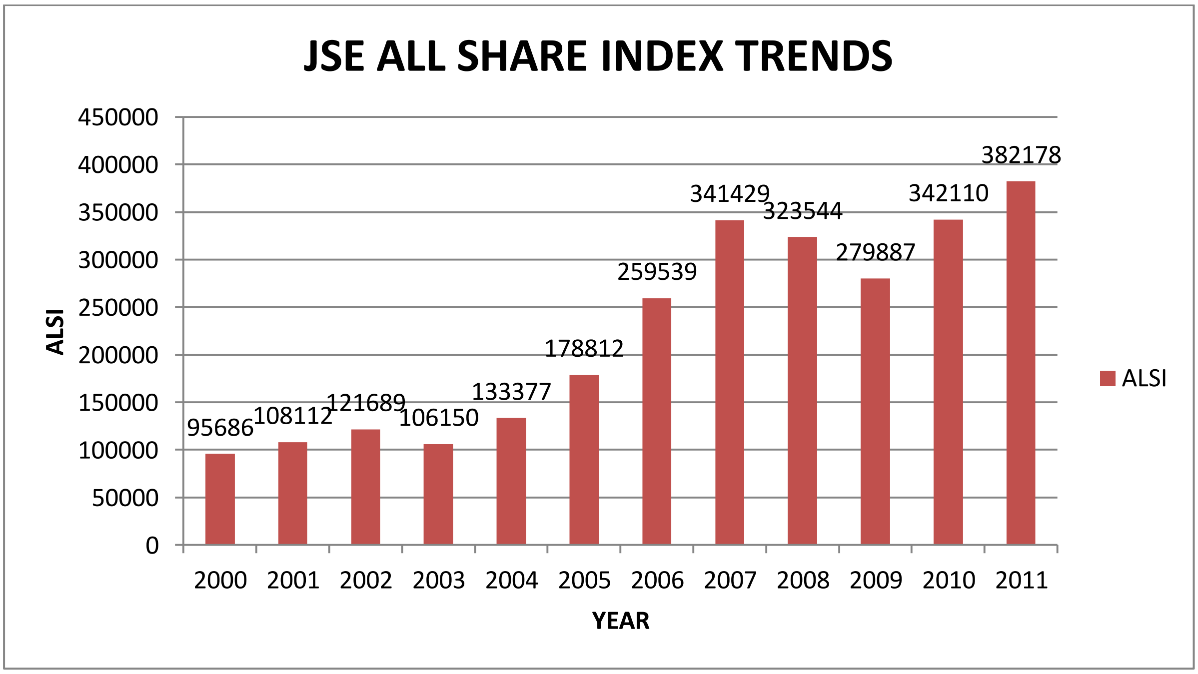
2.5 Trends in the Johannesburg Stock Exchange

2.5.1 Performance of the ALSI

The daily performance of the JSE All Share Index (ALSI) is brought to attention everyday as it is a major item of the business news report on SABC news. An index is a statistical measure of the changes in a portfolio of stocks representing a portion of the overall market.

This number summarises the fluctuation of share prices on a given day. An index's primary purpose is to reflect the aggregate movement of the market it represents hence a single index value would be meaningless if not compared to a previous/ historical value. The All Share index (ALSI) is used as a benchmark in the South African market and in this way it acts as a proxy for the performance of all companies listed on the JSE. Indices can also be used to measure performance, for instance, one can use the bank's index to measure the performance of the banking sector. Because indices are calculated from different base values, the percentage change is more important than the actual numeric value. Precisely speaking, one cannot actually invest in an index but one can invest in products like Exchange Traded Funds (ETFs) or derivatives which are based on these indices (Standard Bank, 2010). The changes that occurred in the ALSI or the trends thatfollowed from 2000 to 2011 are shown in Figure 2.1 below.

Figure 2.1 All Share Index Performance



Source: JSE Ltd, 2012

The performance of the JSE has been outstanding as indicated in the figure above. As shown in the graph above, the JSE ALSI has shown an upward trend on average since 2000. The index has been increasing with a sharp increase in the year 2007, and it decreased in 2008 and 2009, likely reflecting the impacts of the global financial crisis of 2007.Mishkin, (2010) explains that the financial global crisis that began during the end of 2007 began increasing as the value of mortgage-backed securities on financial institutions balance sheets plummeted. The crisis affected most markets and shows how volatile the market can be and also how the financial system changes over time. South Africa, according to the Business Day of July 13 2009, entered its official recession in May 2009 as the global crisis had hit on key drivers of growth.

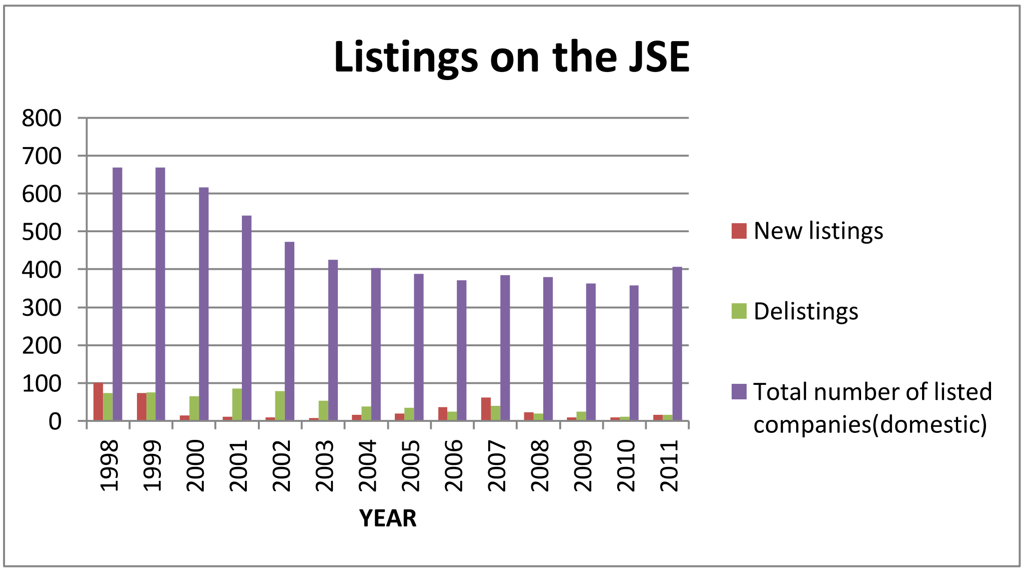
The global financial crisis affected the JSE as well as most financial markets in different countries. The global financial crisis, brewing for a while, really started to show its effects mid-2007 and into 2008 and early 2009. Around the world stock markets fell, large financial institutions collapsed and governments in even the wealthiest nations had to come up with rescue packages to bail out their financial systems (Mishra, 2009). The crisis was triggered by a liquidity shortfall in the United States banking system. South Africa was not an exception. The JSE dropped by about 5% in its value during the 2008 period and about 13% between 2008 and 2009 (JSE, 2012). Aglobal financial meltdown affects the livelihoods of almost everyone (as the economy suffers) in an increasingly inter-connected world, and it can be said that the global financial crisis of 2007/2008 can be the reason for the decline in the share price in the South African stock market.

2.5.2 Listings on the JSE

A number of South Africa's biggest listed companies moved their primary listings to London in the late nineties to be more attractive to international investors. This loss caused concern in the South African market and resulted in decreased trade on the JSE. The first major change occurred in November 1995, when the Stock Exchanges Control Act changed the way in which stocks were traded in South Africa, opening doors to non-South Africans, and allowing brokers to buy and sell stock for their own account (where previously they could only act as agents for their clients) (JSE, 2012).

Since the institution of the South African bourse a century ago, the composition of the listed companies has changed with mining now overtaken by the industrial sector. Both the number and type of companies listed on the JSE have changed dramatically over the years. According to StatsSA, (2011) the South African economy expanded, the rapid growth of the JSE is reflected in the growth of the number of listed companies which changed greatly over the past ten years. The JSE Securities Exchange South Africa (JSE) released its final amendments to the Listings Requirements on 15 May 2003 in which it stated that if a company wishes to delist, it is required to obtain the support from its non-controlling shareholders. A fair and reasonable opinion should be obtained to support the offer that will be made to the minorities at the time of delisting. This may be the explanation of the declining number of delisting as shown in Figure 2.2 below adapted from Correia, et al.(2011, p.13-5). The figure presents the total number of listed companies (domestic), number of new listings as well as the number of delisting on the JSE from the year 1998 up to 2010. New listings compose those activities on the primary market. The primary market is a market for new issues of finance whereas the trading of securities already issued takes place in the secondary market. Over the past years, the JSE has been able to attract new listings or new equity capital. There have been new listings and delisting on the JSE which in a nutshell changed the number of listed companies as shown in the figure below.

Figure 2.2 Listings on the JSE



Source: Correia, et al. 2011

The number of listed companies has been dropping in recent years with more companies delisting suggesting that there may be disadvantages to listing on the JSE. Some of the disadvantages as outlined in Correia, et al. (2011, p. 13-5) include onerous disclosure requirements and reporting standards of the JSE which may end up requiring companies to invest more in information systems increasing costs of listing, loss of privacy of shareholders, and also increased responsibilities on directors to name but just a few. The JSE has gone far in trying to encourage new listings even to small firms. The introduction of the Development Capital Market (DCM) and the Venture Capital Market (VCM) to enable the listings of small to medium sized companies, with reduced requirements has done a lot in encouraging new listings. Over the years, the ALTX has taken over the work of the DCM and VCM and as a result the JSE has been encouraging the transfers of companies to the ALTX (JSE, 2012).

2.5.3 Market capitalization and liquidity

Although South Africa dominates other African stock markets in terms of both size and sophistication, it is relatively illiquid, and ranks lower in terms of turnover. While market capitalisation has not grown much over the past decade, the turnover has, rising from $8 billion in 1992 to $77 billion in 2000. Consequently, liquidity has also increased, from 5 per cent to 34 per cent, over the same period. The market capitalization for the period 2000 to 2011 is presented in the table below and the data was obtained from World Federation of Exchange website.

Table 2.1 Market capitalisation

YEAR	MARKET CAPITALIZATION
2000	R994100million
2001	R1011700million
2002	R986774.3million
2003	R1123156.3million
2004	R2493100million
2005	R3484000.6million
2006	R5014756.8million
2007	R5660149.8million
2008	R4514451.6million
2009	R5883851.1million
2010	R6698.7billion
2011	R6908.5billion

Source: world exchange organisation, 2012.

Source: world exchange organisation, 2012.

Percentage change in terms of market capitalisation in domestic currency is presented below.2001/2000 1.8 per cent.

2003/2002	13.8per cent.
2005/2004	39.7per cent.
2007/2006	12.9per cent.
2009/2008	30.3per cent.
2011/2010	3per cent.

Providing the deepest liquidity is a primary goal of all financial markets. According to the report released on the JSE website, liquidity is said to have remained low due to the domination of share ownership by large conglomerates linked either to mining companies or financial holding companies. This concentration of ownership is to a certain extent a result of strict exchange controls on the capital account, which restricted South African firms from exporting capital and left them with little option but to take over other domestic firms. The JSE has benefited from substantial inflows of foreign portfolio investment since the ending of apartheid and the lifting of sanctions in 1994. There are no restrictions on the ownership of shares by foreigners, although prior to March 1995 transactions had to be carried out using the rand, a dual exchange rate which applied to capital transactions. Since the abolition of the dual exchange rate regime, foreign investors have not been subject to any exchange control regulations, although domestic investors remain restricted in their ability to export capital (JSE, 2012).

Liquidity is the ability to quickly convert an investment portfolio to cash with little or no loss in value. Stocks and bonds that are easily traded on an open exchange are fairly liquid. Liquidity is characterised by a high level of trading activity and assets that can be easily bought or sold are known as liquid assets. The capacity of the stock exchange to provide primary equity capital is dependent on its ability to offer investors a high level of liquidity as a secondary market. If a security market if characterised by high liquidity, investors can buy and sell a large number of shares quickly at the current price (Correia, et al., 2011).

The JSE, in a bid to improve liquidity introduced an automated trading system, low trading costs and other developments. This has resulted in a significant increase in the liquidity as indicated by an evaluation of the percentage of turnover to market capitalisation. However, liquidity is still a problem on the JSE especially to the small firms as reviewed by Correia, et al.,(2011).There are various effects of having low liquidity. Investors will find it difficult to or will not be able to trade shares and this may result in companies becoming less willing to list on the JSE if the level of liquidity is low. According to Correia, et al. (2011, p. 13-11) the low level of liquidity may be the cause of a fall in the number of listings from the Main Board from 668 in 1999 to 337 in September 2010, as shown in Figure 2.2 in page 17.

Since the stock market is characterised by free and transparent trading and that prices of all stocks are determined by forces of demand and supply, bid and ask, it in this way provides liquidity for investors seeking to transact sales of their holdings through this active pricing mechanism (Mishkin, 2010).

2.6 Regulation framework of the JSE

The financial market is one of the most regulated institutions of most countries. One of the reasons labelled for this vast regulation is to increase information availability to all investors (Bailey, 2005). Information is vital as information asymmetry may mean that investors are subjected to adverse selection and moral hazards problems leading to inefficient markets. Also, the financial market is most regulated so as to ensure soundness of the financial system and intermediaries. Indirectly, regulation ensures competition and guard against fraud activities. The CEO of the JSE noted that in an environment that is highly competitive only markets with a strong regulation, solid infrastructure and thriving institutions may be better positioned in attracting sustainable capital flow (JSE, 2012). Most importantly, investors in a regulated financial market have more confidence, and believe there if fairness thereby attracting investors.

Regulation of the stock market can be done on entry which may include tight rules governing who is allowed to trade on the market. Regulation can also be of disclosure requirement which are reporting requirements for financial intermediaries. Under the regulation of disclosure, listed firms may be asked to follow certain strict principles in their bookkeeping and the books may be subject to periodical inspection (Mishkin, 2010). The regulation may also stipulate the information that should be made available to the public. There is also restriction on assets and activities so as to prevent the firm from deliberately entering into high risk activities at the expense of the investor. All the restrictions are done so as to ensure the smooth running of the financial market and each market is subject to its own designed regulations.

Buying and selling transactions in securities at the stock exchange is governed by rules and regulations of the stock exchange and no deviation from the rules and guidelines is allowed in any case. Investors always need to have confidence when dealing in the stock exchange. For the stock market to function successfully, it is vital that it provides a regulatory system that enforces confidence that investors can deal at genuine.In addition, fair prices and the fact that the market is not manipulated to their disadvantage. An appropriate regulatory framework that is adhered to by all market participants, and is imposed by the appropriate regulatory authorities, brings about this confidence and integrity. It is argued that all financial markets are self regulatory but in addition to that they need to have a sound regulation system (Fourie, et al., 2003).

In South Africa the Financial Services Board (FSB) is the overseer of all the regulations of financial markets and institutions excluding banks which are under the South African Reserve bank (South African Reserve bank, 2012). The FSB is responsible for assessing, developing as well as maintaining the regulatory framework and ensuring compliance with regulation. It is also the duty of the FSB to investigate complaints and has an educational role to ensure a better understanding of the regulatory system and the financial market as a whole (FSB, 2011).

The JSE’s activities are licensed and regulated by two Acts of Parliament, namely the Stock Exchanges Control Act, 1 of 1985 ("SECA"), which governs the equities markets, and the Financial Markets Control Act, 55 of 1989 ("FMCA"), which governs the derivatives markets. SECA aims at protecting the general public when buying and selling shares. The JSE also acts as regulator of its members and ensures that markets operate in a transparent manner, ensuring investor protection. Similarly, issuers of securities must comply with the JSE Listings Requirements, which aim to ensure sufficient disclosure of all information relevant to investors. The JSE's roles include regulating applications for listing, and ensuring that listed companies continue to meet their obligations. The JSE monitors applications for alterations to existing listings, and scrutinises company disclosures to the public.

There is a BESA’s Market Regulation Division (MRD) which also forms part of the regulation of the JSE. The Bond Exchange of South Africa (BESA) became a wholly-owned subsidiary of the Johannesburg Stock Exchange (JSE) on 22 June 2009. BESA’s Market Regulation Division (MRD) has been integrated into the Surveillance Division and the Clearing and Settlement Division of the JSE. The regulation relating to the trading aspects of cash bonds now falls within the JSE Surveillance Division, whereas, the settlement thereof falls within the JSE Clearing and Settlement Division (JSE, 2012).

Introduced in 2004 is another Act that governs activities in the stock market namely theSecurity Service Act (Act 36, 2004). The Act requires the JSE to draft its own rulebook which must first be approved by the Financial Services Board. Any changes made must also be approved by the FSB. The rules in the rulebook detail things like security and reporting procedures, listing requirements and disclosure rules which have been harmonised with the London Stock Exchange (LSE) (JSE, 2012). The ACT governs the laws relating to regulation and control of central securities depositories and the custody and administration of securities and the prohibition of insider trading to name but a few. The major aims of the ACT as presented by the JSE (2009) include increasing confidence in the South African financial markets by means of ensuring that trade is provided in a fair, efficient and transparent manner. It also promotes the protection of all regulated persons and clients and most importantly promotes international competitiveness of securities in the country. By promoting competitiveness, the act ensures that the stock market prices behave in an efficient manner and thisimplies that they follow therandom walk process.

Other ACTS that can be used on the day to day running and regulation of all activities on the stock exchange include the Financial Services Board Act, 1990 (Act No. 7 of 1990), the Insider Trading Act, 1998 (Act No. 135 of 1998) and Financial Institutions Act, 2001 (Act No. 28 of 2001)

2.7 Unique characteristics of stock market

There are many unique characteristics of the stock market which makes it exceptional and potentially following a random walk. Though these characteristics are not sufficient in themselves to ensure a market following a random walk, they go a long way into making the stock market a perfectly competitive market, as would be defined by an economist, and therefore efficient. Some argue that the larger in terms of market capitalisation and turnover, the higher the possibility of the market prices to follow a random walk process. In this sense the JSE would be expected to follow a random walk as it is regarded to be the largest in Africa. The other factors and characteristics which are important indicators of random walk include liquidity and maturity in terms of transparency, organisation and the regulation framework (Huang, 1995). These factors only indicate the possibility of the stock market being efficient and following a random walk but are not sufficient to conclude that the market follows the process.

Liquidity

A market with very low levels of liquidity relative to its size is less likely to have an adequately active price formation process for the market to follow a random walk. This is because if turnover is low, there might not be any trade from one period to the other leading to constant predictable prices that is no price change. Liquidity is highly vital in any stock market (JSE, 2012).

Transparency

The public nature of trading maintains transparency in financial transactions. Efficiency, growth, freedom and variety are all possible because of transparency that allows all participants to access the bid and ask prices of all securities traded on the market and because all participants have access to the same information. There is pricetransparency in the stock market and because all trades for a stock flow through one exchange, this means that everyone sees and has the opportunity to execute on the same exact price as everyone else. The JSE has engaged in information dissemination activities of late which are likely to improve transparency (Bodie, et al., 2003). When information is withheld from the market, share prices are less likely to reflect the true value of stocks and hence price dependency may be high. Despite some problems with insider trading, JSE market governance seems to be of high quality.

Organisation

The stock market provides a degree of protection to investors through the SEC, FINRA and other legal regulatory and self-regulating bodies on state and professional levels that serve to create an organised and liquid group of stock exchanges and stock trading platforms. The direction of trading activity in the stock market provides an indication of the state of commerce and overall confidence in the economy. An organised and regulated stock market serves as a way for investors who seek large returns on their investments to access organised, liquid, regulated and transparent risk investing. All this attracts a lot of investors enhancing competition and efficiency of stock markets (Bodie, et al., 2003).

Regulatory Framework

The stock exchangemarket provide a standardised regulatory framework that all participants must adhere to, and a method for resolving disputes should they arise. This makes people more comfortable and more likely to trade, which increases liquidity and competition and once again aiding to the efficiency as well as indicating possibilities of a random walk process (JSE, 2012).

2.8 Conclusion

The chapter presented an overview of the South Africa's stock market. There have been various changes and developments on the JSE that have transformed it in a bid to make it more efficient. The JSE has in a nutshell performed well over the period 2000 to 2011 with a huge decline in 2009 attributed to the effects of the 2007/2008 global financial crisis. However the JSE suffers from low liquidity and high levels of delisting companies. The JSE is the most regulated market because it is the most fundamental as it reflects the well being of an economy. The chapter further gave a few features of the stock market that help in creating a market whose prices are independent of each other, in other words an efficient market. The following gives a detailed insight of the literature surrounding stock market price behaviour.

