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Modelling and Forecasting Portfolio Inflows: A Comparative Study of Support Vector Regression, Artificial Neural Networks and Structural VAR Models

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DECLARATION

I, Rapoo Mogari Ishmael, declare according to the best of my knowledge that this dissertation is the outcome of my own investigation unless otherwise stated. It has never been submitted previously as a whole or in part for any other degree whatsoever to the North-West University or any institution.

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(23809213)	Signature	Date

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DEDICATION

To my entire family and the support, they have shown in me. I sincerely dedicate this dissertation to all of you. My father, mother, brother, girlfriend, son, niece and uncle. To my late grandparents. Lots of love.

ABSTRACT

The current study analyses the efficiency of the Support vector regression, artificial neural networks and structural VAR models in terms of in-sample forecasting of portfolio inflows. The study used a time series daily data of portfolio inflows as the dependent variable and real GDP, exchange rate, inflation linked bonds as the independent variables sourced from rand merchant bank and the South African Reserve Bank respectively, and covering the period of 1st March 2004 to 1st February 2016 consisting of a total of 3111 observations. The study assessed nonlinearity and non-stationarity prior to modelling the data and based on the results all the variables are nonlinear and nonstationary respectively. The UVAR model employed the SBC criteria in selecting the lag length of the model and the VAR (8) model was selected. Based on the results of the SVAR model 69% of variation in portfolio inflows are explained by the shocks of pull factors (real GDP and inflation linked bonds) and the results are in line with the findings of Egly et al. (2010) who employed VAR model and only 9% is explained by the shocks of push factor (exchange rate) respectively. Furthermore, it is shown by the results that pull factors are the key drivers of portfolio inflows into South Africa. In evaluating model performance, the following error measures are used: Mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean absolute squared error (MASE) and root mean scaled log error (RMSLE). The overall results show that support vector regression (SVR) model outperformed competing model(s) as it had the smallest measurement error. The results obtained however can be improved by applying the model to the hybrid technique to improve forecasting accuracy.

ACRONYMS AND ABBREVIATIONS

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criteria
ANFIS	Adaptive-Network-based Fuzzy Inference Systems
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
BDS	Brock-Dechert-Scheinkman
BG	Breusch-Godfrey
BIC	Bayesian information criterion
B-NADF	Bierens Nonlinear Augmented Dickey-Fuller
BoP	Balance of Payment
BPNN	Back propagation Neural Network
CFM	Capital Flow Management
CUSUM	Cumulative Sum
CUSUMSQ	Cumulative Sum Squared
DM	Diebold-Mariano
DW	Durbin-Watson
EGARCH	Exponential GARCH
EM	Emerging Markets
FCI	Financial Conditional Index
FDI	Foreign Direct Investment
FIML	Full Information Maximum Likelihood
FPI	Foreign Portfolio Investment
FTSE	Financial Times Stock Exchange
GA	Genetic Algorithms
GARCH	Generalized Autoregressive Conditional Heteroscedasticity

GDP	Gross Domestic Product
HQC	Hannan Quinn Information criteria
IMF	International Monetary Funds
JB	Jarque-Bera
KSS-NADF	Kapetanois-Schmidt-Shin Nonlinear Augmented Dickey Fuller
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Squared Error
MLP	Multilayer Perceptron
MLFFNN	Multilayer Feed Forward Neural Network
MSE	Mean Squared Error
MS-AR	Markov Switching Autoregressive
NNARX	Neural Network Autoregressive with Exogenous output
NMSE	Nonlinear Mean Squared Error
RMB	Rand Merchant Bank
RMSE	Root Mean Squared Error
RMSLE	Root Mean Squared Log Error
SVAR	Structural Vector Autoregressive
SBC	Schwart Bayesian Criteria
SVM	Support Vector Machine
SVR	Support Vector Regression
STR	Support Transition Regression
SVR-GA	Genetic Algorithm based SVR
SVR-FA	Firefly based SVR
SVR-CGA	Chaotic Genetic Algorithm based SVR

TAR	Threshold Autoregressive
UVAR	Unrestricted Vector Autoregressive
VAR	Vector Autoregressive
VECM	Vector Error Correction Model

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

STUDY ORIENTATION

1.1 Background

In recent years, the research based on the portfolio inflows has been studied and researchers have been using conventional econometric models in modelling portfolio inflows. These econometric models are significant in certain aspects of analysing the data since they are linear in nature. However, time series data are nonlinear in nature and most especially financial series. Linear models fail to capture and address the underlying characteristics of nonlinear time series data sets. This is because the dynamics and patterns of the series is nonlinear whereas the linear models assume a linear structure of the series. Since the recent discovery of the financial data being nonlinear this has led to nonlinear models taking the centre stage in analysing financial data. Nonlinear models have the best modelling properties of analysing the series with utmost accuracy, thereby making them the most reliable models utilized in predicting financial time series. In the recent situation of nonlinear models there have emerged machine learning models which are powerful approximators and they also are nonlinear. Recent machine learning models have been utilized in analysing time series data in different disciplines. In instances where linear models cannot address the fundamentals of time series data, nonlinear models are used as they capture those fundamentals. These machine learning models are self-adaptive, good approxiamtors and data driven. They are used to train the series and there is no prior assumption of the distribution that the models are ought to follow since they are classified as nonparametric models. The architecture, parameters of the models are determined as the model(s) are training the data. Furthermore, the series is also required to be in a specific interval depending on which activation function is to be used, this helps in the case that the model(s) is not to be trapped in local minima. In the framework of the current study, the researcher analyses historic data of portfolio inflows into South Africa using two machine learning models (SVR and ANNs) and one econometric model (SVAR).

1.2 Problem statement

In the literature the effect(s) of strong wave of portfolio inflows are highlighted; under ordinary conditions capital flows have valuable impacts for developing economies. In a few events, floods of strong portfolio flows have gone before scenes of money related instability, for instance, the Mexican emergency of 1994 and the Asian emergency in 1997 (Lo Duca, 2012). As this is the case, the negative effect of portfolio inflows to receiving economies calls for appropriate policies to be put in place, in which case the drivers of these flows may be used in developing these policies.

There are various techniques which have been utilized in the literature to model portfolio inflows and its drivers to emerging markets. Commonly used are conventional econometric methods, for example SVAR is used in the studies of (Korap, 2010, Çulha, 2006, Ahlquist, 2006); VAR model used in the studies by De Villiers (2015) and Egly et al. (2010); finite distributed lag model and VECM model used by Ekeocha et al. (2012). Therefore, the study would like to investigate if machine-learning models are effective in modelling portfolio inflows. The study will use econometric model of Structural VAR to identify the key drivers of portfolio inflows into South Africa and furthermore assess the efficiency and performance of machine learning models namely support vector regression (SVR) and artificial neural networks (ANNs) models in modelling and forecasting portfolio inflows respectively.

1.3 Significance of the study

The study seeks to model portfolio inflows using the three stated models. The study also seeks to develop an empirical model to depict portfolio inflows by including machine-learning methods. Furthermore, the study will seek to empower portfolio investors to make educated and efficient investment choices. Once more based on the key drivers of portfolio inflows, appropriate policies may be designed to attract investments into the economy that will encourage domestic savings. Other possible recipients of the study are investors, executives, controllers and additional money related institutions and in addition researchers in the scholarly world.