CHAPTER THREE

LITERATURE REVIEW

3.1 Introduction

This chapter provides the theoretical and empirical literature surrounding stock market behaviour. The first part outlines the theoretical framework of stock markets and the second presents the empirical literature with much interest centred at balancing the empirical framework between developed and developing economies. Lastly, the chapter presents a brief assessment of the literature reviewed.

3.2 Theoretical framework

The theoretical framework presents the theories that surround the financial market particularly theories on how stock market prices behave. Stock indexes fluctuate as a result of fluctuation of individual stocks that make up theses indexes. There are many theories of stock price determination which include some that emanate from the fact that the price of a financial asset is equal to the present value of the payments to be received from owning it (Hubbard & O'Brien, 2012). This research, however, is not concerned about how prices are determined but rather how the prices behave. The theories discussed here, though they can be considered in some instances as theories of price determination, mainly focus on explaining the behaviour of prices or price changes. The theories that explains how stock prices behave are the random walk hypothesis which forms the basis of this research, the efficient market hypothesis which is described as the chief theory and forms the basis of most asset pricing models and the arbitrage pricing theory. All these theories explain how stock market prices behave. The Arbitrage Pricing Theory is used by investors to inform strategies that take advantage of mis-priced assets. Also forming part of the theoretical literature of this research are theories that are more skewed towards explaining how prices of stock are determined and these are the Capital Asset Pricing Model (CAPM) and the Gordon growth model.

3.2.1 The Random Walk Hypothesis (RWH)

Random walk hypothesis is an investment theory which claims that market prices trail a random path up and down, without any influencefrom past pricemovements, making it impossible to predict with any accuracy which direction the market will move at any point (Mishkin, 2010). In other words, the theory claims that the path a stock'sprice follows is a random walk that cannot be determined from historical price information, especially in the short term. Keane, (1983) states that investors who believe in the random walk theory feel that it is impossible to outperform the market without taking on additionalrisk, and believe that neither fundamental analysis nor technical analysis have any validity. Applying fundamental analysis or technical analysis to time the market is a waste of time that will simply lead to underperformance. The randomness of stock prices can be confirmed by analysis of successive price changes, indicating low serial correlation coefficients, and by simulated charting of random numbers, indicating patterns of price movements similar to actual price movement patterns (Brooks, 2008). On this basis, proponents of the random walk hypothesis dismiss the usefulness of technical analysis an approach for predicting stock prices based on the price patterns developed by prior price data.

According to the random walk, the past movement or direction of the price of a stock or overall market cannot be used to predict its future movement. Stock price fluctuations are independent of each other and have the same probability distribution. It also states that over a period of time, prices maintain an upward trend (Gujarati, 2009). In other words, if a stock market is said to be following the random walk process, it takes a random and unpredictable path. The random walk hypothesis also states that stock market prices evolve according to a stochastic process, preventing the prediction of future stock market movements (Brooks, 2008). The concept follows from the weak version of the efficient-market hypothesis, which asserts that future stock market movements are not correlated with past movements. In other words, the movement of share prices one day does not affect the movement of share prices on subsequent days (Black, 1990). When price changes are highly predictable, it could mean that investors are not always rational, and an autocorrelated structure exists.

Random walk is the path of a variable over time that exhibits no predictable patterns at all. If a price, *p*, moves in a random walk, the value of *p* in any period will be equal to the value of *p* in the period before, plus or minus some random variable (Brooks, 2008). The random walk hypothesis (RWH) states that the present market price is the best indicator of the future market prices with an error term that is stochastic in nature. Hence the next time period price is not anybody's guess. In an efficient market it is not possible to make profit based on the past information hence the prediction of future price conditional on the past prices on an average should be zero. The more efficient a market is the more random and unpredictable the market returns would be. In the most efficient market the future prices will be totally random and the prices formation can be assumed to be a stochastic process with mean in price change equal to zero (Black, 1990).

The random walk process can be said to be one of the main indicators of weak form efficiency although the rejection of the random walk hypothesis in a particular market does not necessarily mean the market is inefficient. In other words, it should be noted that rejecting the random walk hypothesis does not necessary contradict market efficiency. As Summers (1986) argues, contradicting the random walk hypothesis in a given market may only mean that the obtained results are consistent with the particular martingale process of random walk. From existing literature, it is hard to say how much truth there is to this theory as there is evidence that supports both sides of the debate. This research thus aims at drawing conclusions based on whether price changes are independent of each other in the South African stock market.

The independence assumption of the RWH is an adequate description of reality as long as the actual degree of dependence in the series of price changes is not sufficient to allow the past of the series to be used to predict the future in a way which makes expected profits greater than they would be under a buy-and-hold model (Taylor & Allen, 1992). The random walk hypothesis is related to the weak form of the efficient market hypothesis in that current stock price already incorporates all known information of the past stock prices. If a stock market follows the random walk process, prices quickly adjust to new information and it is virtually impossible to act on this information. Furthermore, price moves only with the advent of new information and this information is random and unpredictable. The consequence of the efficient market hypothesis is that no structural model for stock return determination can outperform the random walk model.

3.2.2 Efficient Market Hypothesis (EMH)

An efficient market is defined as a market where there are large numbers of rational or sensible, profit-maximisers keenly competing, with each trying to predict future market values of individual securities, and where vital current information is almost freely available to all participants (Mishkin, 2010).In such a market, price discovery is rapid and accurate.In other words, market efficiency is a description of how prices in competitive markets respond to new information. A capital market, therefore, is said to be efficient if it fully and correctly reflects all relevant information in determining security prices. The efficient market hypothesis claims that current price of share reflects everything that is known about the company and its future earnings potential, and that it is impossible to beat the market consistently. Stock markets are considered the best example of efficient markets as their prices are said to respond immediately to available information (Fama, 1970).

Tobin (1984, p. 2-3) indicates that there are at least four separate concepts of efficiency by which the financial system can be considered or explained. There is the informational arbitrage efficiency which measures the extent to which it is possible to gain on average from trading on the basis of generally available information and complete information arbitrage efficiency in turn implies that it is impossible to gain from such trading. The other concept is fundamental valuation which measures the degree to which market values of financial assets reflects accurately the present value of the stream of future payments associated with holding that asset. The third concept, full insurance efficiency measures the degree to which the financial system offers ways of hedging (insuring) against all possible future contingencies (states of the world) and the last concept is functional efficiency which relates to the two main economic functions of the financial sector, administering the payments mechanism and intermediating between savers and investors (Fry, 1995). The EMH asserts that financial markets are informationally efficient, and if it were to be put in accordance with the four concepts given by Tobin (1984) it would be said the EMH it looks at the information arbitrage efficiency.

Efficient Market Hypothesis (EMH) is a theory which evolved in the 1960's and states that it is impossible to beat the market as prices already incorporate and reflect all relevant information (Fama, 1970). The efficient market hypothesis is based on the assumption that prices of securities in the financial market fully reflect all available information. It tells us that when purchasing a security, we cannot expect to earn an abnormally high return, a return greater than the equilibrium return (Mishkin, 2010)**.**The EMH contradicts the basic tenets of technical analysis by stating that past prices cannot be used to profitably predict future prices. Supporters of this model believe it is pointless to search for undervalued stocks or try to predict trends in the market through fundamental analysis or technical analysis. Under the efficient market hypothesis, any time you buy and sell securities, you are engaging in a game of chance and not skill. If markets are efficient and current, it means that prices always reflect all information, so there is no way one will ever be able to buy a stock at a bargain price. According to this theory, a market is said to be efficient if it functions in such a way that transaction costs to buyers and sellers in the market are relatively low and information on new developments is quickly disseminated to all parties. Market prices will reflect such new information (Mishkin, 2010).

The efficient market hypothesis stands for the proposition that there are many participants in an efficient market who have access to all relevant information affecting stock prices and such participants compete freely and equally for the stocks, causing, because of such competition and the full information available to the participants, full reflection of the worth of stocks in their prevailing prices. EMH argues that while individual market participants do not always act rationally (or have complete information) their aggregate decisions balance each other, resulting in a rational outcome (optimists who buy stock and bid the price higher are countered by pessimists who sell their stock, which keeps the price in equilibrium) (Fama, 1970). Likewise, complete information is reflected in the price because all market participants bring their own individual, but incomplete knowledge together in the market

As new information randomly develops and is acted upon and reflected in prices, stock prices in turn behave randomly. Also the EMH supports the RWH in that it states that prices of any tradable instrument are essentially unpredictable. There are three levels of efficiency according to the EMH which are weak-form, semi strong and strong level of efficiency. These different levels are a result of different kinds of information that can be made available in a market, meaning at each level of efficiency there is a different information set reflected. The degree to which the market is efficient depends on the quality of information reflected in market prices.

3.2.2.1 Weak-form level of efficiency

The efficient market hypothesis in its weakest variant stands for the proposition that successive stock prices are mostly unrelated and tend to move in a random manner (Mishkin, 2010). It is the lowest level of efficiency and it holds that investors cannot use historical market trading data (such as prices and volume) to increase returns over what would otherwise be expected. The weak form asserts that all past market prices and data are fully reflected in securities prices and that prices on traded assets (for examplestocks, bonds, or property) already reflect all past publicly available information. In other words, technical analysis is of no use.

In weak-form efficiency, future prices cannot be predicted by analysing prices from the past. Excess returns cannot be earned in the long run by using investment strategies based on historical share prices or other historical data. Technical analysis techniques will not be able to consistently produce excess returns, though some forms of fundamental analysis may still provide excess returns. Share prices exhibit no serial dependencies, meaning that there are no patterns to asset prices. This implies that future price movements are determined entirely by information not contained in the price series. Hence, prices must follow a random walk. According to Blake (1990, p. 246) this soft EMH does not require that prices remain at or near equilibrium, but only that market participants should not be able to systematically profit from market inefficiencies. The weak-form level of efficiency is consistent with the random walk hypothesis. The randomness of the stock prices is evidenced by analysis of successive price changes, indicating low serial correlation coefficients. It is on this basis that proponents of the random walk hypothesis and those of the weak-form efficiency dismiss the usefulness of technical analysis, an approach for predicting stock prices based on the price patterns developed by preceding price data.

3.2.2.2 Semi-strong level of efficiency

The second level or variant of the efficient market hypothesis is the semi-strong form. This form applies to all publicly available data, such as annual reports, published brokerage reports, or newspaper articles, and all weak-form information. The semi-strong form claims both that prices reflect all publicly available information and prices instantly change to reflect new public information. In other words, fundamental analysis is of no use. The semi-strong level stands for the proposition that there are many participants in an efficient market who have access to all relevant information affecting stock prices. These participants compete freely and equally for the stock causing, because of such full information available to the participant, full reflection of the worth of stocks in their prevailing prices (Correa, et al., 2007).

In semi-strong-form efficiency, it is implied that share prices adjust to publicly available new information very rapidly and in an unbiased fashion, such that no excess returns can be earned by trading on that information. As new information randomly develops and is actedupon and reflected in prices, stock prices in turn behave randomly. Semi-strong-form efficiency implies that neither fundamental analysis nor technical analysis techniques will be able to reliably produce excess returns (Black, 1990).

3.2.2.3 Strong level of efficiency

A third variant of the efficient market hypothesis stands for the proposition that prevailing stock prices fully reflect and discount not only publicly available information but also private and expert analysis and information, such as that made available to institutional investors in consideration of routing commission business to particular brokerage firms, and research boutiques (Mishkin, 2010). The strong-form EMH in other words claims that prices instantly reflect even hidden or "insider" information thus even insider information is not useful. The strong-formefficiency asserts that all information is fully reflected in securities prices. In strong-form efficiency, share prices reflect all information, public and private, and no one can earn excess returns. If there are legal barriers to private information becoming public, as with insider trading laws, strong-form efficiency is impossible, except in the case where the laws are universally ignored. Since performance of institutional investors such as investment companies is found to be not much different from results of non-institutional portfolios and from randomly selected portfolios, it is concluded again that prevailing stock prices in responding promptly to randomly developed information, whether publicly or privately available through expert analyses, behave randomly, and that professional money managers do not achieve consistently superior performance because of superior access to superior information (Correa, et al., 2007).All three variants of the efficient market hypothesis challenge the validity of fundamental analysis and technical analysis, and in turn are challenged by adherents of the fundamental and technical approaches. Expectations are imperative in that they play an important role in the economy since many transactions require participants to project the future.

The EMH is closely related to the random walk hypothesis and this random arrival of information will result in random price fluctuations, informationally efficient markets will result in a random walk in stock prices. In other words, a share price will follow a random walk, much like the progress of a very drunk man, where no-one can confidently predict the direction of his next step. An implication of the EMH is that prices are not predictable and this is where the EMH meets the random walk hypothesis. However, rejection of the RWH does not necessarily mean inefficiency because the EMH suggests that information is fully and accurately reflected in prices, so that prices will be close estimates of true intrinsic value. The random walk refers to price changes, not to the prices themselves (Allen, 1985). Securities markets are flooded with thousands of intelligent, well-paid, and well-educated investors seeking under and over-valued securities to buy and sell. This means that the more participants and the faster the dissemination of information, the more efficient a market should be. The efficient market hypothesis hinges on the assumption that individuals are rational and consequently make optimal decisions which are based on the information available to them. Prices should thus reflect all available information and therefore investors cannot outperform the market unless they are privy to special information.

The EMH has been greatly criticised and especially bytechnical analysts. The critics of this theory argue against the efficient market theory that many investors base their expectations on past prices, past earnings, track records and other indicators. Because stock prices are largely based on investor expectation, many believe it only makes sense to believe that past prices influence future prices. There are other analysts who question the validity of the efficiency market hypothesis especially active traders as they are more hesitant about whether or not markets behave as proposed by the proponents of the EMH. According to Hubbard and O'Brien (2012, p. 174), these investors point three differences between the theoretical behaviour, the financial markets and their actual behaviour. First they argue that pricing anomalies in the market allow investors to earn consistently above-average returns. This is disputed by the EMH which argues that such opportunities of above average returns should never exist in a market with rational investors. Secondly, they argue that some price changes are predictable using available information. The EMH, however, states that investors should not be able to predict future price changes using information that is publicly available. Thirdly these analysts argue that changes in stock prices sometimes appear to be larger than changes in the fundamental values of the stocks. According to the EMH prices of securities reflect their fundamental values.

With the arguments about the behaviour of stock market prices being inconclusive, this research aims at adding to the existing debate by evaluating whether or not the JSE price index follows a random walk or not.

3.2.3 Arbitrage Pricing Theory (APT)

Financial arbitrage can be defined as a process of buying and reselling securities to profit from price changes over a brief period of time (Hubbard & O'Brien, 2012). The Arbitrage Pricing Theory (APT) is generally a theory of asset pricing that holds that the expected return of a financial asset can be modelled as a linear function of various macro-economic factors or theoretical market indices where sensitivity to change in each factor is represented by a factor-specific beta coefficient.

The Arbitrage pricing theory was proposed by Ross (1976) as an alternative to the capital asset pricing model (Blake, 1990) and hence APT is a theory that is closely related to the CAPM but unlike the CAPM.The APT implies that there are multiple risk factors that need to be taken into account when calculating and determining risk-adjusted performance or alpha. The derived rate of return is the one that will be used to price the asset correctly and according to this theory, the asset price can be expressed as being equal to the expected end of period price discounted at the rate implied by the model. The APT seeks to calculate the most appropriate price of an asset while taking into account systematic risks common across a class of assets. It describes a relationship between a single asset and a portfolio that considers many different macroeconomic variables. According to the theory of APT, an asset with a price different from the one predicted by the model is said to be mispriced and provides an opportunity for arbitrage.

In the case that the price of an asset diverges form this price arbitrage, which is the practice of taking positive expected return from overvalued or undervalued securities in the inefficient market without any incremental risk and zero additional investments, should bring it back into line (Allen, 1985). In other words, in competing to buy securities where earnings arbitrage profits is possible, traders force prices up to the level where arbitrage profits can no longer be earned. This therefore also means prices adjust hastily to eliminate arbitrage profits because of very large numbers of traders participating in financial markets and the speed of electronic trading. Investors therefore may use the APT to find undervalued securities and take advantage of them, however, their actions will bring the price back to equilibrium.

According to Allen, (1985, p. 119) the arbitrage pricing model assumes a linear return-generating process. Equilibrium requirement in the stock market according to this theory is that there should be no opportunity for arbitrage profits. Blake (1990, p. 306) reveals that the model assumes that individuals believe that security returns are determined by the K-factor generating model given asbelow:

$$r_i = \bar{r}_i + \sum_{j=1}^{K} \delta_j \beta_{ij} + \varepsilon_i \text{..........} \quad (3.1)$$

where r_i is the actual return on the *ith* security, $\bar{r}_i$ is the expected return on the *ith* security, δ_j is the zero-mean *jth* factor common to all security returns, and the coefficient β_{ij} measures the response of the return to the *jth* common factor. The common factor δ_j is the systematic components of risk, and ε_i is the unsystematic component of risk peculiar to the asset alone (Gujarati, 2004).

In equilibrium, a portfolio that costs nothing and embodies neither systematic nor unsystematic risk (i.e. riskless to achieve) must generate a certain return equal to zero. In this model there is thus a linear relationship between expected return and the common factors. The Arbitrage Pricing Theory describes a mechanism used by investors to identify an asset, such as a share of common stock, which is incorrectly priced. Investors can subsequently bring the price of the security back into alignment with its actual value. If the expected risk premium on a stock is lower than the calculated risk premium using the formula above, then investors will sell the stock. If the risk premium is higher than the calculated value, then investors will buy the stock until both sides of the equation are in balance. Arbitrage therefore is a term used to describe how investors can go about getting this formula, or equation, back into balance (Allen, 1985).

The theory helps in ensuring that markets are efficient, and hence the dependences of price changes. Once an opportunity for arbitrage is noted, investors will act in such a way that prevents it from happening in the future leading to prices falling back to actual prices.

3.2.4 Capital Asset Pricing Model (CAPM)

According to Jackson and Staunton (2001, p. 129) the CAPM rests on the premise that there is only one optimal risky portfolio and that the single portfolio is the market portfolio in which all shares are held with weights equal to the proportion of the total market they represent. The model starts with the idea that individual investment contains two types of risk, systematic risks which are market risks that cannot be diversified away, for example interest rates, wars and recessions, and unsystematic risks also known as specific risks which are risks that are specific to individual stocks and can be diversified away as an investor increases the number of stocks in his or her portfolio. The unsystematic risk represents the component of a stock's return that is not correlated with general market moves (Allen, 1985). When calculating a deserved return, what plagues most investors is the systematic risk and the CAPM therefore evolved as a way to measure this systematic risk so as to determine the price of an asset.

Weston and Brigham (1978) explain that the theory has been developed with a number of assumptions made so as to be able to explain how the price of an asset can be determined (Weston & Brigham 1978). The assumptions are listed below:

- All investors are single period expected utility of terminal wealth maximises who choose among alternative portfolios on the basis of mean and variance (or standard deviation) of returns
- All investors can borrow or lend an unlimited amount at an exogenously given risk-free rate of interest, and there are no restrictions on short sales of any asset;
- All investors have identical subjective estimates of the mean, variance and covariances of return among all assets, i.e., investors have homogenous expectations;
- All assets are perfectly divisible, perfectly liquid (that is, marketable at the going price), and there are no transactions costs;
- There are no taxes;
- All investors are price takers; and
- The quantities of all assets are given

According to the CAPM, beta, a share's covariance with the market, is the only relevant measure of a stock's risk (Jackson & Staunton, 2001). The beta measures a stock's relative volatility, in other words it measures how much the price of a particular stock jumps up and down compared with how much the stock as a whole jumps up and down. If a share price moves exactly in line with the market, then the stock's beta is 1. A stock beta, for example, of 1.5 would rise by 15% if the market stock price rose by 10%, and fall by 15% if the market stock price fell by 10%.