1.4 Research aim and objectives

The study aims to find the likelihood of developing an empirical models equipped for predicting portfolio inflows and its key determinants. Many statistical techniques have been used to model and forecast portfolio inflows from an economics point of view. Included in the study are machine-learning techniques (SVR and ANN) that are utilized in modelling portfolio inflows. The study assesses the accuracy of the machine-learning methods in terms of modelling portfolio inflows and using SVAR model to identify both the push and pull factors of portfolio inflows. The structured objectives are as follows:

- To assess if the underlying characteristics of the portfolio inflows are non-linear in nature.
- To determine the performance or the efficiency of Support Vector Regression, Artificial Networks and Structural VAR models.
- To evaluate the key drivers of portfolio inflows into South Africa.
- To compare the predictive efficiency/accuracy of Support Vector Regression, Artificial Neural Networks and Structural VAR models.

1.5 Methodology

For achieving or meeting the research outlined aim and objectives, the study (which is explanatory in nature) used the historic time series data of portfolio inflows obtained from the Rand Merchant Bank (RMB). The time series data were chosen based on the notion that strong portfolio inflows can be of a negative impact to the recipient economy. Different models in the literature have been utilized in modelling and forecasting portfolio inflows, and furthermore utilized to explore which models give accurate predictions of portfolio inflows. SVR, ANN and SVAR are the fundamental statistical techniques utilized for the analysis in the current study. Schwarz Bayesian Criterion (SBC) developed by Schwarz (1978) will be utilized as a model selection method in the study. Forecasting efficiency of the model(s) will be evaluated based on the accompanying error metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Squared Error (MASE) and Root Mean Scaled Log Error (RMSLE).

1.6 Novelty of the study

Portfolio inflows and its key drivers to South Africa are modelled and predicted by employing three powerful models. There is an abundance of empirical literature concerning portfolio inflows particularly to emerging markets; however, there has been a gap in modelling the inflows using the most powerful methods in machine-learning perspectives. The study will apply both SVR and ANNs models to enhance the literature of inflows. By using these three models the study will seek to determine the key drivers which influence the inflows to South Africa. In the overall context, the determinants of inflows will be understood and the movement of inflows will also be understood in the framework of the South African economy.

1.7 Limitations of the study

- The study is restricted to using the historic data of portfolio inflows and its key drivers sourced from RMB and SARB respectively covering the period of 01st March 2004 to 01st February 2016 on the basis of accessibility of data.
- There exist numerous models that can be used, but for the current study, only three models are considered based on their empirical literature. These models are SVR, ANNs and SVAR.
- Due to limited empirical studies on machine-learning models, the study used sources which are older than ten years.
- Due to a lack of appropriate syntax, the KSS-NADF is not employed in the current study.

1.8 Organisation of the study

The dissertation will comprise of five chapters.

Chapter 2 presents the empirical literature of portfolio inflows and that of the models used in the study based on previous empirical studies. Based on previous literature, the machine-learning models have not been utilized to demonstrate the ability to model and forecast the portfolio inflows. It is documented in the literature that even if this is the case, artificial intelligence (machine-learning) has gained a lot of attention in time series analysis.

Chapter 3 gives the methodology of the models employed together with the entire tests employed to assess the key features of the time series data.

Chapter 4 contains empirical results obtained as well as the interpretation of those results.

Chapter 5 presents a detailed conclusion and summary of the entire study.

1.9 Concluding remarks

This chapter has outlined the important issues which should be addressed. Taking direction from the background of the methods used in the study, aims and objectives of the study will be addressed using various methods and tests. The research aim and objectives are cornerstones of the study; they have to be addressed as fully as possible although some limitations were also outlined.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This section reviews the methods used in the literature to model portfolio inflows and their drivers to emerging markets. Furthermore, included in the study are the machine-learning methods, which have been gaining a lot of attention in time-series forecasting; thereby the study will also seek to develop new models for portfolio inflows and review the machine-learning methods in time series analysis. The chapter is structured as follows: Section 2.2 gives a brief definition of portfolio inflows. Section 2.3 presents factors influencing portfolio inflows. Section 2.4 outlines trends of portfolio inflows into emerging markets, particularly South Africa. Section 2.5 outlines advantages and disadvantages of portfolio inflows. Section 2.6 presents policies to manage capital flows. Whereby, section 2.7 presents forecasting methods, sections 2.8 and 2.9 presents the literature on economic time series methods and machine-learning methods respectively. Last part of the chapter, section 2.10 presents concluding remarks.

2.2 Definition of portfolio inflows

According to De Villiers (2015) portfolio inflows can be characterized as foreign investors obtaining items, stocks, currency advertise instruments or bonds in another country. Whereas Ekeocha et al. (2012) defines FPI as a part of global capital flows including trade of cash related assets, for instance, money; stock or securities crosswise over global outskirts needing financial advantage. It happens when financial investors purchase non-controlling interests in foreign associations or purchase outside corporate or government securities, short-term securities, or notes. The terms portfolio inflows and portfolio investment inflows will be used interchangeably in the study.

Investments comprise of either short or long term depending on the nature of the investment. Short-term investments consistently characterized as theoretical investments that include acquiring and offering of assets with the goal being to abuse ideal exchange rate developments (De Villiers, 2015). Assets are being held up for an extended period by foreign investors in long-term investments.

In making these investments, investors take into account the economic status of the country of interest together with basing their decisions on personal profile and appetite (De Villiers, 2015). According to Ahmad et al. (2014), as of late foreign portfolio investments (FPI) is transforming into a distinctive type of investment in various nations of the world. Forecasting market boom is the key decision making of portfolio investors who are investing for a shorter period unlike the direct investors.

For the past decades both the developed and developing economies in the world have significantly used this investments as a form of funds in supporting other investments (Ekeocha et al., 2012). Investors take into account the various conditions before placing their investments into different economies particularly in the emerging markets. This has been highlighted in the study of Siamwalla et al. (1999), who stated that industrial economies have low yields as opposed to economic growth and impressive returns in developing countries. It is found that behaviour of government is used as a benchmark by portfolio investors and also there can be reallocation of funds as a certain information is apparent, fiscal policies are also used as a reference in making these investments (Ahlquist, 2006).

Portfolio inflows has conditions which are associated with allocation of the investments and this conditions can be classified into two branches which are both the push (external) and pull (internal) factors in the worldwide economy. Ahlquist (2006), states that there are those attributes that can push investments outward from a particular economy and they are known as push factors, whereas pull factors are characteristics that are used to attract this investments. A basic pull factor is the rate of profit for domestic assets weighed against the riskiness of the investment.

There are three risks associated with the portfolio investment, namely: default risk, currency risk and inflation risk (Mosley, 2003). Default risk can be defined as the company having a possibility of not meeting their financial obligations in the future and inflation risk stipulates that cash flow from investment will be able to purchase as much due to purchase power (Garlappi et al., 2006). U.S. corporations incorporating those with no foreign activities and no foreign currency resources, liabilities, or transactions are for the most part presented to foreign currency risk (Adler and Dumas, 1984). There are several economic risks which are faced by consumers and investors respectively (Bekaert and Wang, 2010). The following section centres around the variables that push and pull portfolio inflows into and from developing markets.

2.3 Factors influencing portfolio inflows

A portfolio inflow, as a form of investment as outlined in the previous section, is driven by several factors in and out of a particular economy, especially in emerging markets. Those factors are called pull and push factors, respectively. Several economics studies have found the factors that influence the movement of portfolio inflows. Egly et al. (2010) studied the factors influencing portfolio inflows into the United States; the determinants of foreign portfolio investment into Nigeria were studied by Ekeocha et al. (2012); and Lo Duca (2012) modelled the time differing determinants of portfolio inflows into emerging markets amongst others.

In the past, Mexico and Asia experienced financial instability due to strong waves of portfolio inflows. According to Lo Duca (2012) factors influencing portfolio inflows change across time, however, the study believes that these pull and push factors can help in policy making to combat any negative financial instabilities to the recipient economies. Therefore, it is of the vital importance that these factors are studied and reported on.

2.3.1 Push factors

Push factors as defined in the above section, are those attributes that can push the investment outward of a particular economy. According to De Villiers (2015) there are both cyclical and structural forces present in push factors. There are main push factors, namely global liquidity, risk aversion, and long-term interest rate differentials ((De Villiers, 2015).

i. Global liquidity

Global liquidity to date has no universal definition. Eickmeier et al. (2014) global liquidity is when goods or assets are purchased in a global perspective and there is availability of funds for the purchaser. Customarily, experimental studies have assessed worldwide liquidity conditions in light of some worldwide sums of expansive money (Eickmeier et al., 2014). Distinctive measures of global liquidity have remained suggested already in the literature. In the perspective of financial stability, credit has been viewed as a suitable measure of liquidity.

The study of Eickmeier et al. (2014) revealed three factors that drive the conditions of global liquidity, these are worldwide monetary policy, worldwide credit supply and worldwide credit demand. Furthermore, these features cannot be summarized into a one factor. Global liquidity is believed to be of the greater significance in the area of international financial stability and for any vulnerabilities and when any financial imbalances unwind.

Landau (2011) highlighted the impact of global liquidity: with expanding financial combination, global money related conditions growingly affect domestic economy. This influences international capital flows and the flow of credit, financially related resource and property costs in every single significant economy. Global liquidity can add to the development of monetary framework vulnerabilities as substantial criss-crosses crosswise over currencies, developments and nations. Deficiencies of worldwide liquidity are able to bring critical ramifications for economic growth, as experienced in 2008– 09; and ultimately approach reactions to these deficiencies, for example, the amassing of prudent stores, can impact capital stream designs and money related markets more broadly.

Global liquidity can be of two branches which are both official liquidity created by the public sector what's more, private liquidity. Official liquidity can be described as the subsidizing that is truly available to settle claims money related specialists, where the national bank is in charge of making liquidity in their residential cash. The conditions under which these mediators can fund their monetary records, in return, rely upon the willingness of other private segment participants to give financing or market liquidity. This reliance underlines the endogenous character of private liquidity.

ii. Risk aversion

Pratt (1975) defined risk aversion as the condition which states that the equal risk premium π(x, z) ought to be a diminishing function of initial wealth x, for every random addition, z, to wealth. Extreme strain created a more elevated amount of powerlessness and frenzy, which suggested portfolio ventures stream was driven by hazard avoidance, while local advancements expected only a peripheral part (De Villiers, 2015).

Egly et al. (2010) in their study analysed the relationship of portfolio inflow, with an attention on two variables, to be specific, foreign investors risk aversion and the US equity (stock) market. Utilizing a vector autoregressive model (VAR), they found that a positive paralyze to the US stock market, corporate securities would experience an immaterial response, instead of net corporate stock, which has a vital without further ado positive response. Net corporate stock, on the other hand, did not respond to any risk evasion, while security inflows showed some basic confirmation of a mid-term response to a development in chance shirking. At long last, they additionally revealed a few outcomes demonstrating that domestic variables may impact portfolio inflows, which strengthened their conflict that draw factors were the fundamental determinants for the surge of portfolio inflow to developing nations.

iii. Long-term interest rate differentials

(De Villiers, 2015) stated that in a broad scale maybe portfolio inflows are significantly driven by interest rate amongst other factors or drivers. Studies on the effect of interest rate to capital flows have been conducted over the years as documented by De Villiers (2015), as well as Bhaskaran et al. (2005) and Montiel and Reinhart (1999).

Zoega (2016) the extent of the interest rate differential can lead to capital inflow surges and currency appreciation, just like the case post the financial emergency of 2007/2008 which originated in the United States of America. In the study of Makhetha-Kosi et al. (2016) it was found that in the context of South Africa, capital flows have a unique way of behaving towards interest rate differentials although South Africa has a positive interest rate differential.

Zoega (2016) found that interest rate differential, currency appreciation and the rise of stock prices benefited speculators from 2004 to 2008. Ahmed and Zlate (2014) described several findings but my study focuses only on two of them, the first is that net private capital inflows in EMEs and advanced economies have significant determinants in growth and interest rate differential as well as global risk appetite. The second finding stated that the post crises of global financial markets of recent portfolio inflows have behaved differently to interest rate differentials. This can be evidence that interest rate differentials are indeed factors of portfolio inflows.

2.3.2 Pull factors

Pull factors are as significant as push factors in deciding the movement of portfolio inflows into the developing markets. This study considers five pull factors as they are outlined in the literature and in the study of (De Villiers, 2015). Factors considered are: real gross domestic product (RGDP); inflation; turnover ratio; stock market capitalization as well as law and order.

i. Real GDP

Real GDP measures aggregate rate of products and services within fringes of a specific country, irrespective of who owns the assets or the nationality of the labour used to produce the output. According to De Villiers (2015) the country's economy is mostly or primarily measured by real domestic product. Real GDP is the relevant variable that can be used to describe the status of the economy (Kabundi et al., 2016).

According to De Villiers (2015) foreign portfolio investment and real GDP assumes a positive correlation as per expectation. Thankgod (2014) studied the effect of FPI on monetary development and accordingly the long-run determinants of FPI in Nigeria from 1986 to 2011. There is positive relationship in the long run between foreign portfolio investments, market capitalization and exchange transparency as indicated by the outcomes.

However, Mpofu (2014) showed that GDP and foreign portfolio investment have a negative correlation in the long run. However, in the short run there occur a negative correlation. The results obtained by Thankgod (2014) are contradictory to the results obtained by Ekeocha et al. (2012). Ekeocha et al. (2012) considering the same variables and adding another variables in the quest to establish the long run relationship of foreign portfolio investment in Nigeria for the period 1981-2010, found that amongst all the variables, only market capitalization and trade openness have long-run relationship with FPI in exclusion of real GDP.

ii. Inflation

Inflation can be characterized as consistent increase in costs of products and services. Inflation essentially implies excessive cash pursuing few goods. (Muritala, 2011). Inflation in developed markets is for the most part named as development of money supply. While, conversely emerging markets frequently say that inflation is not just a money related marvel. Inflation specifically impacts the financial investors capital returns.

Inflation in simpler terms is situations where when the price increases reduce the purchasing power of each currency. Rising inflation has a treacherous impact, which brings about higher input prices, thus resulting in consumers purchasing less goods. The ultimate outcome is that income and profit decrease, and the economy moderates for a period until the point when an enduring state is reached (De Villiers, 2015).

Inflation is especially obstructing in portfolios that include essentially of fixed pay investment. Advantage for these investments comes as interest or coupons and these stays fixed until advancement, while the buying power reduces as expansion rises. At last, companies" benefit and earnings move according to the rate of expansion. Swelling, in any case, can injure outside investors" venture choices, in perspective of a nonattendance of trust in the nation and to stock returns that are exaggerated.

Totonchi (2011) based the study in analysing the opposing and complimentary philosophies of inflation. Based on the results it was shown that there are many dynamics which results in inflation and some of the noted dynamics are monetary shocks, demand side, supply side, structural and political factors.

iii. Turnover ratio

According to De Villiers (2015) improvement of countries stock market is measured by turnover ratio as an important indicator of development of securities exchange. The turnover extent measures the liquidity of the stock exchange, which is proportionate to the estimation of the total offers exchanged allotted by the market capitalization. Metaphorically, it measures the exchanging volume of securities exchange concerning its size. Despite the way that, the turnover proportion is definitely not a snappy measure of speculative importance of liquidity, a high turnover proportion is routinely utilized as a marker of low exchanging costs for a foreign investor.