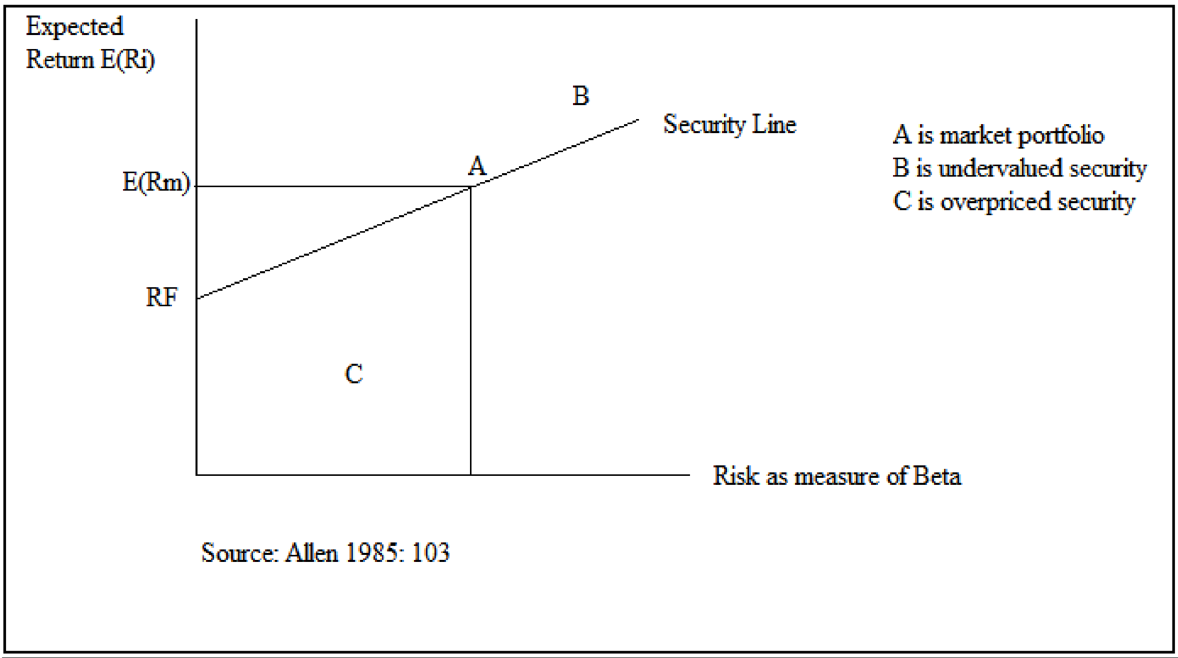
The model is a theory about expected returns on an asset in relation to expected market return and it stipulates that for a fully diversified investor, the only factor that affects expected excess return on share $i, E(R_i)$, is systematic risk of the share (as measured by its beta). Expected value of intercept α for all shares is zero and this can be expressed as follows:

$$E(R_i) = \beta_i E(R_M) \text{.........} \text{....}(3.2) \text{ Since } E(\alpha_i) = 0$$

Where: β_i is defined as $\mathrm{cov}(R_i, R_M)/\sigma_M^2$ and $E(R_M)$ is the expected excess return on the market.

The CAPM explains the pricing of an asset as a trade off between risk and return. It comes up with a Security Market Line (SML) which is a graphical representation of the relation between the required return on a security and the product of its risk times a normalised market measure of risk (Weston & Brigham, 1978). In equilibrium, all prices should plot along the security market line which is shown in Figure 3.1 below. The market portfolio provides the performance benchmark and by definition they have a beta coefficient of 1. This means that any security with a beta of 1 would earn a premium above the risk-free identical to the premier available on the market portfolio. It follows that less risky securities with a lower beta will earn a lower return and those with a higher beta will earn a higher return.

Figure 3.1 Trade-off between risk and return: The security market line



Source: Allen 1985: 103

The intercept of the security market line RF is the risk-less rate of return. These risk-less returns have beta coefficients equal to zero since returns on riskless securities are fixed and constant, they do not move at all with changes in the market (Allen, 1985). The relationship between β and required return is plotted on the securities market line (SML), which shows expected return as a function of β. The intercept is the nominal risk-free rate available for the market, while the slope is the market premium. The securities market line can be regarded as representing a single-factor model of the asset price, where Beta is exposure to changes in value of the Market (Weston & Brigham 1978). The equation of the SML is thus:

$$SML : E(R_i) = R_f + \beta_i (E(R_M) - R_f \text{ ....(3.3)}$$

Once the expected/required rate of return $E(R_i)$ is calculated using CAPM, it can be compared this required rate of return to the asset's estimated rate of return over a specific investment horizon to determine whether it would be an appropriate investment. When the asset does not lie on the SML, this also suggestsmis-pricing.

The CAPM is a useful asset pricing model as it provides a usable measure of risk that helps investors determine what return they deserve for putting their money at risk.

3.2.5 Gordon Growth Model

The Gordon growth model is a tool used to determine the current price of a security. It uses current dividend paid, the expected growth rate of dividends and the required return on equities by shareholders, to calculate the price of a stock (Hubbard, & O'Brien, 2012). The model was developed by Myron Gordon in 1959 as a tool for estimating the fundamental value of a stock. In the model, Gordon (1959) considered the case in which investors expect a firm's dividend to grow at a constant rate, *g*. Many firms strive to make their dividends increase as a constant rate each year. Using this assumption, an equation was developed that shows the relation between the current prices of stocks, current dividends paid, expected growth rate of the dividend and the required return on equity. The model is a simple derivation of a continuous stream of growing dividend payments relative to the required rate of return in the market. The equation, given below, is the one that is called the Gordon growth model (Mishkin, 2010, p. 143).

$$P_t = D_t * \frac{1+g}{r_E - g} \text{.......... (3.4)}$$

Where: P_t is price of stock today,

D_t is current dividend paid

r_E is market required return on equities

g is the expected constant growth rate in dividends

The equation above states that the equilibrium price of the security is determined by its dividend paid its growth rate, and the market required return on equity.In the model, dividends are assumed to continue growing at a constant rate forever. Also the model assumes that the growth rate is assumed to be less than the required return on equity. This is because if the firm's dividends grow at a faster rate than required return on equity, the firm will eventually become larger than the entire economy (Bodie,et al.,2005).

In the Gordon growth model, investors' expectation of the future profitability of firms and therefore their future dividends, are crucial in determining the price of stock. It emanates from the fact there are rational expectations in investors who invest in the stock market. The investors always want to be rewarded for expected inflation so that their money does not lose purchasing power. The model is popularly used because valuation calculation is easily performed and is useful among companies or industries where cash flows are typically strong and relatively stable (Mishkin, 2004).

The constant growth model is vital in the analysis as it gives a picture of how stock prices are determined and from such information one can deduce the likely behaviour of the stock prices. Given the fact that the current price is determined by dividend paid, required rate of return and the growth rate, and also that the dividend paid changes with the level of income or profit, the company makes vital implications to the possible behaviour of changes in the stock prices. Since the dividend paid depends on the level of profits made and the level of profits is not expected to follow a trend but can change randomly, it can thus be said that this theory of price determination can be used to confer a certain behaviour followed by prices.

3.3 Empirical framework

Researches has been carried out on random walk hypothesis across developed countries and in developing economies with those on developed countries being prevalent. This section briefly presents various researches that have been conducted onproperties of stock market prices in different countries with their various findings and conclusions. Although there have been numerous studies on whether stock market prices follow a random walk process or not, it has been shown that there still exists some inconclusiveness on the matter as some still argue against the random walk hypothesis and better still the economy changes every now and again hence changing the behaviour of the financial market as well, making this research not only relevant but also vital. Empirical literature can be divided and presented in different ways that make it easier to understand. For the purposes of this study, this section is divided into empirical literature from developed economies, developing economies and finally narrowed down to empirical literature from South African market as it is the focus of this study. This is because it is believed that the financial market in countries that are more developed tends to be efficient in the weak form and hence the stock prices are expected to be following the random walk process and the opposite for developing economies.

3.3.1 Empirical literature from developed countries

There have been a large number of research papers on random walk hypothesis across developed countries. Most researchers conclude that there is a tendency of stock market prices following a random walk process in markets whose economies are developed.

Kleman (2002) conducted a study to investigate the existence of random walks and market efficiency with evidence from international real estate markets. Heused the indices for geographical regions which are Europe, Asia, North America and a sample of monthly data from 1983:12 up to 1997:12. Employing the Augmented Dickey Fuller test and Phillips-Perron unit root and Cochrane variance test the results showed that each of these markets exhibited random walk behaviour. In addition, they further employed non-parametric runs test that supported that the markets followed random walk. To further substantiate their results they employed the Johansen-Juseliuscointegration procedure and vector error correction model. The cointegration models revealed that the paired real estate markets Europe- Asia and Europe-North America were co-integrated whereas paired real estate markets of Asia-North America were not co-integrated.

A research on the Asian stock markets by Worthington and Higgs (2006) who examined the weak-form market efficiency of Asian equity markets concluded that none of the emerging markets are characterised by random walks and hence are not weak-form efficient, only the developed markets in Hong Kong, New Zealand and Japan were consistent with random walk criteria.

In a research by Mwamba (2011) which investigated the predictability of stock prices in the USA and the UK, it was found that both markets have predictable stock prices. The study used daily stock prices of the S & P 500, Dow Jones (DJIA) and FTSE 100 encompassing the period 02 January up to 31 December 2012. The research used two econometric methods parametric (random walk) and non parametric (Kernel) methods. The results obtained showed that forecasts generated from non-parametric method were closer to actual or observed prices than those generated from the parametric model. Parametric models assumed normality and non-linearity in the underlying stock prices, thus by relaxing these assumptions predictability of stock prices can be improved.

3.3.2 Empirical literature from developing economies and emerging stock markets

Evidence of random walk process in stock prices is weak in developing economies. Butler and Malaikah (1992) conducted a study in which they examined the behaviour of individual stock returns in Saudi Arabia and Kuwait for the period of 1985 to 1989. The serial correlation method and runs testswere employed. It was concluded that theKuwait stock market price index followed a random walk whereas the Saudi Arabia stock market represented a significant departure from random walk theory.

Dockery and Vergari (1996) tested the random walk in the Budapest Stock Exchange (BSE) in Hungary. They used the variance ratio tests with both homoscedastic and heteroscedastic error variances using weekly observations for the BSE share price index covering the period from January 1991 up to May 1995. Their results indicated that BSE is a random walk market. The variance ratio estimates under homoscedasticity refuted the hypothesis of random walk for every k interval except for the short interval. However, interestingly, the evidence furnished by the heteroscedasticity consistent variance ratio test indicated that the market obeys the hypothesis of random walk for every level of k. This, according to the researchers, is in contradiction to the findings reported by other researches on both developed and emerging capital markets.

Daheland Laabas (1999) examined the behaviour of the daily stock prices over the period 1994-1998 in four markets: Bahrain, Kuwait, Oman and Saudi Arabia. The data consisted of weekly stock price indexes from September 1994 to April 1998. The authors used the methodology of unit root and variance ratio and tested the hypothesis that returns tag along random walk and conducted regression tests for autocorrelation of returns. The results obtained significantly supported the weak-form of efficiency for the Kuwait market. For the other three markets, only the regression test rejected the weak-form of the efficiency for the whole sample period. When the sample is split into two sub periods, the efficiency hypothesis is not rejected for the second sub-period in two of the markets and only by a small margin in the case of the Saudi Arabian market.

Researches for the market efficiency on the Arab market and especially on the Gulf States are very few. Gandhi (1980) used monthly data for the period 1975-1978 for the Kuwait Stock Exchange and established that both simple linear regressions of returns on lagged returns and runs tests for autocorrelation rejected the random walk hypothesis for the all share and industrial indices. Butler and Malaikah (1992) used daily data for Kuwait for the period 1985-1988 and Saudi Arabia for the period 1986-1989. Using autocorrelation and run tests found that the prices of approximately 60 per cent of the sample of more-liquid Kuwaiti stocks were serially independent but not one of the samples of Saudi stocks followed a random walk.

Research by DarratandZhong (2000) examined random walk hypothesis for the stock exchanges in China using two different approaches-the variance ratio test and comparison of NAÏVE model (based on assumption of random walk) with other models like ARIMA and GARCH. They rejected the random walk in newly created Chinese stock exchanges using both the methodologies.

Yilmaz (2001) employed the variance-ratio-based multiple comparison test (MCT) on weekly and daily returns for 21 emerging stock markets over the period 1988-2000 in testing weak-form efficiency. In 12 of the countries, the data used were weekly as well as daily returns from the period of January 1988 up to March 2000, however for the other 9 emerging stock markets data was available from January 1993, as a result, data that was used for the 9 was from 1993 and not 1988. The empirical methodology was to test for random walk behaviour by applying the MCT to two of subsample windows, one with fixed end points and the other with fixed starting points. The countries with emerging stock markets included Malaysia, Indonesia, Philippines, Taiwan, Argentina, Chile, Mexico, Turkey, Greece, SriLankar, Venezuela, Israel, Parkistan, India, Colombia, China, Brazil, South Korea, Peru, China, and Japan. For each country, the researcher used MCT to test for random walk on both weekly and daily returns series and results indicated that over time there was a move towards market efficiency. In some of the countries that showed rapid development of the stock markets like Japan, the random walk process was true as series showed no properties of predictability. In other words for countries that have similar features to Japan in the late 1980 their stock market prices followed random walk hypothesis in this research irrespective of the subsample window used. The results obtained also showed that financial crises such as the Mexican and the East Asian crises adversely affected the emerging markets' ability to price stocks efficiently. Finally, the results for Malaysia clearly indicated that as a result of the imposition of capital controls, stock price behaviour could diverge from random walk.

Smith, et al. (2002) tested the random walk hypothesis using data from selected African stock markets using the multiple variance test of random walk. The research found four categories of formal stock markets which are South Africa, medium sized markets, small new markets which have experienced rapid growth and small new markets which has yet to take off. They tested the hypothesis for South Africa, five medium sized markets (Egypt, Kenya, Morocco, Nigeria, and Zimbabwe) and two small new markets (Botswana and Mauritius). The data used in conducting the test were weekly commencing in the third week of January 1990 and ending in the last week of August 1998 except for Egypt and Nigeria whose series started in the first week of January 1993 (295 observations) and 1994 (243 observations) respectively. The results obtained show that the hypothesis is rejected in seven of the markets because of autocorrelation of returns and only one market, South Africa, was found to be characterised by series that exhibited a random walk process.

In 2008, a research done by Asiri that measured behaviour of stock prices in the Bahrain Stock Exchange (BSE), confirmed that the returns in that market followed a random walk with no drift and trend. The study employed random walk models which are unit root and Dickey Fuller tests as basic stochastic tests for non-stationarity and in addition, the ARIMA and exponential smoothing methods were also used. The data used was daily prices of all listed companies in the BSE (40 listed companies) over the period of 1June 1990 till 31 December 2000. The results obtained indicated that there was evidence of series following a random walk process. Similar results were also obtained from ten years earlier by Khababa(1998) who also examined random walk hypothesis using Bahrain stock market data.

The Dickey-Fuller test (unit root test), Exponential smoothing test and the ARIMA (1, 0, 0) methods where employed. The research concluded that the Bahrain Stock Exchange followed the random walk process and was weak form efficient.

In another research, Mobarek, et al. (2008), sought evidence on whether the return series on Bangladesh's Dhaka Stock Exchange (DSE) is independent and follows the random walk model. Using both non-parametric (Kolmogrov-Smirnov: normality test and run test) and parametric test (Auto-correlation test, Auto-regressive model, ARIMA model) for the period of 1988 to 2000 (DSE Daily price Index), they found that the security return did not follow the random walk model and the significant auto-correlation coefficient at different lags rejected the null hypothesis of weak-form efficiency.

Research on Zimbabwe’s Stock Exchange conductedby Sunde and Zivanomoyo (2008) sought to test random walk hypothesis of ZSE prices using monthly data for the period from January 1998 to November 2006 and concluded that the ZSE did not follow a random walk process. The study applied the unit root tests, (Augmented Dickey Fuller test) with a lag length that was necessary to remove autocorrelation from residuals. The results show that past prices had an influence in the determination of future prices.

Okpara (2010) investigated whether or not Nigerian security prices follow the random walk hypothesis. Yearly data for the period from 1984 up to 2006 was used and the study employed non parametric test, run test and a more scientific test the autocorrelation involving correlograms and the Ljung-Box Q-statistic. The results indicated that the Nigerian stock market was efficient in the weak form and therefore follows a random walk process. The possibility of making excess returns in the market was ruled out.

In the same year, Oskooe (2010) tested the random walk in an emerging economy of Iran that is the Iran Stock Market (ISM). The study used the Augmented Dickey Fuller test, Phillips-Peron (PP), and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) unit root test. Also used to substantiate the findings was the Perron (1989) model which is a structural break Perron unit root test. They employed all these methods to daily stock price index of Tehran Stock Exchange (TEPIX) for a sample period covering January 1999 up to October 2009. All the methods used supported the fact that the Iran Stock Market has a unit root and follows a random walk process.

Sharmin and Charity (2011) conducted a research designed to measure market efficiency level of Dhaka Stock Exchange to explain the relationship between information and share price, following whether or not returns follow a random walk process. Evidence of the Dhaka not being efficient in the weak form and hence not following the random walk process was found. The data used were two types of indices of Dhaka Stock Exchange which are the All Share Indices and the DSE General Indices for the period of January 1 1993 up to June 30, 2011 and 1January 2000 to June 30, 2011 respectively. They employed three methodologies, the normality test using Q-Q (Q is quantile) probability chart or plot and goodness of fit test and the test for serial dependences which are the Dublin Watson test, Autocorrelation tests and the Ljung- Box Q statistic at 5% level of significance with 30 (lags) degrees of freedom. The third method used to capture robustness was the ARIMA which showed that changes in the returns did not depend on past information. The results showed that return series of both indices of the DSE did not follow normal distribution which is against the random walk model. Results from serial correlation and auto correlation tests also indicated the non random nature of return series for both indices and lastly the ARIMA forecasting strengthens the non random nature of DSE. These results are similar to the ones found in the research by Mobarek et al (2008) presented earlier on.

3.3.3 Empirical literature from South Africa stock market

Empirical evidence on South Africa provide mixed results and most of them made use of method serial autocorrelation test and unit root test which are traditionally used. Research on the South Africa's JSE by Jammine and Hawkins (1974), who tested for the random walk over the period 1966 to 1973 using weekly changes in price indices, concluded that technical analysis could be used to profit since price changes did not follow a random walk.

Hamman, et al. (1995) examined the concept of earnings changes as a random walk for industrial companies listed on the JSE. They obtained results that overwhelmingly support the hypothesis of higgledy piggledy growth or earning growth as a random walk using three different test procedures. Their sample included South African industrial companies listed on the JSE between 1973 and 1992 yearly data. The serial correlation test supported that serial correlation coefficient are equal to zero, secondly results from binomial tests confirmed these results and thirdly the observed EPS –growth per quintile supported the hypothesis of random earnings growth.

Applying unit root tests to stock market prices to assess efficiency of South Africa, Botswana and Zimbabwe's stock markets, Jefferis and Okeahalam (1999a) found out that for South Africa and Zimbabwe, the stock markets were efficient during the period 1989 to 1996. In another study, Jefferis and Okeahalam (1999b) used an event study of the same three markets to test responses of individual stock prices to new information by evaluating the speed and efficiency with which the information is incorporated into market price. The findings were that while the JSE exhibited efficient in the weak form, Zimbabwe and Botswana did not.

Smith, et al.(2002) used multiple variance ratio tests for random walk to investigate whether aggregate stock price indices for eight African markets followed random walks. They tested the hypothesis for South African market, five medium sized markets (Egypt, Kenya, Morocco, Nigeria and Zimbabwe) and two small new markets (Botswana and Mauritius). Of the eight markets (South Africa, Egypt, Kenya, Morocco, Nigeria, Zimbabwe, Botswana and Mauritius), only the JSE was found to follow a random walk process. The research further suggested that South Africa's stock market has these results because of the size of the market which is relatively bigger that the other countries under study. In addition to this, it was also noted that the JSE is well incorporated with the international markets, for example the London Stock Exchange.

In a study that was concerned about the robustness of the efficient market hypothesis, Mabhunu (2004) tested the weak form efficiency of the JSE by performing correlation tests. The research evaluated behaviour of stock returns on the JSE using weekly closing prices and trading volumes from the week ending 01 January 1999 to week ending 25 July 2003. Weekly returns for periods before 1997 were not available, as a result the research used monthly closing index for the periods in which weekly data was not available. The correlation tests and graphical analysis methods were used and the results obtained from correlation tests showed little evidence of dependence in successive returns on shares listed on the JSE hence it follows a random walk process. Results from graphical analysis also supported this conclusion.

Cubbin, et al. (2006) examined mean reversion on the JSE for the period from 31 October 1983 up to 31 December 2005 using monthly data and adapted the De Bondt and Thaler (1989) methodology which uses cumulative relative returns. They used data that included returns for all shares listed on the JSE All Share Index and concluded that the JSE does not follow the random walk hypothesis.

In another research in the same year, Smith and Rodgers (2006) used the variance ratio tests to test the random walk hypothesis in South African stock futures. The test was on four stock index futures and a sample of 36 single stock futures (SSFs) traded on the JSE securities exchange. The data used in this study was the four stock index futures (from the first week of March 1998 up to the last week of June 2005), derivative products of the All Share 40 and financial 15 and for SSFs the data used started from the last week of August 2000 to June 2005.The variance tests were based on i) ranks and signs and ii) wild boostrapping. The conclusions drawn were that there was a high degree of weak-form efficiency in all stock index futures and 25 of the 36 samples of single stock futures followed a random walk process.