Portfolio inflows are driven to the emerging markets by the market liquidity. (Bhaskaran et al., 2005). High trading markets attracts foreign investors for a mere fact that they can be able to buy and sell they are shares with relative ease. Good indicator in estimating the nature of smaller scale structure of nations markets is the turnover proportion and can likewise quantify the venture exchanging frameworks. The liquidity of nations security markets and its proficient exchanging frameworks, are basic in drawing in both local and foreign investments (De Villiers, 2015).

iv. Stock market capitalization

The proportion of recorded shares and GDP of a nation can be utilized to quantify stock market capitalization. The general market size can be estimated by stock market capitalization. Furthermore, it is a centre individual for assessing the cash related difference in a nation. The intermediary does not measure the efficiency of the general market; spectators essentially utilize this proportion as a pointer of the stock exchange improvement progression with the uncertainty that cash markets size of a nation is unequivocally associated with the capacity to develop hazard and start capital (Levine and Zervos, 1998).

In the study of Lo Duca (2012) states that in assessing the importance of the drivers of capital flows is that their importance alters over time. Ekeocha et al. (2012) examined the determinants in a long-run of foreign portfolio investment in Nigeria. The study found that market capitalization and trade openness have long run relationship to FPI. Moreover, factors influencing portfolio investment in Pakistan was examined. The results found that market capitalization, weighted average rate of return on deposit, trade openness, broad money (M2), one period slacked all have positive correlation to net portfolio investment.

v. Law and order

Hypothetical and empirical discoveries with respect to the nature of organizations uncovered that great and viable establishments likewise help to advance capital inflows (Wei and Wu, 2002). Ahlquist (2006) discovered that portfolio financial specialists are weary to past government lead and fiscal policy results, the choice on the reallocation of funds changes when new information about government approach becomes accessible. Estimating the nature of institutions, the record of law and order can be utilized as an intermediary. With regards to South Africa since the 1994 there have been an immense number of portfolio inflows into the country which is recorded on the money related records of the balance of payments under direct investments, portfolio investments, and distinctive investments or as a change in the Reserve Bank's net foreign reserves.

2.4 Trends of portfolio inflows into emerging markets particularly South Africa

Kumar et al. (2014), at certain point in time, it is felt that monetary policy adjustments can make less strong or magnify the volume of capital inflows. The nature of portfolio inflows as a source of investments to emerging markets have been on the high as of the study of Ekeocha et al. (2012) since the mid-1980s. According to Ekeocha et al. (2012) the Nigerian capital market has assumed an important role in the relative importance of the investment of portfolio into an emerging market like Nigeria. As the market of Nigeria was deregulation in 1993 later internationalized in 1995.

In or before the 1986, the foreign direct investment (FDI), ODE and bank loans were on the centre stage of investment of capital flows. However, that took a swing as foreign portfolio investment was the core focus of investment and other capital flows were declining in real terms from 1986. The decline of the net capital inflows has also been attributed to a gradual and broad-based weakening of the currencies of EMEs. Between 2011 and 2015 was the period of currencies been on a downward trend. This came about because of the US dollar strengthening amid a gradual market expectation of a tightening US monetary policy. It was only in 2016 that EMEs currencies started to recover. The following graph shows the net capital inflows to major emerging market economies, where capital inflow is characterized as total or net foreign direct investment (FDI), net portfolio streams and net of other investment.

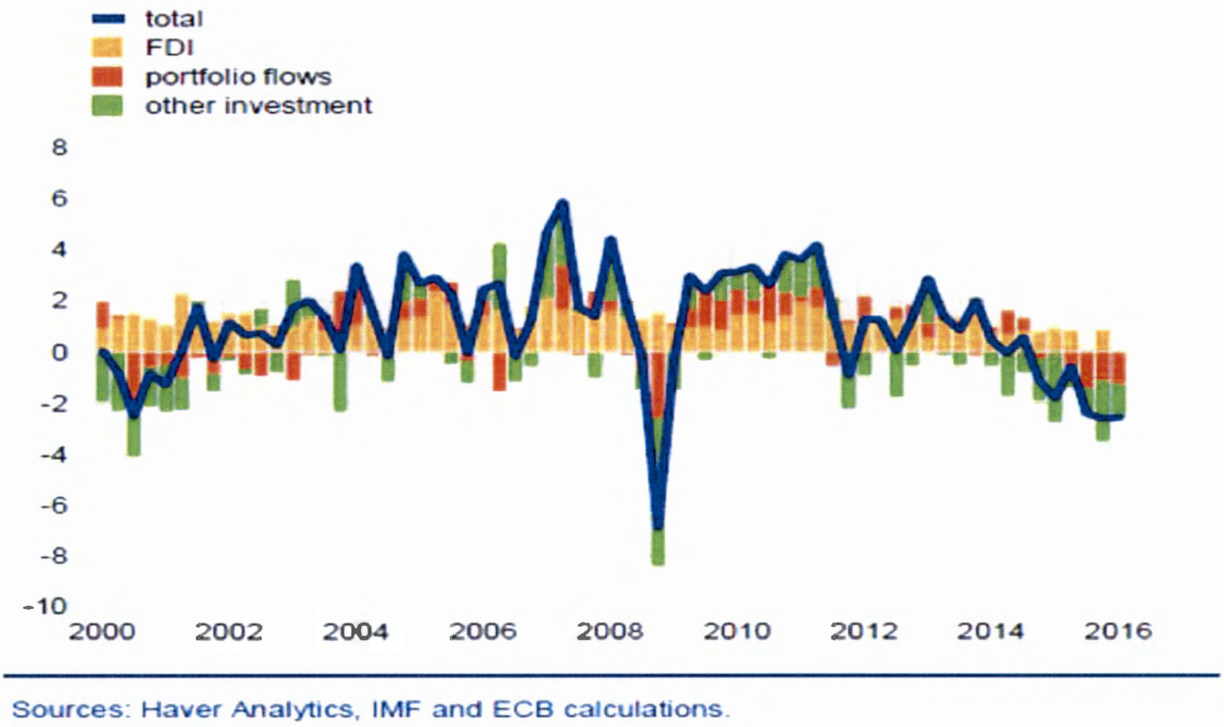

Figure 2. 1: South Africa's investment

The South African economy has been getting a considerable measure of capital flows as this is trusted that they will help enhance the saving rate (the South African savings are low). The balance of payment current account shortfall remained stable all through 2016. A reduction in import volumes and increments as far as exchange were balanced by a pressure in trade volumes. The current account shortage stayed at 4.1 percent in the second from last quarter of 2016, down from 4.3 percent recorded in 2015. The current account deficiency reflects inadequate levels of household reserve funds to sponsor domestic investment and the high reliance on foreign savings. This adds to South Africa's defenselessness to capital outflows. The accompanying figure shows the patterns

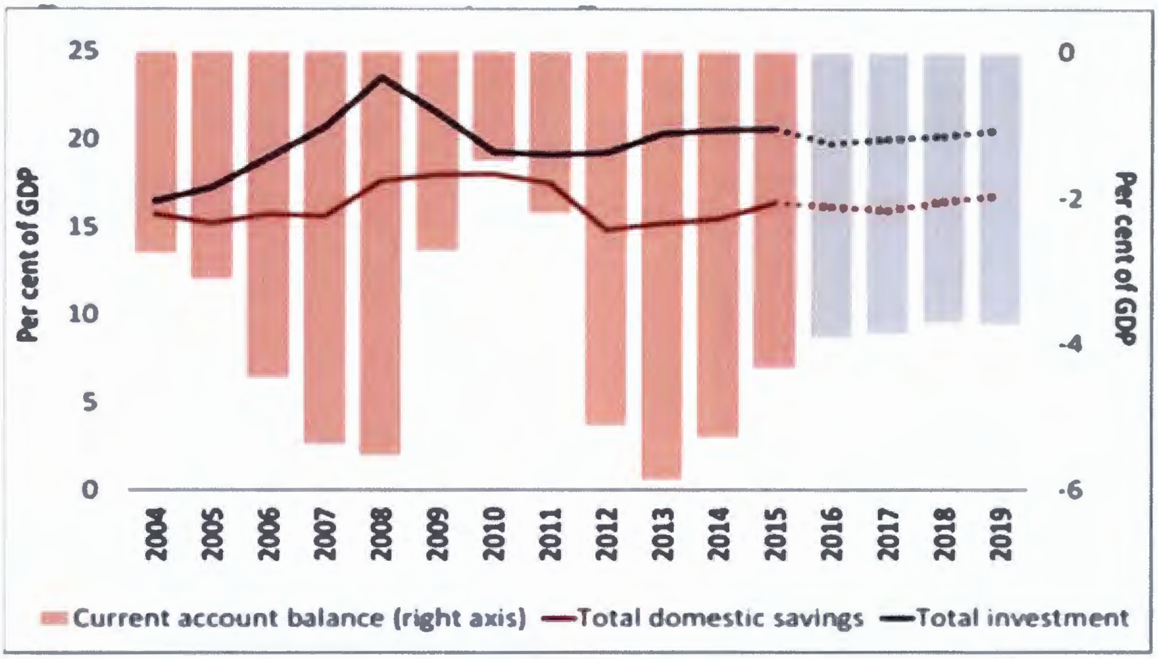

FIGURE 2. 2: CURRENT ACCOUNT, SAVINGS AND INVESTMENTS

Feeble business affirmation and low levels of profit keep weighing on investment streams. Inside the initial three quarters percent of 2016, interest in settled capital fell by 3.9 percent – the principal decrease since 2010. As Figure 2.3 shows, speculation by private establishments continued on through the primer agree to the lowest pay permitted by law allowed by law permitted and changes to overhaul work relations. A diminishing in strong products spending and lull in sustenance buy weighed on family utilization. Speculation by open associations in like manner fell as they kept yielding capital consumption designs. Venture development will be relied on to recover from 1.5 percent in 2017 to 2.8 percent in 2019. Everything considered, levels of local reserve funds remain lacking to fund investment expenditure.

(a) Growth in investment in fixed capital

Percentage	2014	2015	2016[1]
By industry			
Mining and quarrying	1.3	-1.1	1.3
Manufacturing	-3.0	-0.2	-4.3
Electricity, gas and water	6.4	2.1	4.1
Transport, storage and communication	5.8	4.6	-8.8
Finance, real estate and business services	-4.0	0.8	-6.8
Community, social and personal services	5.6	12.4	-0.7
By type of organisation			
General government	8.5	14.6	0.8
Public corporations	0.7	3.5	-1.5
Private business enterprises	0.3	-0.6	-6.9
Total gross fixed capital formation	**1.5**	**2.5**	**-3.9**

(b) Ratio of investment and savings to GDP, 2015

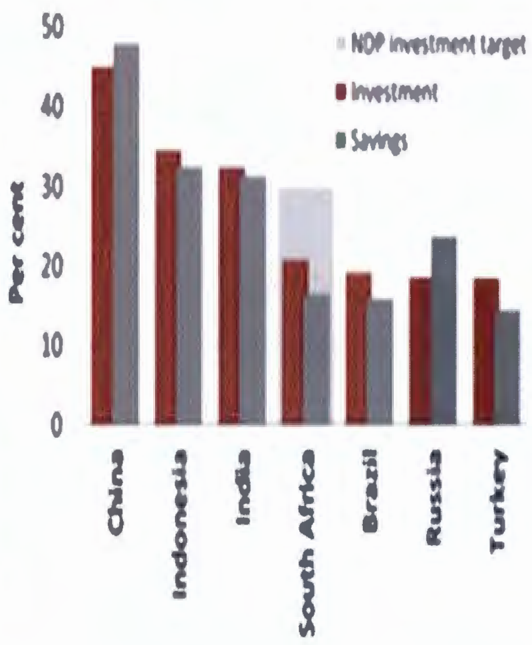

FIGURE 2. 3: GROWTH AND RATIO OF INVESTMENT

Balance of payment has had a change since mid-1994 as a result brought by capital account liberalization and other improvement in the economy of South Africa. Domestic savings has been improved since 1994 by using capital inflows in order to alleviate its key structural constraints. Increasing receptiveness to both trade and capital flows has likewise implied that South Africa has turned out to be vulnerable against new sources of external shocks as surges and reversals in international capital flows, posturing new difficulties for macroeconomic management. Capital inflows since the progress have been commanded by portfolio investment, emerging from the experience of various other developing and emerging economies where FDI has had a more important part, at least regarding the composition of flows. The accompanying figure demonstrates the amount of capital flows especially portfolio inflows into South Africa in the vicinity of 1960 and 2016.

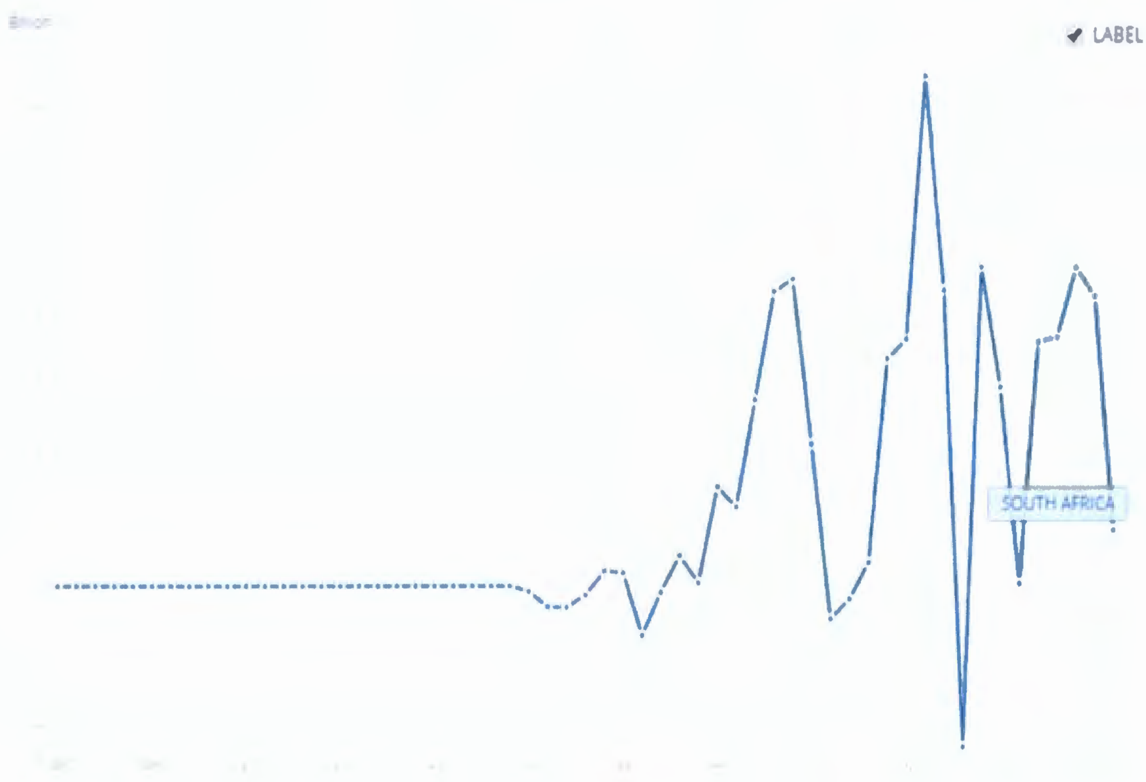

FIGURE 2. 4: PORTFOLIO EQUITY, NET INFLOWS (BOP, CURRENT US$)