3.4 Assessment of literature

In the light of the mixed empirical results in the literature, this study is motivated to find the empirical support for the random walk hypothesis in the JSE, a stock market that plays a pivotal role in Africa. The case of South African stock market is of particular interest due to a noticeable change in the pace of economic growth, policy changes and also because of significant growth in the transactions volume and number of listed companies in JSE. It should be noted that the methodologies that most researches on JSE used are considered weak and hence this study aims at using a more reliable methodology in testing the random walk hypothesis using JSE data. ln addition, empirical literature on South Africa is inconclusive because of mixed results from the reviewed studies, as such this research aims at contributing to the existing literature by re-examining the random walk hypothesis. The studies reviewed also indicate that these particular researches were done in early 2000 and a lot of changes may have happened to influence the behaviour of stock market prices after the global financial crisis of 2007-2008. The empirical literature can be summarised as shown in Table 3.1 below which also provides a quick check for methodologies used and results obtained.

Table 3.1 Summary of empirical literature in South Africa

Study	Methodology	Period of study and data used	Results obtained
Jammine and Hawkins (1974)	Unit root test	Weekly data	No random walk
Hamman, Jordaan and Smit (1995)	Variance ratio test	Yearly data 1973 to 1992	JSE was efficient in the weak sense.
Jefferie and Okeahalam (1999a) Jefferie and Okeahalam (1999b)	Unit root Event study (a statistical method of assessing the impact of an event on value of stock.	1989 to 1996	South Africa was efficient in the weak form in both studies.
Smith et al (2002)	Multiple variance ratio tests.	1992 up to last week of December 1997	JSE followed a random walk
Mabhunu (2004)	Correlation tests andgraphical analysis method.	1 January up to 25 July 2003 weekly closing index	Little price dependence and hence JSE follow random walk process
Cubbin, Fire and Gilbert (2006)	De Bondt and Thaler (1985) cumulative relative returns	Monthly data from the period 31 October to 31 December 2005	Returns in the JSE were predictable
Smith and Rodger (2006)	Variance ratio test	First week of March 1998 up to the last week of June 2005	High degree of weak form efficiency in 25 individual futures and 11 are not efficient

Empirical literature from South Africa as shown above indicates that the majority of the studies done show that the JSE's price index follows a random walk, but these were done in the 1990's and early 2000. However, recent researches done and presented here show the inconclusiveness of the studies. It has been the JSE's major intention of late to increase information dissemination which is expected to increase efficiency. Also of concern is the methodologies used in the presented studies. Most of the studies used unit root and correlation tests which alone cannot be relied on. Of the researches presented, none used the ARIMA which is used as the chief methodology in this research.

3.5 Conclusion

The main objective of this chapter was to review existing literature surrounding stock market price determination and the behaviour of these prices. There are many theories that have been developed that explain how the price of an asset is determined and how price changes behave. Among the many theories, the ones discussed in this chapter are the Random Walk Hypothesis (RWH), which forms the basis of the current investigation, the Efficient Market Hypothesis (EMH), the Arbitrage Pricing Theory (APT), the Capital Asset Pricing Model (CAPM) and the Gordon growth model.

Empirical literature presented in this chapter indicates that someresearches support the existence of random walk process in stock prices in the developed economies with emerging economies still face inefficiency problems.The analysis of empirical literature presented in this chapter helped to sum the studies that have been done in South Africa in the area of random walk, thus shading light on the gap that this researches aims at filling.

CHAPTER FOUR

METHODOLOGY AND SOURCES OF DATA

4.1 Introduction

This chapter provides an explanation of the methodology employed in investigating whether there exists a random walk process in the stock market prices of the JSE for the period from January 2000 to December 2011. The chapter advances the foundations laid in the literature reviewed in the preceding chapter on the random walk hypothesis and clearly brings out the method employed to test the stated hypothesis. The chapter is divided into the following main sections, model specification, justification of variables used and the data sources. The estimation techniques employed in testing the random walk hypothesis will be detailed here, and the last part of the chapter presents the conclusion of the chapter.

4.2 Model specification

The model is developed following the random walk theory presented in the preceding chapter. To determine whether the JSE follows a random walk process, this research will modify the model developed by Box-Jenkins (1986) specified as follows:

$$Y_t = \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots\ldots\ldots \alpha_n Y_{n-1} - \theta_1 \varepsilon_{t-1} - \ldots\ldots\ldots -\theta_1 \varepsilon_{t-1} - \ldots\ldots\ldots \theta_n \varepsilon_{n-2} + \varepsilon_t \ldots\ldots (4.1).$$

The BJ-type time series model allows the dependent variable to be explained by its past or lagged values and stochastic error terms (Gujarati, 2004). Such a model states that the current value of the series ALSI depends linearly on its own previous values plus a combination of current and previous values of a white noise error terms (Brooks, 2008). In this research the model above is modified and specified as below:

$$ALSI_t = \alpha_1 ALSI_{t-1} + \alpha_2 ALSI_{t-2} + \ldots.. + \alpha_p ALSI_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots.. + \theta_q \varepsilon_{t-q} + \varepsilon_t \ldots\ldots (4.2)$$

Where:

$ALSI_t = All\ Share\ Index\ in\ the\ current\ period\ t$

$ALSI_{t-1} = ALSI\ of\ previous\ period\ i.e\ current\ period - 1$

$\alpha = autoregressive\ parameter$

θ=$moving average parameter$

$\varepsilon_t = error term$

p =$the number of autoregressive terms and q is the number of moving average terms$

4.3 Review of estimation techniques

To capture for robustness of the conclusions made about whether or not the JSE follows a random walk process, the stock indices are tested for random walk using four different methodologies namely; the Augmented Dickey Fuller test, Correlograms and Q statistics, the AutoRegressive Integrated Moving Average (ARIMA) and the Variance Ratio test (VRT). Based upon the work of Sultana and Sharmin (2011) the Augmented Dickey Fuller (ADF) test is the traditionally used method for testing randomness of price changes. The ADF is employed first in this study, followed by two autocorrelation tests, the use of graphical analysis (correlogram) and the Q-statistics (Ljung-Box test). Also, used as the main methodology and as the third method in this research is a more reliable test for price dependency in financial time series, the Auto Regressive Integrated Moving Average (ARIMA) (Brooks, 2008). To further substantiate the findings, the variance ratio test is also employed.

4.3.1. Augmented Dickey Fuller Test for unit root

To confirm whether or not the JSE follows a random walk process a unit root test (stochastic) is first employed which is the Augmented Dickey Fuller test (ADF). The ADF test is used to determine whether series in question are stationary or not. The ADF test includes lagged differences in the regression such that error term corresponds to white noise. A stationary series is one whose mean and variance does not change over time or in other words are constant over time (Studenmund, 2011). A unit root test is applied to detect pattern of the trend in a stock price series. If there is no unit root in time series of stock prices or if there is a deterministic trend in stock prices, it means that it has a constant mean, variance and covariance. This in turn means there is no stochastic trend in the stock price series and future movement pattern of stock prices can be identified based on past behaviour patterns. On the other hand, if there is a unit root or if stock prices fluctuate based on a stochastic trend, the prediction of future stock prices movements would be impossible and series would be said to be following a random walk. The hypothesis of the unit root test is stated as below:

H0 (Null hypothesis): There is a unit root in the series (non-stationary)/ random walk

H1 (Alternative hypothesis): There is no unit root in the series (stationary) / no random walk

If there is a unit root in the time series, it means that the time series is non-stationary or that it has a stochastic trend and $\delta = 0$. Alternatively the series can be stationary possibly around a deterministic trend and $\delta < 0$ (Gujarati, 2004).

If series are non-stationary and become stationary at first difference, then stock price indices series behave according to stochastic process and follow a random walk process. Random walk process is a non-stationary process. Although unit root tests have been traditionally used to test for random walk,they are not sufficient tests for random walk process. Non-stationarity is a necessary prerequisite of the random walk hypothesis but is not a sufficient condition. Time series can be non-stationary and at the same time predictable. Unit root tests are not able to detect predictability. Tests for the random walk hypothesis are concerned with the unpredictability of future share price changes. In unit root tests, residual terms are allowed to be an arbitrary stationary process under both the null and alternative hypothesis, implying that future share price changes may be predictable. The unit root test is also criticised because of the size and power of the test. Size of test refers to the level of significant that is probability of committing type 1 error (rejecting a true null hypothesis) and power of the test means the probability of correctly rejecting the null hypothesis when it is false (Gujarati, 2004). This leads to the use of other methods to substantiate the conclusions drawn about the randomness of the JSE. Thus the ADF test is used here because it has been traditionally used, butin addition to it, more reliable methodologies that look at predictability of stock prices are employed and discussed below.

4.3.2 Correlogram and Ljung-Box Q-statistic

Autocorrelation tests will also be employed to substantiate the results because the unit root test cannot be relied on.A correlogram is an image of correlation statistics commonly used for checking randomness in a data set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. If random, such autocorrelations should be near zero for any and all time-lag separations. If non-random, then one or more of the autocorrelations will be significantly non-zero (Brooks, 2002).

The graphical observation of the correlogram usually known as the autocorrelation function (ACF's) and partial autocorrelation function (PACF's) can help in determining whether returns are dependent on each other or not. According to Gujarati (2004; 842), the ACF measures correlation between (time series) observations that are k time periods apart and the current observation. On the other hand, the PACF measures correlation between observations that are k time periods apart after controlling for correlation at intermediate lags. The absence of correlation in a series indicates that the series follows a random walk process. In the analysis of data, a correlogram is an image of correlation statistics. A correlogram, also known as an autocorrelation plot, is a commonly used tool for checking randomness in a data set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. A graphical analysis or observation of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) will be done. The ACF is the one often referred to as correlogram and the PACF is similar to ACF except that it looks at the correlation between a particular lag and the current value after the effect of other lags have been removed (Brooks, 2008). If autocorrelogram only dies out gradually over time, then it suggests that time series are non-stationary and hence the presence of a random walk process, and if series are stationary the correlogram decay quite rapidly from its initial value of unity at zero lags.

The ACFs and PACFs of AR (p) and MA (q) processes have opposite patterns. In the AR (p) case the ACF declines geometrically (or exponentially) whereas the PACF cuts off after a certain number of lags. A MA (q) process is characterised by PACF that declines exponentially and the ACF cuts off after a certain number of lags. What it therefore means is that if ACF drops off to zero quickly, the series may be said to follow a non-random process. The partial autocorrelation functions (PACF) should all be close to zero for a white noise series.If the time series is white noise, the estimated PACF are approximately independent and normally distributed (Griffiths, et al., 1993).

Another autocorrelation test employed is the **Ljung-Box test** often referred to as the Q-statistic. The Ljung-Box test is based on the autocorrelation plot, however, instead of testing randomness at each distinct lag, it tests the overall randomness based on a number of lags. For this reason, it is often referred to as a portmanteau test. It is used to test whether any of a group of autocorrelation of a time series is different from zero. The Ljung-Box test can be defined in the following way:

H_0: The data is independently distributed (the correlations in the population from which the sample is taken are 0, so that any observed correlations in the data result from randomness of the sampling process).

H_1: The data are not independently distributed.

For a large sample the Box-Ljung follows a chi-square distribution (X^2) with m degrees of freedom and is given by the test statistic is given by the equation below.

$$Q^* = T(T+2)\sum_{k=1}^{m}\frac{\hat{\tau}_k^{\,2}}{T-k} \sim X_m^{\,2} \ldots\ldots(4.3)$$

Where T is sample size, k is lag, and m is number of lags being tested. $\hat{\tau}_k^{\,2}$ is the sample autocorrelation at lag k. For a significant level α , the critical region for the rejection of the hypothesis of randomness is $Q > \chi^2_{1-\alpha,h}$ where $\chi^2_{1-\alpha,h}$ is the α -quantile of the chi-squared distribution with h degrees of freedom (Studenmund, 2011).

The Box-Ljung is used in ARIMA modelling as it is applied to residuals of a fitted ARIMA model to test whether the residuals from the ARIMA model have no autocorrelation. If the Q-statistic is significant at a certain significant level and degrees of freedom, then the returns do not follow a random walk. In general, the data are not white noise if the values of Q or Q^* are greater than the value given in a chi-square table with α = 5% or if the p-value is greater than 0.05 the null hypothesis cannot be rejected. If the time series is white noise, the estimated series are approximately independent. In this study, for higher order serial correlation the correlogram and the Ljung-Box Q-statistic will be used.

4.3.3 Box-Jenkins

Following the Ljung-Box method is the Auto Regressive Integrated Moving Average (ARIMA) methodology which in this research is used in this study as the most reliable method to test randomness in the JSE. ARIMA, popularly known as the Box-Jenkins (BJ) methodology, was developed by George Box and Gwilym Jenkins in 1976 (Gujarati, 2004). For time series modelling and/or forecasting univariate time series models are used, where one models and predicts financial variables using only information contained in their own past values and possibly current and past values of error terms.

An ARIMA model is comprised of two distinct parts, first it has an integrated component (d) which represents the amount of differencing to be performed on the series to make it stationary and the second component consist of ARMA model for the series rendered stationary (Brooks, 2008). The ARMA component can be further broken down into AR and MA components with the autoregressive (AR) responsible for capturing the correlation between the current value of the time series and some of its past values. With this in mind, AR (1), for example, would mean that the current price is correlated with its immediate past value at time t-1. Moving Average (MA) represents the interval on the influence of a random (unexpected) shock, for example, MA (1) means a shock on the value of the series at time t is correlated with the shock at time t-1.The AR, autoregressive parameters in the ARIMA is represented by (p), the number of differencing by (d) and moving average parameters by (q), and these are referred to as the order of a process. The 'I' in the middle of the ARIMA is a result of the fact that most time series observations are non-stationary and they can be transformed by differencing the time series, one or more times to make them stationary and such time series are then referred to as integrated processes. Thus the 'I' represents the fact that the time series has to be differenced d times to achieve stationarity (Griffiths, et al., 1993). The number of times (d) that the integrated process has to be differenced to be stationary is said to be the order of the integrated process. In order to know how many times a series needs to be differenced to achieve stationarity one can observe the autocorrelation function for the time series process. If series are non-stationary they have to be differenced so as to be able to regress, resulting in ARIMA (p, d, q).

The main advantage of ARIMA forecasting is that it requires data on the time series in question only. In other words, the ARIMA model does not involve independent variables in their construction but makes use of information in the series itself. These univariate models are usually a-theoretical, meaning their construction and use is not based upon any theoretical model of the behaviour of the variables (Brooks, 2008). Unlike regression models where the dependent variable, Y, is explained by a number of regressors, the BJ type time series model allows the explained variable Y, to be explained by past or lagged values of itself and stochastic error terms. For a given time series process $\{Y_t\}$, a first order auto regressive process is denoted by ARIMA (1, 0, 0) or simply AR (1) given by $Y_t = \mu + \alpha_t Y_{t-1} + \varepsilon_t$. And a first order moving average process is denoted by ARIMA (0, 0, 1) or simply MA (1) given by $Y_t = \mu - \theta_t \varepsilon_{t-1} + \varepsilon_t$.The ARIMA model is combination of AR and MA which gives us the following equation $Y_t = \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots\ldots\ldots \alpha_n Y_{n-1} - \theta_1 \varepsilon_{t-1} - \ldots\ldots\ldots - \theta_1 \varepsilon_{t-1} - \ldots\ldots\ldots \theta_n \varepsilon_{n-2} + \varepsilon_t$

Under the random walk model, ARIMA model is (0, 1, 0) where future values of share return cannot be determined on the basis of past information. The significant coefficients different from zero would suggest dependency of the series thereby violating the assumption of the random walk model.

Briefly the ARIMA method takes into account historical data and decomposes it into AR process, where there is a memory of past events, an integrated (I) process which accounts for making data stationary, and a MA process of the forecast errors, all combined and recomposed into the ARIMA (p, d, q) model. ARIMA is superior to common time series analysis, which makes it the major method in this research. It has the major advantage that it takes into account error residuals. As the error residuals can help to predict current error residuals, one can take advantage of this information to form a better evaluation of dependency of series. Also the ARIMA is chosen because it fixes the problem of bias and inconsistence which is usually found when there are lagged dependent variables set as regressors (Huang, 1995).

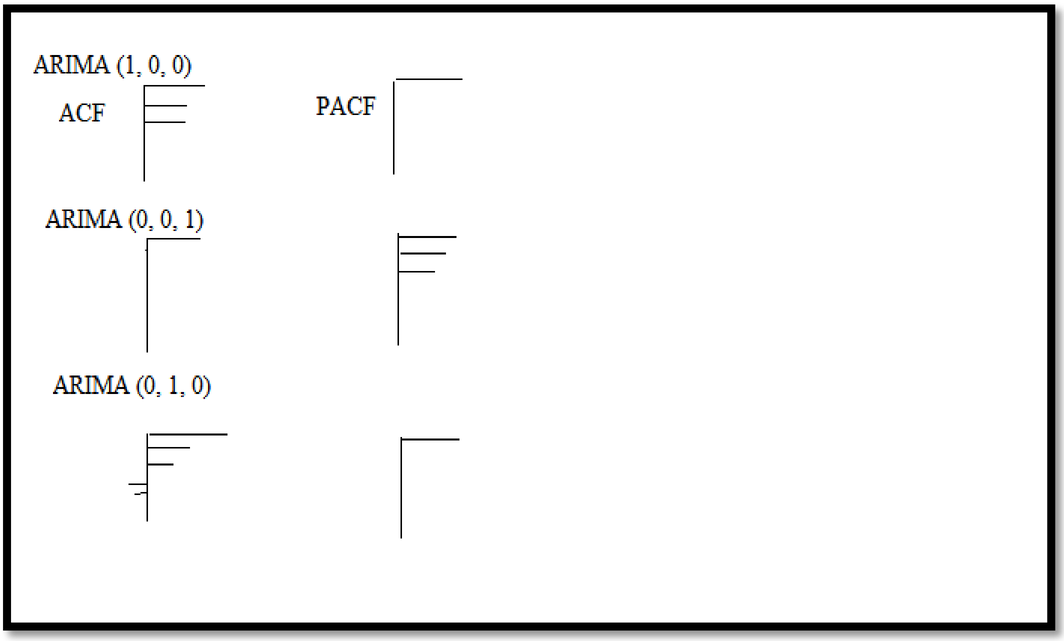
The ARIMA has three steps which are identification, estimation and diagnostic checking in that order (Brooks, 2008). However, the ARIMA may also include a forth step which is forecasting (Gujarati, 2004).

4.3.3.1 Step 1: Identification of the order of the process

The first step in building an ARIMA is identification which involves determining the order of the model required to capture the dynamic features of the data. Identification of the most appropriate model is the most important stage of the process. Correlograms are used in the model identification stage for Box–Jenkinsautoregressive moving averagetime series models. Firstly, the step starts with determining if the variables are stationary, and this can be done by correlogram. If it is not stationary, it needs to be first-differenced and this leads us to integrated part of our model, d. If the ACF taper offer slowly or does not die out, non-stationarity is indicated and may be removed by differencing the data until it is stationary. If there is need to difference the data, it must be done or carried out with care so as to avoid introducing correlation unnecessarily (Gujarati, 2004).

The next stage is to determine the p and q in the ARIMA (p, d, q) model (the d refers to how many times the data needs to be differenced to produce a stationary series). The primary tool of determining the p and q is by observing the autocorrelation plot and the partial autocorrelation plots (Brooks, 2008). To determine the appropriate lag structure in the AR part of the model or the order of the AR process (p), the PACF or Partial correlogram is used, where the number of non-zero points of the PACF determine where the AR lags need to be included. In other words, for an AR (p) process the partial autocorrelation $\theta_{kk} = 0$ for k > p and the ACF taper off. To determine the MA lag structure, the ACF or correlogram is used and again the non-zero points suggest where the lags should be included (Gujarati, 2004). For an MA (q) process the autocorrelations $\rho_k = 0$ for k > q and the partial autocorrelations taper off. This then means the order of the MA and AR components may be inferred from the pattern of autocorrelation and partial autocorrelation (Hansen, 2009). Generally, if there is an autoregressive process ARIMA (p, 0, 0) the ACF declines exponentially and the PACF spikes on the first ρ lag and by contrast, for a moving average process ARIMA (0,0,q) the ACF spikes on the first ρ lag and the PACF declines exponentially. For mixed processes ARIMA (p, d, q) there will be declines on both ACF and PACF and if the ACF or PACF declines slowly. Below are some of the corellograms that can be observed to determine the order of the model (Sloman, &Jones, 2011).

Figure: 4.1 Theoretical ACF and PACF for common ARIMA model



Source: Sloman, &Jones 2011

Theoretically it is easy to produce correlograms that can help us determine the order of the process as summarised in the table below adapted from Gujarati and Porter (2009, p. 781) which shows the theoretical patterns of correlograms and their respective order of the process.