Just before global financial crisis of 2008/2009 the portfolio inflows, which is net recorded its lowest deficit in the BoP by amounting to -4.707 billion US dollars. Just after this deficit, the amount of net portfolio inflows increased to 9.364 billion US dollars just after financial crisis Since the year 2009 it went down until the year 2011, in 2012 it picked to a value of 7.159 billion US dollars which was still less than the amount recorded in 2009. The trend continued until recently in 2015 when the amount of net portfolio inflows dropped and the current account in 2016 was at 1.64 billion US dollars. The lowest deficit of net inflows was recorded at the year 2008 where a deficit of -4.707 billion US dollars was recorded. This happened just prior to worldwide financial crisis.

2.5 Advantages and disadvantages of portfolio inflows or capital inflows

The likelihood of universal capital flows rotates around perfect yield looking conduct – be it through longer term FDI or shorter term, more fluid, portfolio and other investments (de Beer, 2015). This types of investments can provide receiving economies access to foreign capital and to possibly impact positively on economic growth and their real development. However, the general standard is that capital flows ought to be monitored keeping in mind their potential effect.

These effects incorporate overheating the economy, loss of competitiveness and growing helplessness to swing in capital flows.

Mohamed (2012) using the end of apartheid as a reference point analysed the consequences of capital flows proceeding the economic growth of South Africa. The experimental outcomes have revealed that the long-term impacts of the extended progression of cash related markets and uncontrolled streams of unpredictable foreign capital raised macroeconomic financial precariousness and furthermore the economic growth way moved towards dispensing capital, infrastructure and abilities towards speculation, use and inefficient services and provoked deindustrialization.

Recent studies also highlighted that significant capital swings have serious macroeconomic implications (Arias et al., 2016, Zoega, 2016). However, in contrast to the above mentioned disadvantages of foreign portfolio investment; Thankgod (2014) showed that portfolio investment is positively correlated with economic growth. The investigation supported for progressing endeavours to sanitize the capital market to be vivaciously sought after, as this would boost domestic investment.

Muritala (2011) examined the growth of the economy of Nigeria based on the effects of inflation and investment. The results show that economic growth and investment are positively correlated, it is shown that a percent increment in investment will result in 0.3 percent of increase in economic performance.

An analysis of South Africa's involvement with capital flows since the global financial crisis has been done. The empirical analysis demonstrates that South Africa has ceaselessly gained progress in the course of recent years and has particularly honed its method since the emergency in recognizing and executing different procedural enhancements and developments to consistently enhance the precision, legitimacy and at last the reliability of their universal capital flows statistics. According to the study broader statistics will enhance and enable investors to make sound investment decisions (de Beer, 2015).

The study examined the effect that capital inflows have on South Africa's macro-economy and on the transmission instruments of credit extension, asset prices and expenditure based on consumption of the households. Capital inflows are comprised of portfolio inflows, FDI and different inflows. It is discovered that capital inflows have contrasting macro-economic effects. Moreover, capital inflows might increase the exchange rate, because of an expanding interest for South Africa's currency, which might bear negative outcomes for exporting firms (Gossel and Biekpe, 2012).

With respect to effects that capital inflow has on the transmission mechanism, the outcome show that only portfolio inflows positively affect private sector credit extension, mortgage expansions and charge card consumption (Gossel and Biekpe, 2012). Be that as it may, while thinking about every single capital inflow, just portfolio inflow positively affects both mortgage expansions and charge card extensions, which in reality expands residential investments.

2.6 Policies to manage capital flows

As it is evident that capital flow has been flooding into emerging market economies also some of the impacts have also been highlighted by the empirical studies. It is only relevant that the appropriate measures or policies to be implemented in order to deal with or manage the capital flow to emerging markets. Notwithstanding, there are conditions that ought to be met before nations can consider using measures that go past macroeconomic approaches, for example, capital controls.

2.6.1 Macroeconomic policies

Macroeconomic strategies are essential given the current worldwide economic conditions, as a significant part of the factors that influence capital inflow to emerging nations are auxiliary in nature, reflecting much-overhauled public and private sector accounting reports in emerging economies with respect to developed nations. Such improvement would propose that the equilibrium of the medium-term real exchange rates for developing economies is maybe stronger than presently evaluated.

As a rule, countries made plans to exchange rate flexibility can lessen the part for possibly destabilizing theoretical financial investors, and furthermore guaranteeing the policy validity structure in nations with exchange rate regime as the main focus point of inflation. A sharp and kept up increment in inflation can be dangerous, particularly when there is request that the exchange rate is overstated. Nations with foreign exchange reserves are abler (from a preliminary perspective) to react to capital inflow by working up reserves. Intercession can be cleaned due to higher liquidity development that could incite overheating or be in struggle with inflation objectives.

Experts in countries need to consider fixing fiscal strategy or to diminish strategy rates, to permit flexibility of money related facilitating, which could offer a superior kept up response in overseeing capital inflow. It is important that money related strategy facilitating be as per the countries inflation objective.

The accompanying figure showing this policy framework in a more helpful manner, exhibiting to direct capital inflow under particular conditions. Each one of the three circles speaks to a circumstance where the significant condition is met. For example, because of the circle (a), where exchange rate is thought to be for the most part as per the essentials or exaggerated. Zone (c), where each one of the three circles meet with each other, traces where CFM measures may be appropriate. It reflects circumstances where the economy is overheating, the exchange rate is not underestimated and the stores are seen as adequate. Other joining, similar to zone (c) speak to different intersections of components. For instance, territory (b) is for this circumstance outside of the ("economy overheating") circle. This territory speaks to circumstances where the economy is not overheating, the exchange rate is not exaggerated and reserves are believed to be adequate (De Villiers, 2015).

Area where there is no crossing point, presents conditions where just a single of the circles (case circle (e), and (g)) are proper. For instance, locale (g) introduces a circumstance where the economy is overheating, the reserves are deficient and the exchange rate is underestimated. Lower rates/rebalance approach mix in district (a) suggests to unwinding monetary policy; to a point where fiscal policy is fixed, so that there is more space to cut down policy rates.