Table 4.1 Theoretical patterns of ACF and PACF

Type of model	**Typical Pattern of ACF**	**Typical Pattern of PACF**
AR(p)	Decays exponentially or with damped sine wave pattern or both	Significant spikes through lags p
MA(q)	Significant spikes through lags q	Declines exponentially
ARMA(p, q)	Exponential decay (can also be called geometric decay)	Exponential decay

Source: Gujarati, 2004

In practice, the pattern of the correlogram of differenced series is difficult to use to find the ARMA pattern that best describes the time series under study. In other words, unless the ACF and the PACF are not well defined, it is hard to choose a model without trial and error. After differencing to make the series stationary, the identification process is done by trial and error. The trial and error can be done by estimating a number of possible ARMA processes for example estimating AR (1), MA (1), ARMA (1, 1), ARIMA2,2), to name but just few (Brooks, 2008). This is where assumptions are made and estimate for the assumed process and conduct residual test to see if the chosen model, or one of the assumed models fits the data that we have and then we interpret that chosen model in accordance with the feature of a random walk process to see if the series suggest that there is a random walk or not.

4.3.3.2 Step 2: Estimation of the model

In step two of the ARIMA, the parameters of the model specified in step one are estimated or regressed. If a pure AR process is identified then the parameters can be estimated using least squares estimation. The method used here depends on the model specified in the initial step. It is at this stage that the confidence intervals for the parameters are calculated (Gujarati, 2004).

In this research, the trial and error discussed in step one will estimate two possible processes. It is assumed here then that the process that generates the (first differenced) LALSI (logged All Share Index) is either ARIMA (1, 1, 1) or ARIMA (2, 1, 2). These two processes are estimated using the LS-Least Squares (NLS- and ARMA) on EViews. Thus the study is going to estimate two equations and run residual tests on the two, in order to find the model that best fits the data at hand and use that chosen process.

4.3.3.3 Step 3: Diagnostic checking

Diagnostic checking, also called model checking, involves checking the model adequacy. Box and Jenkins suggest two methods for checking the model adequacy which are over-fitting and residual diagnostics. Over-fitting is where one estimates a model ARIMA (p+1, d, q) or ARIMA (p, d, q+1) instead of ARIMA (p, d, q) and check the significance of the additional parameters. In other words, it involves deliberately fitting a larger model than that required to capture the dynamics of the data. If the model is ARIMA (p, d, q) then the additional parameters introduced by the larger model should not be significantly different from zero (Brooks, 2002).

Residual analysis is a method based on the fact that if an ARIMA (p, d, d) model is an adequate representative of the data generation process, then the residuals should be uncorrelated random disturbances. Thus the plots of the residuals should show no pattern of correlation and there should be no unusual values or outliers (Griffits, et al, 1993). An ACF fit to the residuals should also reveal no significant autocorrelations. Residual autocorrelations may be checked for significance by comparing them to $\pm 2/\sqrt{T}$.

In addition to the visual inspection of the graphs, the *Q* statistic can also be used. To test the overall acceptability of the residual autocorrelation, one can use the test statistic developed by Ljung and Box in 1978 known as the Ljung-Box test or Q-statistics. The residual analysis, according to Brooks (2008, p. 231), is much more commonly used than over-fitting in the Box-Jenkins methodology. This research will as a result adopt the residual analysis as suggested by Brooks (2008) and also because an analysis of the residuals helps to analyse if they are free from autocorrelation and hence dependent of price changes. Although it is a diagnostic test, it can also be used to test price dependence which is the main idea of this research. The random walk process can be described by a particular ARIMA model which is ARIMA (0,1, 0), the first zero referring to Autoregressive process and the second zero to the moving average process which indicates some extent of dependency and correlation in the series, which is in conflict with random walk properties. In other words, the random walk needs to fit the model ARIMA (0, 1, 0) where the share price cannot be determined on the basis of past information, specifically future prices will not depend on past or lag values of share price or on disturbance terms. Given that the modelled series do not give the ARIMA model for the random walk process, it can be concluded that the model is not a random walk and results in rejecting the hypothesis that the JSE's ALSI follows a random walk process. The significant coefficients different from zero suggests dependency of the series which violates the assumption of random walk model and weak-form efficiency.

4.3.3.4 Step 4 Diagnostic tests

As noted in step 3, in this research the graphical analysis of correlograms of residual and the Q-statistic of residuals will be used as they are suggested by Box and Jenkins as the diagnostic tests for ARIMA. However, in addition to these, tests for normality and heteroscedasticity will be conducted first and then after the residual tests of the ARIMA model further diagnostic tests will be employed which are forecasting tests that aid in the identification of the most appropriate model. The diagnostic tests to be conducted in this research are presented in their order below.

Normality tests

One of the basic assumptions of the random walk model is that the distribution of the return series should be normal. The normality assumption is that for two or more normally distributed variables, zero covariances or correlation means independence of the two, or more, variables. What this means is that with normality assumption, variables are not only uncorrelated but also independently distributed (Gujarati & Porter, 2009). There are many or several tests of normality, but in this research normality tests are done using the Jarque-Bera (JB) test because it is an asymptotic or large sample test. The BJ uses the property of a normally distributed random variable that the entire distribution is characterised by the first two moments- the mean and the variance. The JB test statistic asymptotically follows a X^2 under the null hypothesis that the distribution of the series is symmetric. The null hypothesis of normality would be rejected if the residuals from the model are either significantly skewed or leptokurtic/ platykurtic (or both). The null hypothesis tested here is that residuals are normally distributed. If the probability or p value is reasonably high, we cannot reject the null hypothesis of normality.

Heteroscedasticity tests

Heteroscadasticity occurs when the variance of the error terms differ across observations and the model where variance of errors is not assumed to be constant can be presented as below.

$$Y_i = \beta_0 X_i + \varepsilon_{it} \text{.......... .....} 4.4$$

Heteroscedasticity tests, according to Brooks (2002, p. 148) test for constant variances and there are a number of formal statistical tests for heteroscedasticity and one such test is the White's general test. This test is useful here because it assumes that the regression model estimated is of the standard linear. It tests the joint significance of the regression and the null hypothesis of the white test is homoscedasticity and if we reject the null we conclude that there is heterocsedasticity which represents a random walk process in the series. If there is heteroscedasticity of residuals, it suggests that the variance is not the same between price changes which is a basic assumption of the random walk hypothesis (Brooks, 2002).

Correlogram and Q-statistics of Residual

These are the diagnostic tests suggested for ARIMA models by Box and Jenkins and is also be conducted here where correlogram of the residuals of each estimated equation will be conducted and interpreted. In the analysis of data, correlogram is an image of correlation statistics. The correlogram is a commonly used tool for checking randomness in a data set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. If random, such autocorrelations should be near zero for any and all time-lag separations. If non-random, then one or more of the autocorrelations will be significantly non-zero.

In observing the correlogram and using the Q-statistic to test randomness, it means we are looking at time dependence in the data. For the Q-statistics, the p value for all the lags should be larger than 0.05 or 5% to indicate the adequacy of the model.

Forecasting tests

Attempting to determine the values that a series is likely to take is what is referred to as forecasting (Brooks, 2008). Determining the forecasting accuracy of a model is a significant test of its adequacy and it is also vital as it aids in determining whether or not series can be predicting which will then answer the random and non random question of this study. Also in this research, forecasting tests are used to choose the model that best fits the series where the model with a smaller Mean Absolute Percentage Error (MAPE) are considered the best model.

4.3.4 Variance Ratio Test (VRT)

The variance ratio test is also employed as an alternative test for random walk hypothesis to further substantiate the findings in this study. The variance ratio test has been historicallyused and is used here to compare the findings with other researches mentioned in the empirical literature review. Bachelier (1900) asserts that for a random walk, successive price changes between two periods are independent with zero mean and their variance is proportional to the interval between the two time periods. Consequently, the variance of weekly changes should be five times the variance of the daily changes. There are two implications of the random walk model, firstly that future returns are unpredictable both in the short and long-run, secondly that the variance of a sample is proportional to the sample space (Lo &MacKinlay, 1988).This concept is exploited in the variance ratio tests, which has been widely used to test the random walk hypothesis in various markets (Darrat&Zhong, 2000). It was proposed by Lo and MacKinlay in 1988 to test the random walk hypothesis and they recognised that the variance of random walk increments is linear in all sample intervals.

Given the fact that time series can be decomposed into permanent and temporary component, the variance ratio test estimates the size of the random walk or permanent component in a series. It measures the degree of persistence in a time series (Patel et al., 2012). The null hypothesis that is tested under the variance ratio test is as below:

$$H_0 : VR(k) = Var[rt(k)] / (k.Var[rt]) = 1(ix)\ (series\ follow random walk)$$

The null hypothesis above can be interpreted as that the variance ratio at lag k is defined as the ratio of the variance of the k-period returns to the variance of the one-period return divided by k, which is unit under the hypothesis of random walk. In other words, the null hypothesis states that series follow a random walk process. The alternative hypothesis is therefore be that the variance ratio is not an equal as shown below:

$$H_1 = VR(k) \neq 1\ (series do not\ follow random walk)$$

Variance ratio test of about one or higher may indicate the presence of a stochastic trend or unit root and for a pure random walk the ratio will be exactly equal to one. When the series or data in question are stationary, and do not follow a random walk, the variance ratio approaches zero as the number of autocorrelations included approaches infinity.Variance ratios of less than one imply that some negative serial correlations are present, while a variance ratio of greater than one implies positive serial correlation (Gujarati, 2002). For the random walk hypothesis to hold, the null hypothesis that the variance ratio is equal to one should not be rejected (that is the p value should be greater than 0.05).

The variances of most stock returns are conditionally heteroscedastic with regards to time. Chow and Denning (1993) provided a way out of the problem of joint testing with a method for comparing a set of variance ratio estimates with unity. This involves carrying out a set of variance ratio tests for *m* different values of the aggregation parameter, k. This test statistic that has the maximum absolute value is compared to the appropriate critical value from the studentised maximum modulus (SMM) distribution.With this solution, Lo and MacKinlay (1988) advanced the heteroscedasticity-constant asymptotic variance estimator of the variance ratio, $\Phi^*(0)$ which was then standardised asymptotically to a standard normal test-statistic, $Z^*(K)$ which is a follows

$$Z^*(k) = \frac{VR(k)-1}{[\Phi^*(k)]^{\frac{1}{2}}} \xrightarrow{a} N(0,1).......... .(4.5)$$

where $\Phi^*(k)$ is the asymptotic variance of the variance ratio consistent with the null hypothesis (Darrat&Zhong, 2000).In line with the above, thevariance ratio test employed in this investigation uses the asymptotic normal distribution and assumes heteroskedastic increments to the random walk (standard variance test of Lo and MacKinlay, 1988).In order to stabilize the variance of the series over time, the series are expressed in natural logs. The VRT has the advantage that it takes account ofheteroscedasticity and is more powerful than most techniques.

4.4 Data sources and definition of variables

This study uses monthly closing indices of the Johannesburg Stock Exchange (JSE), ALSI, covering the period 2000:1 – 2011:12. A total of 144 observations will be used since monthly data is used. The main advantage of ARIMA forecasting is that it requires data on the time series in question only. Stock returns in the South African Stock market are represented by the index value of the JSE the All Share Index. All Share Index (ALSI) is capitalisation-weighted average of the market prices of all shares listed on the Johannesburg Stock Exchange. It is an index that gives the best indication of general market direction as it includes shares from all sectors of the stock market. It is an index figure based on the current market prices of shares (JSE, 2012). The research will use the ALSI as the only variable as justified below and the data will be transformed to natural logarithms. The table below shows the description of the variable.

Table 4.2 Description of Variables

Name of variable	Proxy	Description
Monthly All Share Index	LALSI	Natural log of All Share Index

4.5 Justification of variables

The overall performance of the stock market is measured using stock market indexes, which are averages of stock prices (Habbard& O'Brien, 2012). This is because stock market indexes are intended to show movements in prices over time, rather than the actual rand value of the underlying stock. It is with this in mind that this research uses the JSE index which is the All Share Index (ALSI) as a measure of overall performance of the South African stock market.

In testing price dependency, the research uses one variable which is the share price index itself. The explained or dependent variable will be the current ALSI which is being examined to see whether it can be determined by observing past prices. The explanatory variables in this study are time-lagged values of the dependent variable, ALSI. This is because the study examines the independence in the ALSI itself. Therefore the ALSI is to be explained by past or lagged values of itself and stochastic error terms.

The logarithm returns are going to be used, that is, logged ALSI denoted as LALSI. This is justified both theoretically and empirically. Theoretically, logarithmic returns are critically more tractable when relating together sub period returns to form returns over longer intervals. Empirically logarithmic returns are more likely to be normally distributed which is prior condition of standard statistical techniques (Strong, 1992).

4.6 Expected priori

Based on the literature review and the information dissemination improvements on the JSE, it is expected that the JSE index follows a random walk process. The ALSI is expected to be characterised by price changes being independent of each other.

4.7 Conclusion

The focus of this research is to test whether or not the stock price index of the JSE, ALSI, follows a random walk process as required by efficiency using four different methodologies, that is, ADF, autocorrelation test, the ARIMA model and the variance ratio test. This chapter outlined the various methods that is employed in the study and they will be estimated using the econometric package EViews 7 and the results obtained are presented in chapter 5. The chapter also highlighted some advantages and weaknesses of the methodologies.

CHAPTER FIVE

ESTIMATION, PRESENTATION AND INTERPRETATION OF RESULTS

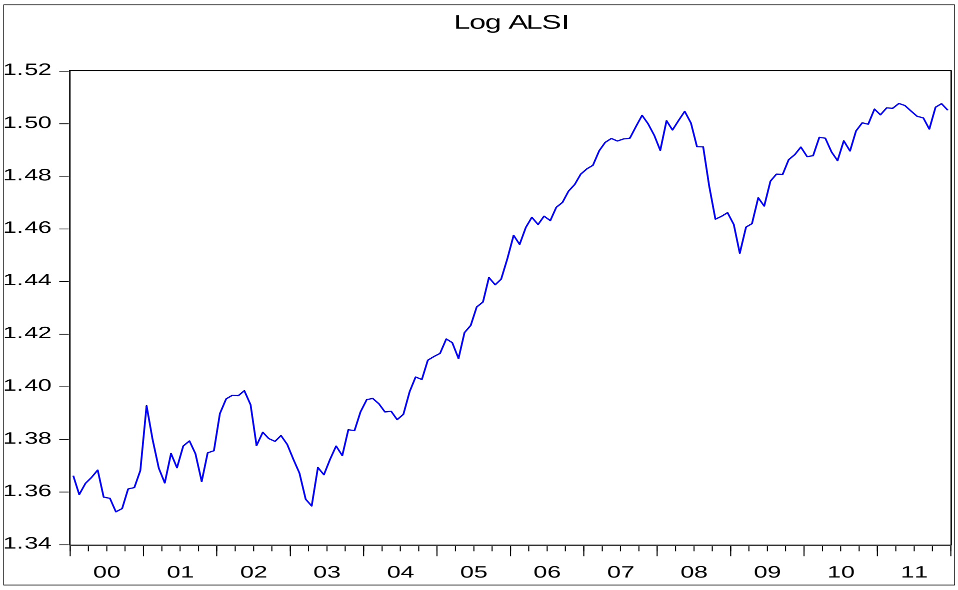
5.1 Introduction

The previous chapter presented the analytical framework and the estimation techniques used in this study, this chapter in turn presents result of the ADF test,correlogram and Q-statistic, the ARIMA and variance ratio test, estimation results as well as their interpretations. The diagnostic tests used in this study are presented in step three of developing the ARIMA model. The last part of the chapter will bring out the summary and conclusions of whether or not the test results evidence the existence of a random walk process in the Johannesburg Stock Market during the specified period of study.

5.2 Augmented Dickey Fuller Test for unit root (ADF)

The ADF test is used to test whether or not series are stationary. For the series to be independent of each other they have to exhibit a non-stationary trend (Gujarati, 2009). The null hypothesis tested would then be that the ALSI has a unit root or is non-stationary. The alternative hypothesis would be that the series are stationary. The visual plot of the series in levels is given in Figure 5.1 below to give an idea of the trends and stationarity of the data set. It is clear from the visual plots of the LALSI (log of All Share Index) that the series are non stationary.

Figure 5.1 Visual plots of the series



The series is non-stationary in levels as shown in the graph above. The table below displays the results of ADF test with intercept, trend and intercept and none included in test equation.

Table 5.1 Augmented Dickey Fuller test for LALSI

	Intercept	**Trend and intercept**	**None**
t-statistic	-0.664657	-1.869283	1.903195
Probability	0.8510	0.6652	0.9863
Critical t-value	1% -3.476472 5% -2.881685 10% -2.577591	-4.023506 -3.441552 -3.145341	-2.581233 -1.943074 -1.615231

Source: Eviews

In absolute terms, the ADF statistics in each case is smaller than the critical values at 5% and 1%. Therefore, the null hypothesis that unit root is present in the series cannot be rejected. The conclusion is that the ALSI is non-stationary. According to the unit root test conducted, the JSE can be said to be following the random walk process, meaning one cannot use past price information to determine future prices of stocks as the market price trend has no historical price data in consideration. The problem with the unit root test is that it cannot be relied upon as it is not a random walk test neither is it designed for that (Brooks, 2008). The ADF unit root test was employed in this study because it has been traditionally used, however in order to validate and make results more reliable other more robust estimation techniques were used and are presented below.

5.3 Correlogram and Ljung-Box Q-statistics

Autocorrelation is used to measure the dependence of a variable on its past values. The graphical analysis of LALSI's autocorrelation function (ACF) and partial autocorrelation function (PACF) can be used to observe whether series follow a random walk or not. The ACF is shown in the first column of the Table 5.2 presented below and the PACF is in the second column. The ACF dies away slowly whilst the PACF dies away after the first lag. Gujarati (2004) states that the rule of thumb in deciding the lag length to be included is to compute ACF up to one-third to one-quarter the length of a time series. Since this study has 144 monthly observations, by this rule lags of 36 to 48 quarters will do. The graph shows that the autocorrelation coefficients (AC) at various lags are very high even up to a lag of 36. The series are highly non stationary, the AC starts at a very high value, at lag 1 (0.982) and declines very slowly towards zero as the lag lengthens. This resembles a correlogram of a random walk model, the time series are non stationary in mean or variance or both.

The PACF drops dramatically after the first lag and most PAC's after the first lag 1 are statistically insignificant, thus non stationary time series and it can then be concluded that the ALSI of the JSE follows a random walk process. As a rule of thumb, a given autocorrelation or partial autocorrelation function is deemed significant if it is in the $\pm 1.96 \times \left(\frac{1}{\sqrt{T}} \right)$ band, T being the number of observations. T in this study represents 144 quarterly observations. The decision rule is thus to reject the null hypothesis that a given coefficient is zero in the cases where the coefficient lies outside the range (−0.163, +0.163). It can be concluded that for the ACF, all autocorrelation coefficients are significantly different from zero at 5% level. This is because they are all falling outside the (-0.163 +0.163) range. However, for the PACF only the first autocorrelation coefficient is significantly different from zero at5% level.

In summary, the ACF for a stationary series drops off to zero quickly as k, the lag length, increases. It therefore means that if ACF drops off to zero quickly, the series may be said to follow a non-random process. In this case, it shows random walk because it does not drop off quickly as the lag length increases. The partial autocorrelation functions (PACF) should all be close to zero for a white noise series.If the time series is white noise, the estimated PACF are approximately independent and normally distributed. This is the case in the table below, the PACF supports the fact that the time series follows a random walk process.