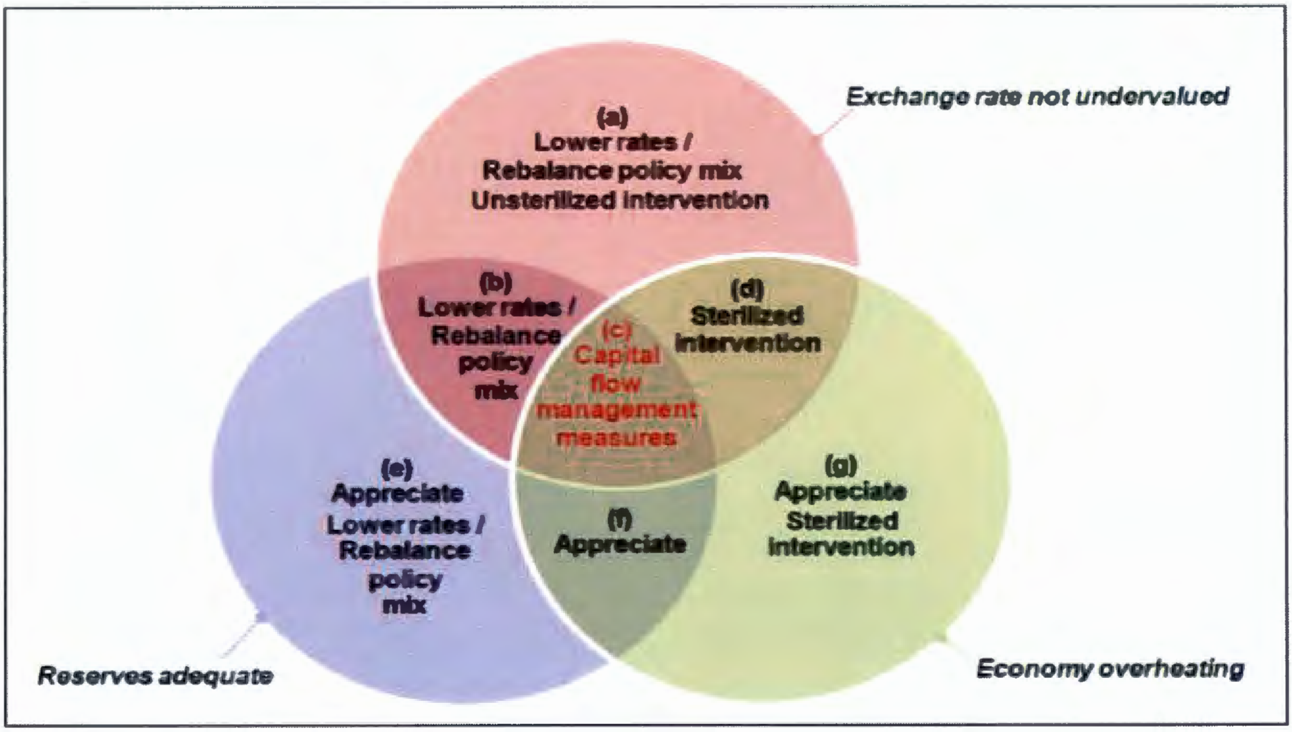

FIGURE 2. 5: COPING WITH CAPITAL INFLOWS: POLICY CONSIDERATIONS

In other instances, managing capital flow there can be included variability of tax, administration and financial procedures which are to govern the flow of capital and are used under Capital Flow Management (De Villiers, 2015). However, CFM can be only utilized when there are appropriate macroeconomic polies in place and can be used to lessen the increasing of exchange rate and monitoring the flow of capital to other countries.

2.6.2 Capital flow management

CFMs can be utilized if the macroeconomic strategies have neglected to address the progressions of potential monetary and macroeconomic soundness risk (De Villiers, 2015). These measures address the threat particularly and in the interim maintaining a strategic distance from loads related with measures concentrating on non-resident (foreigners) financial investors. For instance, if vulnerabilities do create, in perspective of foreign capital inflow, which could incite exchange rate to appreciate, in addition to different variables the vulnerabilities ought to be focused on, regardless the nationality of the investor.

Liquidity requirements and currency-specific reserves can be utilized in supporting banks, additionally, separated risk weights for domestic instead of foreign currency loans. As for organisations which are not banks, for example, renting organisations and corporates, specialists may consider the weight of a separated tax administration of local borrowing against foreign currency borrowing.

Taking everything into account, both the layout and usage of CFMs must be set up dependent upon the nation's particular conditions, and besides on examination of sufficiency. CFMs ought not, in any case, be considered as a long-term and permanent solution and ought to be decreased once the weight of capital inflow eases. This raises the issue of managing taxes on specific inflows as a permanent source of fiscal revenue. On the off chance that inflows into the country are accepted to last, the exchange rate appraisal should be adjusted and experts need to put more conspicuous reliance on the reaction of macroeconomic policy. Along these lines, it is important for experts to frame an ordered analysis and evaluation by measuring the advantages of controls against the risk that such approaches may make an adverse market response. The ease with which the measure can be adjusted ought to be considered in planning CFMs.

2.7 Forecasting methods

In the literature of portfolio inflows several forecasting methods have been used over the years. Conventional econometric time series methods being the most popular. Predictive measures (error measurements) are used as the basis to measure the accuracy of a model in terms of its modelling capability (Xaba, 2014).

2.8 Machine learning or artificial intelligence models

According to Russell and Norvig (2005) artificial intelligence (AI) can be defined in two dimensions in which one dimension measures achievement as far as devotion to human execution and the other dimension measures against an ideal performance measure, called rationality. Artificial Intelligence (AI) symbolises the capability of a machine to perform the functions of a human thought in a broad sense. The term AI has likewise been connected to computer frameworks and programs fit for performing tasks more intricate than direct programming, albeit still a long way from the domain of real idea (Kalogirou, 2003). AI comprises of five branches, i.e. expert systems, ANNs, GA, fuzzy logic and different hybrid systems, which are combination of at least two of the branches specified already.

2.8.1 Support vector regression (SVR) model

Many artificial intelligence models have been employed in the past till to date to model and forecast different time series data, for example artificial neural network, support vector machine for regression purposes which is basically based on the statistical learning theory. SVM has been used in the research field(s) including time series prediction. In prediction purposes SVM has yielded good results in the studies of Tay and Cao (2001) and Misra et al. (2009). Dibike et al. (2001); Asefa et al. (2006); and Wang et al. (2009) have applied SVM in hydrological and water resource planning. Quadratic programming methods is utilized when solving a standard SVM method (Samsudin et al., 2011).

Nonlinear regression problems can also be modelled by employing support vector machines, when this method is employed for regression purposes then it is called support vector regression (SVR) (Hong, 2009). There are several applications of SVR in solving forecasting problems in many fields where the model was successfully employed, such as atmospheric science forecasting (Mohandes et al., 2004, Hong and Pai, 2007), financial time series (stock index and exchange rate) forecasting (Cao, 2003, Huang et al., 2005), engineering and software (production values and reliability) forecasting (Pai and Hong, 2006).

Chen and Wang (2007) employed SVR, back-propagation neural networks (BPNN) and ARIMA to forecast tourism demand and genetic algorithm was employed to select the optimal parameters of the SVR model. The data set used was of China's tourist arrivals from 1985-2001. The results revealed that SVR outperforms both included models based on NMSE and MAPE. The study employed chaotic particle swarm optimization (CPSO) for choosing parameters for the SVR model. The results show that CPSO outperforms both the genetic algorithm (GA) and simulated annealing algorithm (Hong, 2009).

Kazem et al. (2013) forecasted stock market prices employing a model based on SVR, chaotic mapping and firefly algorithm using a time series data of stock prices, bank shares and intel. The adopted or proposed model was in comparison with SVR-CA, SVR-CGA, SVR-FA, ANNs and ANFIS. The obtained results reveal that all the models are outperformed by the proposed model based on the error measurements of MSE and MAPE.

Kim (2003) compared SVM model to back-propagation neural networks and cased-based reasoning to forecast both the stock price index and financial forecasting. The results show that stock market forecasting can be modelled by SVM as the model fitted the series well. The study modelled wind speed prediction comparing SVM and multilayer perceptron (MLP) neural networks using a series of mean daily speed data in Saudi Arabia. Based on the results SVM compares favourably with MLP based on RMSE (Mohandes et al., 2004).