Table 5.2 Correlogram and the Q-statistic

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|*******</td><td>.|*******</td><td>1</td><td>0.982</td><td>0.982</td><td>141.78</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>2</td><td>0.962</td><td>-0.058</td><td>278.89</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>3</td><td>0.943</td><td>-0.001</td><td>411.43</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>4</td><td>0.924</td><td>0.021</td><td>539.78</td><td>0.000</td></tr>
<tr><td>.|*******</td><td>.|. |</td><td>5</td><td>0.905</td><td>-0.048</td><td>663.62</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>6</td><td>0.885</td><td>-0.015</td><td>782.92</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>7</td><td>0.863</td><td>-0.058</td><td>897.29</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>*|. |</td><td>8</td><td>0.839</td><td>-0.077</td><td>1006.2</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>9</td><td>0.815</td><td>-0.010</td><td>1109.6</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>10</td><td>0.792</td><td>0.018</td><td>1208.1</td><td>0.000</td></tr>
<tr><td>.|******|</td><td>.|. |</td><td>11</td><td>0.770</td><td>-0.007</td><td>1301.7</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>12</td><td>0.750</td><td>0.067</td><td>1391.2</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|* |</td><td>13</td><td>0.733</td><td>0.086</td><td>1477.5</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>*|. |</td><td>14</td><td>0.715</td><td>-0.069</td><td>1560.1</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>15</td><td>0.694</td><td>-0.059</td><td>1638.6</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>16</td><td>0.672</td><td>-0.055</td><td>1712.7</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>17</td><td>0.650</td><td>-0.008</td><td>1782.8</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>18</td><td>0.628</td><td>-0.041</td><td>1848.7</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>19</td><td>0.610</td><td>0.068</td><td>1911.2</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>20</td><td>0.590</td><td>-0.035</td><td>1970.3</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>21</td><td>0.569</td><td>-0.042</td><td>2025.7</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>22</td><td>0.547</td><td>-0.034</td><td>2077.3</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>23</td><td>0.527</td><td>0.062</td><td>2125.5</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>24</td><td>0.507</td><td>-0.016</td><td>2170.4</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>25</td><td>0.488</td><td>0.024</td><td>2212.4</td><td>0.000</td></tr>
<tr><td>.|*** |</td><td>.|. |</td><td>26</td><td>0.470</td><td>-0.015</td><td>2251.7</td><td>0.000</td></tr>
<tr><td>.|*** |</td><td>.|. |</td><td>27</td><td>0.453</td><td>0.026</td><td>2288.7</td><td>0.000</td></tr>
<tr><td>.|*** |</td><td>.|. |</td><td>28</td><td>0.439</td><td>0.048</td><td>2323.6</td><td>0.000</td></tr>
<tr><td>.|*** |</td><td>.|. |</td><td>29</td><td>0.425</td><td>0.001</td><td>2356.6</td><td>0.000</td></tr>
<tr><td>.|*** |</td><td>.|. |</td><td>30</td><td>0.409</td><td>-0.055</td><td>2387.5</td><td>0.000</td></tr>
<tr><td>.|*** |</td><td>.|. |</td><td>31</td><td>0.394</td><td>-0.002</td><td>2416.3</td><td>0.000</td></tr>
<tr><td>.|*** |</td><td>*|. |</td><td>32</td><td>0.376</td><td>-0.081</td><td>2442.9</td><td>0.000</td></tr>
<tr><td>.|*** |</td><td>.|. |</td><td>33</td><td>0.360</td><td>-0.005</td><td>2467.5</td><td>0.000</td></tr>
<tr><td>.|** |</td><td>.|. |</td><td>34</td><td>0.344</td><td>-0.025</td><td>2490.1</td><td>0.000</td></tr>
<tr><td>.|** |</td><td>.|* |</td><td>35</td><td>0.330</td><td>0.088</td><td>2511.2</td><td>0.000</td></tr>
<tr><td>.|** |</td><td>*|. |</td><td>36</td><td>0.314</td><td>-0.080</td><td>2530.4</td><td>0.000</td></tr>
</table>

Source: Own regression in Eviews

The table also shows the Q-statistic in the sixth column written Q-Stat. As noted in Chapter 4, the Q-statistic or the Box-Ljung is used to test overall randomness based on the number of lag. The null hypothesis tested here is that the sum of 36 squared estimate autocorrelation coefficients is zero ($P_k = 0$). In other words, the data is said to be independently distributed when the probability is greater than 5% then the Q-statistic is insignificant, that is, P_k is not significantly different from zero and there is thus no autocorrelation (then accept the null). From such an angle, the logged JSE share price index, LALSI's Q-statistic at lag 36 is 2530.4 and the probability associated with this statistic is 0 interpreted as that the null hypothesis cannot rejectedand hence conclude that the ALSI follows the random walk process. Stated differently, the value of Q-statistic for LALSI is about 2530.4 and the probability of obtaining such a Q value under the null hypothesis that the sum of 36 squared estimated autocorrelation coefficients is zero, therefore the conclusion drawn is that LALSI time series may be nonstationary and therefore supports the fact that it follows the random walk hypothesis.Inother for a significant level α , the critical region for the rejection of the hypothesis of randomness is $Q > \chi^2_{1-\alpha,h}$ where $\chi^2_{1-\alpha,h}$ is the α -quantile of the chi-squared distribution with h degrees of freedom. In order to substantiate the conclusions drawn from the statistical and graphical methods above, the most relied method in this research is presented below, the ARIMA.

5.4 Box-Jenkins approach to ARIMA

In addition to the above statistical techniques employed, the study also employed the ARIMA methodology. This dynamic methodology which, as noted in the preceding chapter, examines whether or not stock return series depend not only on their past values but also on past and current disturbance terms. The weak form efficiency, theoretically stipulates that the prediction of share prices from its historical price information is not possible. Now when the prediction of share prices is evaluated on the basis of both past data and forecasted errors this give rise to ARMA models and if stationary has to be induced then it gives rise to ARIMA (Cuthbertson, 1996). In this method, the significant coefficients different from zero suggests dependency of the series which violets the assumption of random walk model. The results obtained from conducting the steps of Box-Jenkins's ARIMA building are presented below in the order presented in chapter four.

5.4.1 Identification

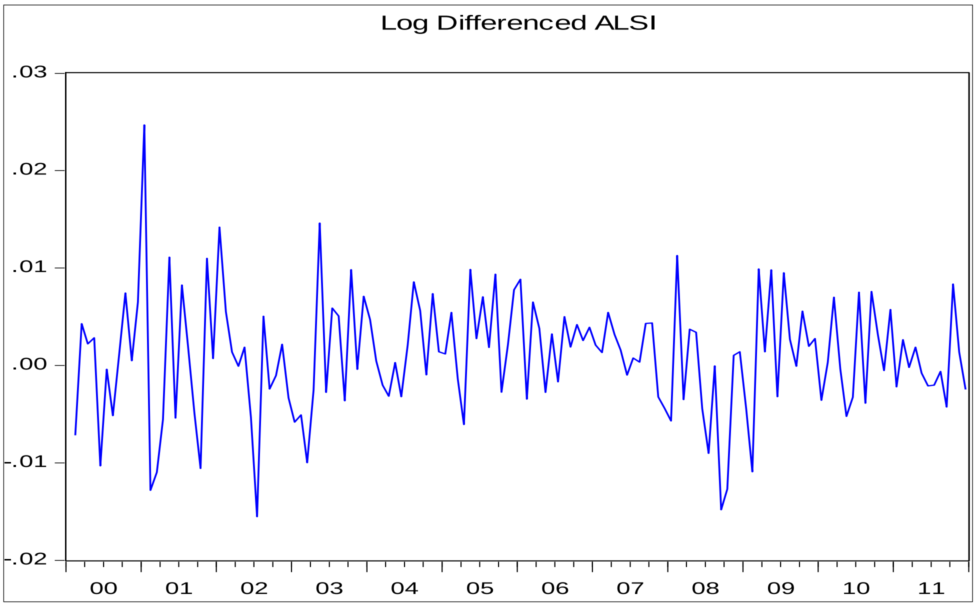
The series is not stationary, it needed to be differenced once, 1st difference and hence there is an ARIMA with the d being 1 and not ARMA because it has to be differenced to arrive at stationary data series. ARIMA (p, 1, q) d is 1.The t-statistic is bigger in absolute terms than the critical values (or the t-statistic is more negative than the critical values) and hence series are said to be stationary at first differencing. As a result we reject the null hypothesis that series have a unit root and conclude that the ALSI is stationary at first difference. The table below (Table 5.3) shows comparisons of the non-stationary ALSI and the differenced ALSI, showing also significant levels at which the series become stationary and the order of integration. The following table is a graphical presentation of the series after they become stationary when differenced.

Table 5.3 Identification of the order of integration (d).

Variable	**Intercept**	**Trend and intercept**	**None**	**Order of integration**
LALSI	-0.664657	-1.869282	1.903195	
D(LASI)	-12.06818***	-12.02485***	-11.76267***	1(1)
Critical t-values	**1% -3.476472** **5% -2.881685** **10%-2.577591**	**-4.023506** **-3.441552** **-3.145341**	**-2.581233** **-1.943074** **-1.615231**	
Values marked with *** represent stationary variables at 1% significance level, **represents stationary variables at 5% and * represents 10%.				

It is clearly seen from the table and the graph drawn below (Figure 5.2) that the series initially are non-stationary and only become stationary after first differencing. The graph shows that series are stationary as seen that they exhibit a constant pattern. This then brings us to a conclusion that the series are integrated of order 1. The next stages in the development of our ARIMA will use DLALSI and not LALSI since the LALSI is not stationary and it is required that the series be stationary before we estimate. The series are then said to be integrated of order one (1). There is therefore have an ARIMA because it includes an integration process, but once the series have been differenced, the model can be estimated using the same procedure as the ARMA since the series have already been differentiated.

Figure 5.2 Differenced time series



Source: Own graph from Eviews

The differenced series have become stationary after being differenced once and the graph above shows the stationary series. The series are then said to be integrated of order one (1). It therefore means there is an ARIMA because it includes an integration process, but once the series have been differenced the model can be estimated using the same procedure as the ARMA. Moreover the random walk model needs to fit the model ARIMA (0, 1, 0) where future value of share prices cannot be determined on the basis of past price information (Jackson & Staunton, 2001).

The next step is to determine the p and q. This is done by observing the correlogram of a stationary time series, D(LALSI), as shown in Table 5.3.

Table 5.4 Determining order p,q

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>-0.015</td><td>-0.015</td><td>0.0335</td><td>0.855</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>0.028</td><td>0.028</td><td>0.1502</td><td>0.928</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>3</td><td>0.032</td><td>0.033</td><td>0.3046</td><td>0.959</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>4</td><td>0.050</td><td>0.051</td><td>0.6807</td><td>0.954</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>5</td><td>-0.143</td><td>-0.144</td><td>3.7629</td><td>0.584</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>6</td><td>0.078</td><td>0.072</td><td>4.6788</td><td>0.586</td></tr>
<tr><td>.|. |</td><td>.|* |</td><td>7</td><td>0.069</td><td>0.077</td><td>5.4027</td><td>0.611</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>-0.019</td><td>-0.016</td><td>5.4587</td><td>0.708</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>-0.010</td><td>-0.007</td><td>5.4739</td><td>0.791</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>10</td><td>-0.053</td><td>-0.088</td><td>5.9171</td><td>0.822</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>11</td><td>-0.119</td><td>-0.108</td><td>8.1571</td><td>0.699</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>-0.017</td><td>0.004</td><td>8.2029</td><td>0.769</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>0.051</td><td>0.052</td><td>8.6228</td><td>0.801</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>14</td><td>0.001</td><td>0.013</td><td>8.6231</td><td>0.854</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>15</td><td>0.069</td><td>0.064</td><td>9.3988</td><td>0.856</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>16</td><td>0.166</td><td>0.151</td><td>13.891</td><td>0.607</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>17</td><td>-0.102</td><td>-0.092</td><td>15.615</td><td>0.551</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>18</td><td>-0.072</td><td>-0.069</td><td>16.481</td><td>0.559</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>19</td><td>-0.004</td><td>-0.027</td><td>16.483</td><td>0.625</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>20</td><td>-0.030</td><td>-0.038</td><td>16.639</td><td>0.676</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>21</td><td>-0.032</td><td>0.004</td><td>16.814</td><td>0.722</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>22</td><td>0.007</td><td>-0.053</td><td>16.822</td><td>0.773</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>23</td><td>-0.004</td><td>-0.023</td><td>16.825</td><td>0.818</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>24</td><td>-0.005</td><td>0.043</td><td>16.830</td><td>0.856</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>25</td><td>0.034</td><td>0.065</td><td>17.035</td><td>0.881</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>26</td><td>-0.126</td><td>-0.100</td><td>19.844</td><td>0.799</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>27</td><td>-0.082</td><td>-0.082</td><td>21.060</td><td>0.783</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>28</td><td>-0.034</td><td>-0.069</td><td>21.263</td><td>0.814</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>29</td><td>0.064</td><td>0.050</td><td>22.009</td><td>0.820</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>30</td><td>-0.080</td><td>-0.057</td><td>23.197</td><td>0.807</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>31</td><td>0.121</td><td>0.075</td><td>25.910</td><td>0.726</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>32</td><td>0.002</td><td>-0.013</td><td>25.911</td><td>0.768</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>33</td><td>0.009</td><td>0.061</td><td>25.925</td><td>0.805</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>34</td><td>-0.073</td><td>-0.028</td><td>26.931</td><td>0.800</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>35</td><td>-0.031</td><td>-0.081</td><td>27.116</td><td>0.827</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>36</td><td>0.026</td><td>0.048</td><td>27.248</td><td>0.853</td></tr>
</table>

From the table above, one cannot detect the order of the process. One considers the ACF and the PACF and associated correlograms of a selected number of ARMA processes such as AR (1), MA (1), ARMA (1, 1) etc. Assumptions are made here because unless the ACF and PACF are not well defined, it is hard to choose a model without trial and error. Thus in step two of building the ARIMA, since the graphical examination of the ACF and PACF cannot be easily used to detect the order of the process, step two of the Box-Jenkins methodology will have to be done by trial and error. In this case, the estimation will be done on two models which will represent p as 1 and q as 1 in the first instance and p as 2 and q as 2 as well in the second estimated model.

5.4.2 Estimation results

This study estimates the models ARIMA (1, 1, 1) and ARIMA (2, 1, 2) using differenced series of LALSI, that is, using DLALSI (denoted as dalsi in EViews since the data was logged before using it in EViews). The results of the estimated models under LS-least squares NLS & ARMA) are shown in Table 5.5 below and also the interpretation of the estimate.

Table 5.5 ARIMA (1, 1, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004137	0.002103	1.967751	0.0511
AR(1)	-0.944977	0.019216	-49.17726	0.0000
MA(1)	0.986428	0.008644	114.1207	0.0000
Inverted AR Roots -.94 Inverted MA Roots -.99				

Source: Eviews

The output from estimating the ARIMA presented above, in theory can be interpreted easily, however in practice it cannot be interpreted in similar ways as other estimation techniques. According to Brooks, (2008, p. 237) it is often desirable not to interpret the individual parameter estimates because the construction of ARIMA is not based on any economic or financial theory, but rather on examining the plausibility of the model as a whole and to determine whether it describes the data well and produces accurate forecasts.

The estimated equation also produced the inverse of the AR and MA roots of the characteristic equation which can be used to check whether the process implied by the model is stationary and invertible. The roots are the ones that are interpreted and then results that are highly relied on are the diagnostic tests which will be presented in the next stage. The roots in each case must be less than one in absolute values and in the case of ARIMA (1, 1, 1) the inverted AR roots 0.94 and the inverted MA roots is 0.99 which is desirable though it is just below the rule of thumb.

For the other estimated model, ARIMA (2, 1, 2), Table 5.6 below presents the results obtained from the estimated equation.

Table 5.6 ARIMA (2, 1, 2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003969	0.002033	1.952521	0.0529
AR(1)	-0.033246	0.029280	-1.135451	0.2582
AR(2)	-0.904056	0.028411	-31.82078	0.0000
MA(1)	-0.033675	0.023254	-1.448150	0.1499
MA(2)	0.989733	0.010871	91.04242	0.0000
Inverted AR Roots -.02+.95i -.02-.95i Inverted MA Roots .02+.99i .02-.99i				

For ARIMA (2, 1, 2), the inverted roots are also all below one, meaning the process implied is both stationary and invertible.

Diagnostic tests were conducted on the two methods which are on trial and error.These are the tests that can be relied on to see the model that best fits the data that is being estimated.The chosen model will be the one from where conclusions about the behaviour of the stock market prices in South Africa during the sample period are drawn.

5.4.3 Diagnostic checking results

Now in order to determine which of the two estimated equations best suits the data at hand, the estimates were subjected to diagnostic tests. One of the basic assumptions of random walk model is that the distribution of the return series should be normal and there should be heteroscedasticity of residuals to suggest that the variance is not the same between price changes. As a result, before employing the diagnostic tests suggested for ARIMA by Box and Jenkins, the normality test as well as heteroscedasticity tests were conducted first,these were followed by diagnostic tests for ARIMA the residual tests, and then lastly forecasting tests were done in order to determine the best model that best suits the ALSI series by observing how strongly it can be used for forecasting.

5.4.3.1 Normality tests

The first diagnostic test is the Jarque- Bera test which tests whether or not regression residuals are normally distributed under the null hypothesis. One of the basic assumptions of the random walk model is that the distribution of the return series should be normal and hence in addition to the normality tests acting as diagnostic test one can draw some conclusions on whether or not returns follow random walk. The Jarque- Bera for the ARIMA (1, 1, 1) has a probability equal to 0.3874033 and that of ARIMA (2, 1, 2) is 0.922736 and we in both cases cannot reject the null and conclude that the residuals are normally distributed. Thus according to the normality test, the series are random in behaviour.

5.4.3.2 Heteroscedasticity

In statistics, a random variable is heteroscedastic. Thismeans that when a series follows a random walk process, it can also be said the series are characterised by differing variance and error terms could vary or increase with each observation. In other words, if the errors do not have a constant variance, they are said to be heteroscedastic. There are many tests that can be used to test for heteroscedasticity, however, in this research the White test is used. The White tests for heteroscedasticity regresses the squared residuals on the cross product of the original regressors and a constant. The hypothesis tested when testing for heteroscedasticity is as follows:

H_0 No heteroscedasticity (meaning the series are homoscedastic)

H_1 There is heterocsedasticity (no homoscedasticity of variance)

The null hypothesis will be accepted if the probability value (p value) is greater than 0.05.At 5% significant level otherwise reject the null hypothesis and conclude that there is heteroscedasticity in the errors of the series.

The results of the heteroscedasticity tests that were done on the residuals of the two models are presented below.

Table 5.7 Heteroscedasticity Test: White

	F statistic	**Probability**
ARIMA (1, 1, 1)	3.261019	Prob. F(9,132) 0.0013
ARIMA (2, 1, 2)	2.346617	Prob. F(20,120) 0.0024

Source: Eviews

The probabilities of both models are less than 0.05 and hence in both cases reject the null hypothesis and conclude that there is evidence for the presence of heteroscedasticity. Judging from this test, it can be said that the series are likely to follow the random walk process where errors or the variances are not related and hence price changes are independent of each other.

5.4.3.3 Residual tests

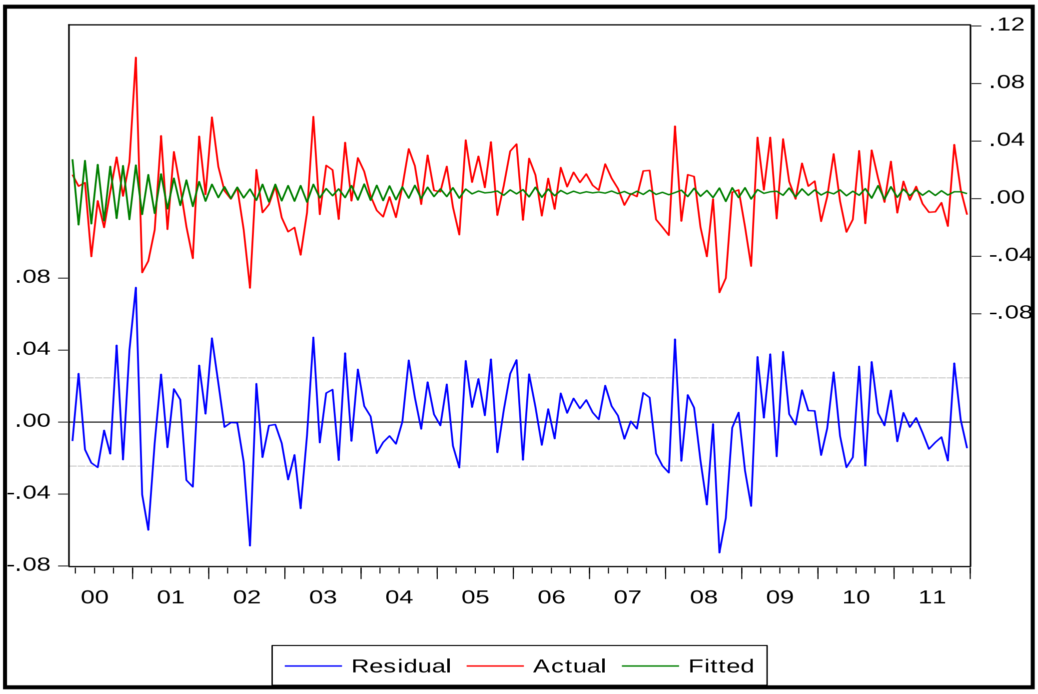
Residual tests were employed on the two estimated parameters and the results and their interpretations are given below. The residual tests used and presented here are the correlogram and the Q-statistics for residuals.

Table 5.8 Correlogram and Q-statistics of residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.008	0.008	0.0083	
.|. |	.|. |	2	0.006	0.006	0.0138	
.|. |	.|. |	3	0.063	0.063	0.6005	0.438
.|. |	.|. |	4	0.016	0.015	0.6376	0.727
*|. |	*|. |	5	-0.125	-0.126	2.9531	0.399
.|. |	.|. |	6	0.048	0.047	3.3022	0.509
.|* |	.|* |	7	0.098	0.100	4.7585	0.446
.|. |	.|. |	8	-0.049	-0.038	5.1237	0.528
.|. |	.|. |	9	0.032	0.028	5.2833	0.625
*|. |	*|. |	10	-0.101	-0.133	6.8681	0.551
.|. |	.|. |	11	-0.056	-0.041	7.3549	0.600
.|. |	.|. |	12	-0.058	-0.034	7.8926	0.639
.|. |	.|. |	13	0.072	0.072	8.7080	0.649
.|. |	.|. |	14	-0.041	-0.031	8.9754	0.705
.|* |	.|* |	15	0.110	0.097	10.925	0.617
.|* |	.|* |	16	0.142	0.131	14.199	0.435
*|. |	*|. |	17	-0.082	-0.074	15.288	0.431
*|. |	*|. |	18	-0.089	-0.091	16.606	0.412
.|. |	.|. |	19	0.012	-0.009	16.630	0.480
.|. |	.|. |	20	-0.062	-0.059	17.284	0.504
.|. |	.|. |	21	-0.014	0.034	17.318	0.568
.|. |	*|. |	22	0.001	-0.067	17.318	0.632
.|. |	.|. |	23	0.007	-0.005	17.326	0.691
.|. |	.|. |	24	0.005	0.036	17.330	0.745
.|. |	.|. |	25	0.032	0.061	17.505	0.784
*|. |	*|. |	26	-0.126	-0.105	20.311	0.679
*|. |	*|. |	27	-0.090	-0.088	21.751	0.650
.|. |	*|. |	28	-0.030	-0.067	21.915	0.693
.|. |	.|. |	29	0.046	0.062	22.291	0.722
*|. |	*|. |	30	-0.086	-0.087	23.636	0.701
.|* |	.|* |	31	0.132	0.101	26.865	0.579
.|. |	.|. |	32	-0.012	-0.063	26.890	0.629
.|. |	.|* |	33	0.020	0.118	26.964	0.674
*|. |	*|. |	34	-0.086	-0.085	28.353	0.652
.|. |	.|. |	35	-0.031	-0.039	28.533	0.689
.|. |	.|. |	36	0.013	0.002	28.567	0.731

The ACF and the PACF both show that the series are stationary and the Q-statistic is statistically insignificant at all lags since the probability at all lags is greater than 0.05. This in other words means that the residuals of our estimated ARIMA (1, 1, 1) are purely random. The graph for the residuals is presented in Figure 5.3 below.

Figure 5.3 Actual versus Fitted Residuals for ARIMA (1, 1, 1)



Source: Eviews

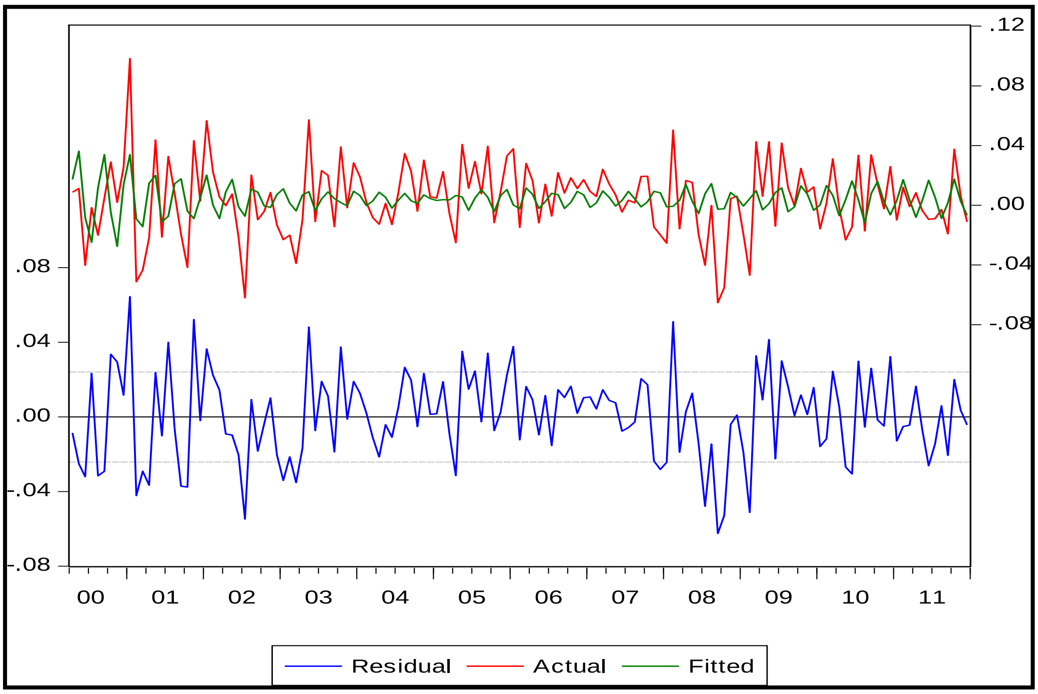
When the residuals of ARIMA (1, 1, 1) are purely random, it may mean that there may not be any need to look for another model but non- the less we will interpret the other estimated model and compare it to this one.

For the second model estimated, ARIMA (2, 1, 2), the correlogram and the Q-statistics are presented in Table 5.9 below. Like in the case of ARIMA (1, 1, 1), the ACF and the PACF plots of ARIMA (2, 1, 2) show little or no evidence of autocorrelation and the series are stationary and the Q-statistic is statistically insignificant at all lags since the probability at all lags is greater than 0.05 indicating that current prices have no memory of past prices. Figure 5.4 shows the diagram presenting the residuals.

Table 5.9 Correlogram for ARIMA (2, 1, 2)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.055	0.055	0.4325	
.|. |	.|. |	2	0.067	0.064	1.0890	
.|. |	.|. |	3	0.008	0.001	1.0992	
.|. |	.|. |	4	0.003	-0.002	1.1007	
*|. |	*|. |	5	-0.110	-0.112	2.9080	0.088
.|* |	.|* |	6	0.103	0.116	4.4790	0.107
.|. |	.|. |	7	0.036	0.040	4.6777	0.197
.|. |	*|. |	8	-0.051	-0.071	5.0792	0.279
.|. |	.|. |	9	0.000	0.001	5.0792	0.406
.|. |	.|. |	10	-0.051	-0.058	5.4730	0.485
*|. |	.|. |	11	-0.094	-0.064	6.8421	0.446
.|. |	.|. |	12	-0.033	-0.020	7.0161	0.535
.|. |	.|. |	13	0.062	0.057	7.6201	0.573
.|. |	.|. |	14	-0.008	0.001	7.6314	0.665
.|. |	.|. |	15	0.071	0.058	8.4467	0.673
.|* |	.|* |	16	0.154	0.144	12.269	0.424
.|. |	*|. |	17	-0.061	-0.077	12.874	0.458
.|. |	.|. |	18	-0.061	-0.061	13.490	0.488
.|. |	.|. |	19	-0.024	-0.031	13.583	0.557
*|. |	*|. |	20	-0.085	-0.076	14.778	0.541
.|. |	.|. |	21	-0.024	0.008	14.874	0.605
.|. |	.|. |	22	0.013	-0.034	14.903	0.669
.|. |	.|. |	23	0.009	0.014	14.916	0.728
.|. |	.|. |	24	-0.023	0.017	15.004	0.776
.|. |	.|. |	25	0.038	0.038	15.252	0.810
*|. |	*|. |	26	-0.097	-0.075	16.915	0.768
*|. |	*|. |	27	-0.085	-0.069	18.202	0.746
.|. |	.|. |	28	-0.056	-0.059	18.758	0.765
.|. |	.|. |	29	0.040	0.022	19.053	0.795
.|. |	.|. |	30	-0.040	-0.037	19.343	0.822
.|* |	.|* |	31	0.124	0.088	22.183	0.728
.|. |	.|. |	32	-0.027	-0.053	22.318	0.766
.|. |	.|. |	33	0.018	0.063	22.380	0.804
.|. |	.|. |	34	-0.030	0.003	22.547	0.833
.|. |	.|. |	35	-0.033	-0.053	22.749	0.858
.|. |	.|. |	36	-0.020	0.015	22.825	0.884

Figure 5.4 Residual for ARIMA (2, 1, 2)



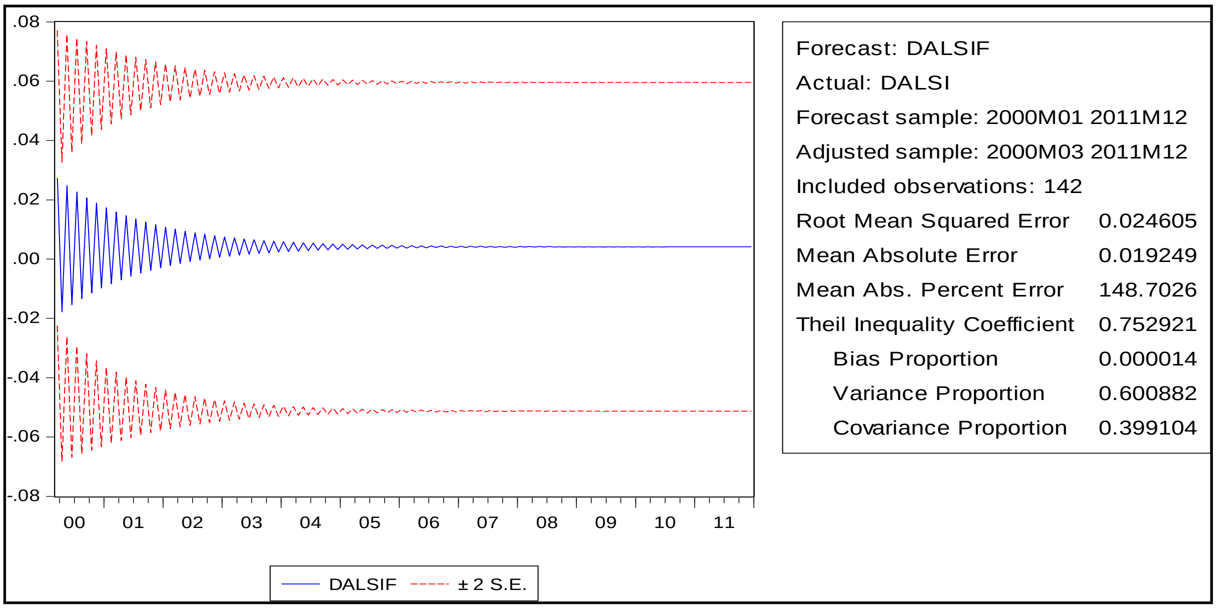
Source: Eviews

5.4.3.4 Forecasting tests

Forecasting tests were also done on the two estimated ARIMA's and the results are presented and interpreted below. The Mean Squared Error (MSE) and the Mean Absolute Error (MAE) are used, however, taken individually, one cannot draw much from them, as a result they have to be compared with those of the other models and the model with the lowest value of the error measure would be deemed to be the most accurate (Brooks, 2008).

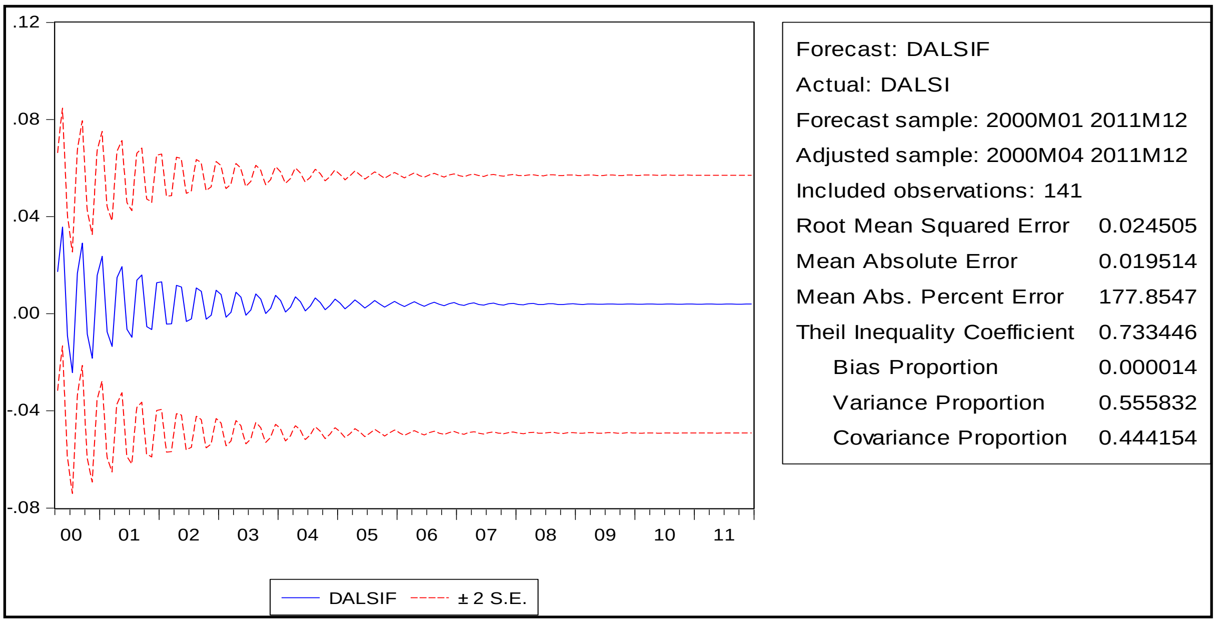
The Mean Average Percentage Error (MAPE) has an advantage over MSE because it can be interpreted as a percentage error. Also MAPE has an advantage that for a random walk in the log level, the criterion takes a value of one or 100%. If then, according to Brooks (2008, p. 254), a forecasting model gives a MAPE smaller than one, it is therefore superior to the random walk model.

Figure 5.5 ARIMA (1, 1,1)



Source: Eviews

Figure 5.6 ARIMA (2, 1, 2)



Source: Eviews

Prediction or forecasting simply means an attempt to determine the values that a series is likely to take. According to Brooks (2008, p. 244) determining the forecasting accuracy of a model is an important test of its adequacy. Time series forecasting involves trying to forecast the future values of a series given its previous values and/or previous values of an error term. The mean squared error (MSE) and/or mean absolute error (MAE) of one model is compared with those of other models for the same data and forecast period and the model with the lowest value of the error measure is argued to be most accurate description for the data in question. The MSE for ARIMA (1, 1, 1) and ARIMA (2, 1, 2) are 0.024505 and 0.024505 in roots respectively. The MAE in percentage (MAPE), that is the mean absolute percent error are 148.7026 for ARIMA (1, 1, 1) and 177.8547 for ARIMA (2, 1, 2). As the rule of thumb state, the model that has a smaller error measure would be chosen and in this case the ARIMA (1, 1, 1) is the most appropriate model for the data at hand and is the one that will be used to draw conclusions of the research questions.

5.4.4 Interpreting best fitted model in accordance to Random Walk Hypothesis

During the whole sample period under study, the model that was found to best fit the series is ARIMA (1, 1, 1) with the coefficients presented in Table 5.10 below.

Table 5.10 Results of ARIMA (1, 1, 1)

	Coefficient	**SE**	**T-ratio**	**Prob**
AR (1)	-0.944977	0.019216	-49.17726	0.0000
MA (1)	0.986428	0.008644	114.1207	0.0000

As discussed earlier, it is not advised to interpret the coefficients**,** but rather the roots of the characteristics equation. In the case of ARIMA (1, 1,1) both the inverted roots for AR and for MA are below one which is the rule of thumb, which can be interpreted to mean that both the AR and MA processes are stationary and invertible. Furthermore, diagnostic tests conducted on this model showed that there is no significant residual autocorrelation in the returns and hence evidence of the JSE index following the random walk process was supported. This shows that the successive price changes are not dependent during the period 2000 to 2011 in the South African stock market.

Also supporting the findings are the forecast tests done on the ARIMA (1, 1, 1) and the forecasts where constructed using the dynamic method. The dynamic method calculates multi-step forecasts starting from the first period in the estimate, gently sloping,the sample forwards one observation after each forecast to use actual rather than forecasted values for lagged dependent variable (Brooks, 2008). The MAPE shown is well above 100% (it is 148.7026) and this indicates that the model forecasts are unable to account for much of the variability of the out-of-sample part of the data. This is in line with what was expected of the JSE market, meaning prices are difficult to forecast.

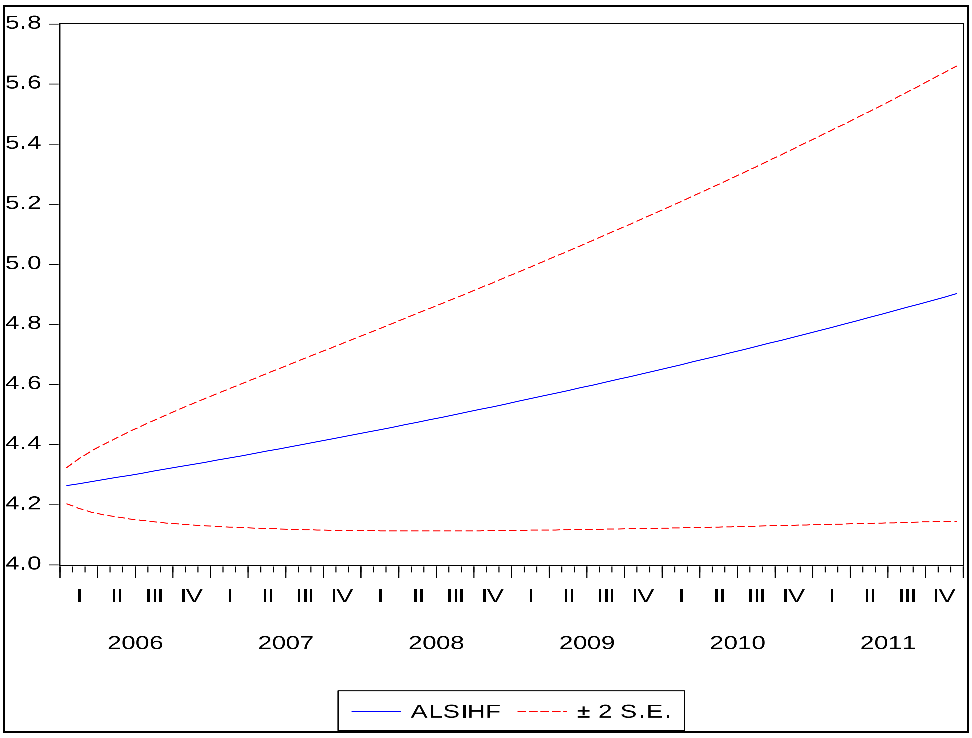
To further prove the existence of random walk in the series, a predictive model is built to see whether the model fitted on part of the observation can be used to predict or forecast the future values of the series in the rest of the observation. This is done, according to Brooks (2008, p. 256), who states that the total observations (144) need to be divided into two, from 2000 up to 2005 (1-72 observations) representing the historical period and the rest of the observation, 2006 up to 2011, will represent the validation period, that is one which will be forecast and see if one can use past information to predict future prices. The equation of the first sample, 2000 to 2005, is estimated first using the model that was chosen to best fit series that is ARIMA (1, 1, 1) and the results are shown below. In other words, what we are trying to do is to first calculate the best fitted model during the historical period and then fit the predictive model to the validation period.

Table 5.11 Results for ARIMA (1, 1, 1) for the historical period 2000-2005 (1-72 observations)

Variable	**Coefficient**	**SE**	**T-ratio**	**Prob**
AR 1	1.007741	0.036889	27.31807	0.000
MA1	-0.045643	0.126551	-0.360670	0.000
Constant	3.385714	2.95595	1.145527	0.2560

Now the validation period is predicted using the historical period to see or observe how far the fitted value deviates from the actual values. The diagram below, Figure 5.7 shows the strength that the forecasting period has in predicting the validation period.

Figure 5.7 Predictive model ARIMA (1, 1, 1) for the historical period (1-72) and forecast the validation period (73-144)



From the above figure, it is clearly shown that the fitted values and the actual are not fitted well, there are vast deviations showing that the prices cannot predicted using past information. It is indicated from the figure that the model forecasts are unable to account for much of the variability of the out of sample part of the data. These findings are expected as forecasting changes in stock market prices, as well as changes in any other asset, are not easy if not impossible. This further provides evidence of random walk process in the ALSI during the period 2000 up to 2011.

The results obtained are in line with the theoretical predictions of the behaviour of stock market prices. According to the Random Walk Hypothesis as well as the Efficient Market Hypothesis, it is impossible to predict the stock market prices as the movements follow a random walk. From the findings in this research, it is impossible for investors to use past prices to make accurate inferences of the future price. The ALSI therefore indicates that the JSE during the sample period is efficient in the weak form, and gaining abnormal profits is merely a game of chance and not skill. Also as expected, after the measures that the JSE has been putting in a bid to improve information efficiency in the stock market, this has improved the efficiency of the market as a whole and hence, the weighted index indicates the fact that there is information efficiency in the South African stock market.

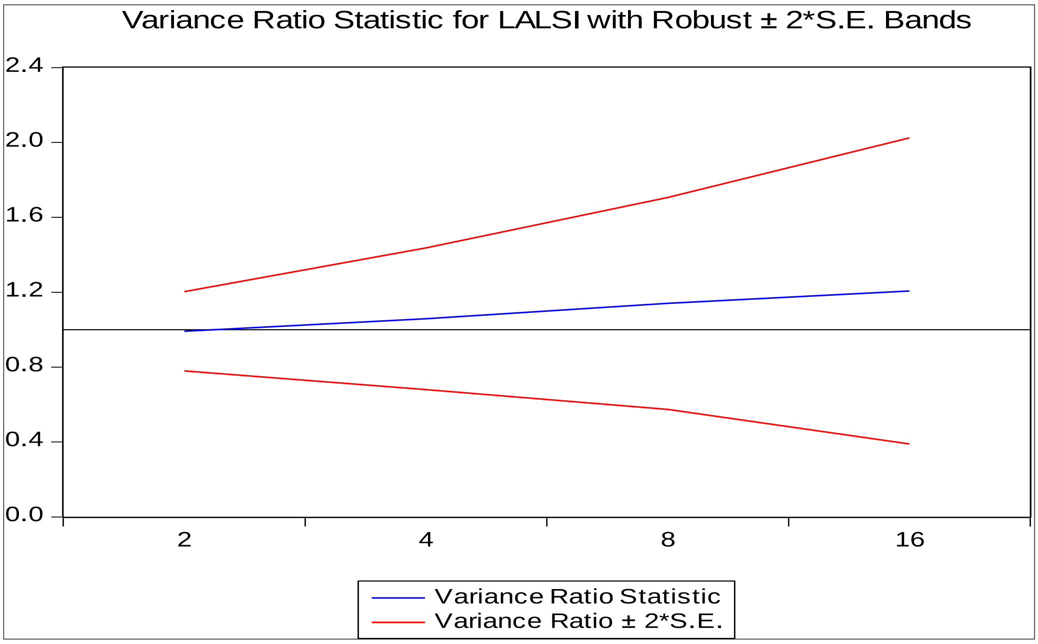
5.5 Variance Ratio Test

Table 5.12 Variance ratio test results

Joint tests	**Value**	**df**	**Probability**	
Max |z| (at period 16*	0.505235	143	0.9777	
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.991701	0.105763	-0.078465	0.9375
4	1.058904	0.189232	0.311278	0.7556
8	1.140317	0.283120	0.495611	0.6202
16	1.206503	0.408727	0.505235	0.6134

Since there is more than one specified test period,there are two sets of test results, that is, joint and individual tests. The joint test which shows the tests for joint null hypothesis for all periods in this case show substantial evidence of series following a random walk as the probability value of 0.9777 leads to the acceptance of the null. Furthermore, acceptance of the null is presented in the individual test with all of them having a p value above 0.05 leading to can also be presented graphically as shown in Figure 5.8 below. The graph is of the variance ratio statistics and plus or minus two asymptotic standard error bands along with a horizontal reference line at 1 representing the null hypothesis. The graph below shows, just like the table above, that the series follow a random walk as the null lies outside the bands.

Figure 5.8 Variance ratio statistic for LALSI



5.6 Conclusion

The chapter presented the estimated regression models, the results obtained and their interpretation. The results obtained showed that successive price or return changes are independent thereby leading to the conclusion that the South African market follows the random walk process. Firstly, the ADF test for unit root was employed on the ALSI and results obtained showed that the critical values at 1% significant level for intercept (-3.476472), trend and intercept (-4.023506) and none (-2.581233) are greater or bigger than the respective t-statistics in absolute terms which are intercept -0.664657 (Probability 0.8510), trend and intercept -1.869282 (Probability 0.6652) and none 1.903195 (Probability 0.9863). This then meant that since all p values are greater than 0.05 we could not reject the null hypothesis and conclude that there is a unit root in the series. This is interpreted to mean that the JSE price index during the sample period resembles a random walk process. To ascertain the reliability of the results obtained, autocorrelation tests were employed and these confirmed that the JSE index is characterised by price independence. The data displayed insignificant autocorrelation pattern at 5 percent significant level. The ACF of the series died away slowly and the PACF diesaway after the first lag showing that series are non stationary and are a resemblance of random walk model correlograms. Also the Q- statistics supported the fact that the JSE follows a random walk process. The probability of the sum of 36 squared estimate autocorrelations coefficient was zero and this meant there is no autocorrelation in the series and thus price changes in the JSE during 2000 to 2011 were independent of each other.

To capture robustness of the results and to draw conclusions about the investigation, the Box Jenkins's approach to time series modelling, ARIMA was used. The model that was chosen to best suit the series was ARIMA (1, 1, 1) and the diagnostic tests conducted on this model showed that the series under consideration exhibited trends that were random and hence it strongly supported the results obtained by the other statistic techniques that there is a random walk process in the Johannesburg stock exchange. These conclusions are as the expected priori was and also similar to the findings of BongaBonga (2012) who conducted a research on the JSE and concluded that it is efficient in the weak form using GARCH models and used weekly data from March 1995 to December 2007.

Furthermore, tests on the predictability of values of the ALSI using dynamic time series statistical techniques, in this case the ARIMA, confirmed that past values of the ALSI cannot be used to predict future prices. Prices are independent of each other and hence investors cannot make correct forecast from past information but it is a game of chance.

The results obtained are similar to those of Hamman, Jordaan and Smit (1995), Jefferis and Okeahalam (1999a) ,Jefferie and Okeahalam (1999b), Smith et al (2002), and Mabhunu (2004) who found evidence of random walk process in the JSE although none of them used the ARIMA methodology. On the other hand, the results contradict the findings of Jammine and Hawkins (1974) and those ofCubbin, Fire and Gilbert (2006) who found that the JSE's stock price index was predictable and conclude that it is not efficient in the weak form at least for the sample periods they used.

The results of the variance ratio test conducted under heteroscedasticityalso stronglycorroborated that random walk hypothesis cannot be rejected in the JSE market. These findings are consistent with the findings of Smith and Jefferis, (2002), who employed multiple variance ratio tests and concluded that the JSE follows a random walk process. Also in another researchpresented in the literature review, Smith and Rodger (2006) made conclusions that are in line with the ones found in this research. They employed variance ratio tests to test whether the JSE follows random walk process or not. They found the JSE following random walk.

CHAPTER SIX

CONCLUSIONS, POLICY RECOMMENDATIONS AND LIMITATIONS OF THE STUDY

6.1 Summary of findings

This study conducted tests of the random walk hypothesis for the Johannesburg Stock Exchange market. It was noted that stock prices provide a yardstick against which returns on investments projects can be judged. Lack of correlation between past and present prices means that there is no market participants that can accurately predict movements of prices and markets are said to be efficient. The important considerations for an investor presented in this research are that when it is established, the JSE does behave according to the random walk hypothesis,then previous prices do not contain information that is valuable in forecasting future prices.

The performance or the trends of the South African stock market in the period of study were assessed through anin-depth presentation of the Johannesburg Stock Exchange. A trend analysis of the weighted market capitalisation index, the ALSI, for the period 2000 up to 2011 was done and on average the ALSI has been increasing save for the year 2008 and 2009 when the effects of the global financial crisis started to show in the financial market of South Africa. In 2010 the ALSI started to recover and in 2011 the analysis shows that the ALSI may have fully recovered. The trend analysis aided in realising one of the objectives of the study which is to examine the trends of the ALSI (All Share Index) from 2000 to 2011.

An empirical model was specified (based on presented literature) that relates current value of the ALSI to lagged values of the past values and past errors of the ALSI. The determinants were the time-lagged values of the ALSI because the study examines independence in the ALSI itself. The explained or dependent variable was the current ALSI which was being examined to see whether it can be determined by observing past prices.

The traditionally used methods for testing random walk hypothesis in stock prices, the unit root test and the autocorrelation tests were used in this study. The Augmented Dickey Fuller (ADF) test was used to test for unit root and the autocorrelation tests were used in this studythrough graphical observation or the correlogram and the Q-statistic (Ljung-Box test). Following the critics of the unit root tests and to capture for robustness and to validate the findings more reliable methods were also employed which are the Auto Regressive Integrated Moving Average (ARIMA) and the variance ratio test. This ARIMA methodology was preferred to others because of the advantages it has. One of the advantages of ARIMA is that it combines autoregression, which fits the current data points to a linear function of some prior data points and moving averages, adding together several consecutive data points and getting their mean and then using that to see if one can compute estimates or forecasts of the next value. The other advantage is that with many elements regressed and averaged, one can fit an approximation to almost any time series at hand and most importantly, the ARIMA relies only on the characteristics of the series being analyzed to project future data.

The estimation techniques were done and results were obtained. The variable of interest here ALSI, was found to be following a random walk process as successive price changes were independent.The unit root test showed that there was a unit root in the series indicating that the series were non-stationary indicating the existence of a random walk. Also supporting these findings are the results from autocorrelation tests. The ACF and the PACF showed patterns of no autocorrelation at all lags (up to 36) showing that series are non stationary and are a resemblance of random walk model correlograms. The Q- statistics supported the fact that the JSE follows a random walk process as the probability of the sum of 36 squared estimate autocorrelations coefficient is zero means no autocorrelation in the series and thus price changes in the JSE during 2000 to 2011 are independent of each other. The ARIMA method which was employed also supported the findings of the other estimation techniques. Of the two estimated models, the ARIMA (1, 1, 1) was found to best suit the data and this model was the one that was then used to make inferences about whether or not series follow the random walk. Diagnostic tests where then conducted on the ARIMA (1, 1, 1) which all indicated the existence of random walk properties and of importance, is the forecasting test done which showed that series cannot be used to forecast future prices. The variance ratio test conducted also mounted evidence of the JSE following a random walk process. Both the joint test and the individual test produced probabilities greater than 0.05 and the null hypothesis of random walk (martingale) could not be rejected.

The four methodologies used in this research all agree that the Johannesburg Stock Exchange, during the period 2000 up to 2011 exhibited random walk process. This led the researcherto conclude that the JSE during the period 2000 to 2011 was characterised by price changes that were independent of each other and hence the JSE, follows the random walk process. This means that in the JSE, the opportunity of making excess profits by studying past prices so as to forecast future prices are ruled out. This indicates that the JSE is weak form efficient since random walk indicates weak-form efficiency but it should be noted that rejecting the random walk does not necessarily mean that the series are weak–form inefficiency.

6.2 Policy implications and recommendations

This research shows that the time series are uncorrelated and provides major implications to investor, policy makers as well as researchers. This is because, among other things, the inability to predict future stock prices means that investors cannot beat the market trading rules. This can only be possible where there is no information asymmetry. What this means is that policies that maintain the availability of information to all investors must be put or must be maintained. Also the findings will help policy makers in understanding that overall market conditions must continue to be improved so as to maintain a desirable environment and to encourage savings and investments. In other words,for policy makers the findingsimply that they need not be worried about imposing laws that will make the market efficient as it is efficient in the weak form, however, policy makers may still need to maintain the condition and also increase the level of efficiency. An option accessible to policy makers to maintain and even increase the level of efficiency in a market is to increase the corporate governance application, and in particular, the disclosure element of it (Brooks, 2008). The authorities could also encourage the involvement of institutional investors in the market, and mainly pension funds, as they are more likely to trade based on information and thus lead to more efficiency on the market (Mishkin, 2010).

It should be noted by policy makers that a well developed financial sector, transparent, accountable institutions, and shareholder protection are necessary preconditions for the efficient functioning of stock markets in Africa. Thus in order to maintain price independency, there must be policies that are aimed at maintaining the above. In other words, a number of extra measures, other than the improvements made on the JSE in improving information dissemination, can be taken into consideration to further enhance efficiency of the market. These include, in addition to information dissemination, financial reporting procedures and also embracing legislations and risk management measures all aimed at making the investors better informed and well protected thereby building confidence in them.

In addition, since the findings in this research of the behaviour of stock market prices are indicative or symbolic of an efficient market, policies that look at improving the economy's wellbeing, since the demand of services of the stock market is derived from the condition of the economy, should be implemented. Having established that the stock market price behaviour is attractive, it remains necessary to try and ensure that the country has a stable environment that will aid in attracting investors. Therefore police makers must ensure that the stock market is monitored so as to continue increasing the level of efficiency and also monitor the economy'swell being.

As indicated before, the efficiency of the stock market is of paramount importance to issuers of equity and portfolio investors. It can attract foreign investors and encourage domestic savings thereby improving the mobility of capital and financial resources. Analysing the behaviour of stock market prices is also of importance to policy makers of any country since the stock market is the major index of economic conditions. If a market follows a random walk process, what it then means is that prices in that market provide adequate and appropriate information as well as indicators for efficient allocation of resources in that country.

The findings of this research have important implications to investors and since the movement of stock price are said to be random, investors need not worry about timing the market. In this case, an investor's ability to perform the market is just about luck and not analytic skill. Investors, put differently, can do better with a buy and hold strategy rather than adopting a strategy that aims at outperforming the market as this cannot succeed. In addition, investors must explore the risk of investment in securities that is the possible gains or losses. Understanding the characteristics of the movements of stock prices helps in decision making. Investors in the JSE should understand that the returns follow a random walk and hence the prediction of future prices is likely to be difficult.

6.3 Areas for further research

This research made use of a weighted average index, the ALSI, thus further research could be done on the prices of individual sectors, for example, the industrial sector may be able to give different insights on the size or liquidity angle since individual stocks data on market liquidity and maturity is usually available. It may also be interesting to look at whether large capitalisation stocks follow the process of random walk. In other words, a research that tests individual stock price behaviour, and not the overall market can shade more light on specific areas of concern and policy measures. Furthermore since the random walk hypothesis is consistent with the weak form level of efficiency, it remains a challenge to test whether or not the JSE is efficient in more higher levels for example the strong level of efficiency. This would include looking at JSE efficiency with respect to unanticipated information and insider information.

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APPENDIX

Appendix 1: Data used in Estimation

YEAR	**MONTH**	**ALSI**
2000	JANUARY	8475
	FEBRUARY	7992
	MARCH	7957
	APRIL	7445
	MAY	7364
	JUNE	7710
	JULY	7738
	AUGUST	8489
	SEPTEMBER	8274
	OCTOBER	8111
	NOVEMBER	7805
	DECEMBER	8326
2001	JANUARY	9072
	FEBRUARY	9013
	MARCH	8159
	APRIL	8978
	MAY	9390
	JUNE	9223
	JULY	8557
	AUGUST	8986
	SEPTEMBER	8126
	OCTOBER	8543
	NOVEMBER	9441
	DECEMBER	10624
2002	JANUARY	10314
	FEBRUARY	10815
	MARCH	10949
	APRIL	11030

	MAY	11219
	JUNE	10658
	JULY	9239
	AUGUST	9677
	SEPTEMBER	9465
	OCTOBER	9376
	NOVEMBER	9564
	DECEMBER	9277
2003	JANUARY	8798
	FEBRUARY	8402
	MARCH	7680
	APRIL	7510
	MAY	8564
	JUNE	8352
	JULY	8810
	AUGUST	9226
	SEPTEMBER	8926
	OCTOBER	9765
	NOVEMBER	9730
	DECEMBER	10381
2004	JANUARY	10849
	FEBRUARY	10896
	MARCH	10693
	APRIL	10386
	MAY	10414
	JUNE	10109
	JULY	10306
	AUGUST	11160
	SEPTEMBER	11761
	OCTOBER	11655
	NOVEMBER	12491
	DECEMBER	12657

2005	JANUARY	12799
	FEBRUARY	13477
	MARCH	13299
	APRIL	12556
	MAY	13787
	JUNE	14155
	JULY	15144
	AUGUST	15414
	SEPTEMBER	16876
	OCTOBER	16433
	NOVEMBER	16775
	DECEMBER	18097
2006	JANUARY	19745
	FEBRUARY	19085
	MARCH	20352
	APRIL	21136
	MAY	20565
	JUNE	21238
	JULY	20886
	AUGUST	21954
	SEPTEMBER	22375
	OCTOBER	23338
	NOVEMBER	23950
	DECEMBER	24915
2007	JANUARY	25448
	FEBRUARY	25796
	MARCH	27267
	APRIL	28171
	MAY	28628
	JUNE	28337
	JULY	28562
	AUGUST	28660

	SEPTEMBER	29959
	OCTOBER	31335
	NOVEMBER	30308
	DECEMBER	29635
2008	JANUARY	27317
	FEBRUARY	30674
	MARCH	29588
	APRIL	30743
	MAY	31841
	JUNE	30413
	JULY	27720
	AUGUST	27702
	SEPTEMBER	23836
	OCTOBER	20992
	NOVEMBER	21209
	DECEMBER	21765
2009	JANUARY	20570
	FEBRUARY	18465
	MARCH	20364
	APRIL	20647
	MAY	22771
	JUNE	22049
	JULY	24259
	AUGUST	24929
	SEPTEMBER	24911
	OCTOBER	26361
	NOVEMBER	26895
	DECEMBER	27666
2010	JANUARY	26676
	FEBRUARY	26765
	MARCH	28748
	APRIL	28636

	MAY	27145
	JUNE	26259
	JULY	28355
	AUGUST	27254
	SEPTEMBER	29456
	OCTOBER	30431
	NOVEMBER	30266
	DECEMBER	32119
2011	JANUARY	31399
	FEBRUARY	32272
	MARCH	32204
	APRIL	32836
	MAY	32566
	JUNE	31865
	JULY	31208
	AUGUST	31006
	SEPTEMBER	29674
	OCTOBER	32349
	NOVEMBER	32813
	DECEMBER	31986

Appendix 2: Regression Results for ARIMA (1, 1, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004137	0.002103	1.967751	0.0511
AR(1)	-0.944977	0.019216	-49.17726	0.0000
MA(1)	0.986428	0.008644	114.1207	0.0000

R-squared	0.058296	Mean dependent var	0.004314
Adjusted R-squared	0.044747	S.D. dependent var	0.025107
S.E. of regression	0.024538	Akaike info criterion	-4.556249
Sum squared resid	0.083697	Schwarz criterion	-4.493802
Log likelihood	326.4937	Hannan-Quinn criter.	-4.530873
F-statistic	4.302402	Durbin-Watson stat	1.980862
Prob(F-statistic)	0.015383		

Inverted AR Roots	-.94
Inverted MA Roots	-.99

Appendix 3: Regression Results for ARIMA (2, 1, 2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003969	0.002033	1.952521	0.0529
AR(1)	-0.033246	0.029280	-1.135451	0.2582
AR(2)	-0.904056	0.028411	-31.82078	0.0000
MA(1)	-0.033675	0.023254	-1.448150	0.1499
MA(2)	0.989733	0.010871	91.04242	0.0000

R-squared	0.109830	Mean dependent var	0.004226
Adjusted R-squared	0.083648	S.D. dependent var	0.025174
S.E. of regression	0.024098	Akaike info criterion	-4.578532
Sum squared resid	0.078979	Schwarz criterion	-4.473966
Log likelihood	327.7865	Hannan-Quinn criter.	-4.536040
F-statistic	4.194934	Durbin-Watson stat	1.889112
Prob(F-statistic)	0.003104		

Inverted AR Roots	-.02+.95i	-.02-.95i
Inverted MA Roots	.02+.99i	.02-.99i

Appendix 4: Regression Results for Variance ratio test

Joint Tests	Value	df	Probability
Max |z| (at period 16)*	0.505235	143	0.9777

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.991701	0.105763	-0.078465	0.9375
4	1.058904	0.189232	0.311278	0.7556
8	1.140317	0.283120	0.495611	0.6202
16	1.206503	0.408727	0.505235	0.6134

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 0.0040875771074)

Period	Variance	Var. Ratio	Obs.
1	0.00063	--	143
2	0.00063	0.99170	142
4	0.00067	1.05890	140
8	0.00072	1.14032	136
16	0.00076	1.20650	128