Wang et al. (2012) constructed financial conditions index (FCI) to investigate the connection between composite index of financial indicators and future inflation using SVR. This model was compared with traditional econometric method. Monthly data of Chinese CPI and other financial indicators were used. The empirical results show that FCI (SVRs) outperforms VAR impulse response analysis.

Kamruzzaman et al. (2003) examined the impact of various kernel functions on forecast error measured by several performance metrics. The data used was that of six various foreign currency exchange rates against Australian dollar. The study showed that radial basis and polynomial kernel are better in forecasting forex markets.

The study used a hybrid genetic algorithm and support vector regression and benchmarking with BP neural network model in predicting CNY exchange rates. The data set was that of USD/CNY, EUR/CNY and CNY/JPY. The results demonstrates that the hybrid model is efficient for studying the CNY exchange rate prediction (Jiang and Wu, 2016).

2.8.2 Artificial neural networks (ANNs) model

The idea of ANN analysis was found almost 50 years prior, however it is just over the recent 20 years that applications software has been created to deal with practical issues (Kalogirou, 2003). Artificial neural networks are classified into two types; dynamic networks (e.g. NNARX) and static networks (e.g. ANN). Static networks as in feed-forward networks have no feedback component and contain no delay in the network. The output of network is got particularly from inputs through the feed forward associations. In dynamic networks, output not just depends on inputs but in addition depends on earlier sources of inputs, outputs and the state of the network.

ANNs learn from the characteristics of the data and with no prior assumptions needed. Nonlinear problems also have been observed to be efficiently solved by the ANNs model in the real world (Adebiyi et al., 2014). Adebiyi et al. (2014) compared ANNs and ARIMA models as far as anticipating precision of the stock market data sourced from New York Stock Exchange. The ANNs model outperformed ARIMA model based on the obtained results. Furthermore, the results clarified the contradiction based on the superiority of these models over one another.

Khashei and Bijari (2010) suggested a hybrid prediction model of ANNs and ARIMA using exchange rate, Canadian lynx and Wolf's sun spot data. The results have shown that the prediction accuracy can be improved by employing the suggested hybrid model, which performed better than ANNs and ARIMA respectively.

Khashei and Bijari (2012) compared the forecasting efficiency of ARIMA as a linear model combined with multilayer perceptron (MLP) in terms of time series forecasting. Included are the hybrid models of Zhang's ANNs/ARIMA, artificial neural network (p, d, q) and the generalized hybrid ANNs/ARIMA model. The results have indicated that these models can improve the forecasting accuracy than used separately. However, the generalized ANNs/ARIMA outperforms all the included models.

Bing et al. (2012) employed BPNN model to forecast Shanghai Stock Exchange Composite Index and the results show that the model was utilized successfully to highest, lowest and closing values of the Index. However, in the short run there is a limitation of the model to predict the return rates.

Ramani and Murarka (2013) employed multilayer feed forward NN to predict stock price using algorithm of back propagation to the model. The study used historical stock prices (closing) for training the network. The results showed that a feed forward network using back propagation is quite reasonable for stock price prediction.

Prediction of stock in terms of future price was examined using hybridized neural network approach in order to better the existing approaches analysing the data set of stock. The empirical results demonstrate that there is a significant improvement (Adebiyi et al., 2012). The prediction was adequate.

Majumder and Hussian (2007) forecasted the movement of index closing values employing the neural network model. A monthly data set of S&P CNX Nifty 50 index corresponding to the period of 1st January 2000 to 31st December was used. The ANNs model has shown efficiency in terms of prediction performance for period of four years.

The study aimed at investigating the profitability of using artificial neural networks in analysing the Taiwan Weighted Index and the S&P 500 in the States. The study found that higher returns are generated based on the ANNs trading rule than the buy-hold strategy (Lin and Yu, 2009). ANNs has likewise been utilized to model seasonal time series data before.

In the study two models for managing demand fluctuation in seasonal time series were examined utilizing artificial neural networks. In the main stage multilayer perceptron model was proposed. Secondly, input variables used will be sourced from the decomposed components of time series, utilizing a casual model based ANNs. The outcomes demonstrate that a similar accuracy is achieved with or without decomposing the original time series. (Benkachcha et al., 2015). In the study the ANN model is discussed and compared to the other nonlinear models, and also the relevance of the ANN model in terms of time series prediction problems (Allende et al., 2002).

The study included factors from both the present record and capital record to forecast the value of Indian rupee against the U.S dollar. Two different classes of frameworks in forecasting exchange rate were used. These classes include, the artificial neural networks based models, MLFFNN and NARX, compared to the GARCH and EGARCH as time series econometric methods. The results show that the MLFFNN and NARX as ANN based methods are most efficient in exchange rate forecasting (Chaudhuri and Ghosh, 2016).

An ANN model has wide application in time series analysis because of its flexibility. Kristjanpoller and Minutolo (2015) employed a hybrid model of ANN-GARCH for forecasting the gold price volatility using oil price index, FTSE stock market index, Euro/Dollar and Yen/Dollar as inputs. The obtained results demonstrate that there is an improvement in forecasting than using GARCH alone.

2.9 Econometric time series models

In the recent years' portfolio inflows and its key drivers to emerging markets have been immensely studied and many statistical techniques have been employed in undertaking the task. Time series models utilizes past observations of the predicted variable, (for example, stock price, interest rate, and so forth.) to analyse and model the trends of the historic changes in the variable keeping in mind the end goal of predicting the future value (Majumder and Hussian, 2007).

In time series, we have two types of methods for modelling and forecasting, which are linear and nonlinear models respectively. Linear models predict variables based on its lagged values and these models includes among others time series regression, exponential smoothing etc., the most popular used linear model being the ARIMA model. Nonlinear models, depending on the characteristics of the dataset, can outperform linear models. Some of the nonlinear models are the TAR, STR and MS-AR which were used by (Xaba, 2014) amongst others.

2.9.1 Structural vector autoregressive (SVAR) model

The compelling article by Sims (1980), describes the utilization of vector autoregressive (VAR) models for macro-analysis as an alternative to the substantial simultaneous equations models that were utilized that time. The later models did not speak to the rich unique structure displlay in time series data of quarterly and monthly recurrence. In VAR investigation, the dynamic associations between the variables are normally explored by impulse responses or forecast error decompositions (Lütkepohl, 2006). In this manner, structural VAR (SVAR) models were established as a framework for joining and recognizing limitations for the innovations to be taken after out in an impulse response analysis.

Çulha (2006) employed SVAR model to analyse the drivers of capital flows into Turkey using a monthly series corresponding to 1992:01 to 2005:12. The results found that due to the post crisis period the significance of some drivers changed and that push factors has a minor impact as compared to pull factors of capital flows into Turkey.

AJIDE and RAHEEM (2015) examined the drivers of capital flows into Nigerian economy. The dynamic effect shocks of the drivers were also examined using structural VAR, variance decomposition and impulse response analysis. Furthermore, the study reveals that there is also a need to put in place policies that can be used to deal with shocks to real variables of economic activity both internal and external.

Raghavan et al. (2014) studied the correlation between portfolio capital flows to domestic credit and their impacts on the Australian economy using the structural vector auto-regression (SVAR) model. The results obtained revealed that debt flows are driving the impact of net portfolio flows in Australia, while equity flows have no real effect on the domestic macroeconomic variables.

Korap (2010) employed SVAR model in analysing the key determinants of capital flows (portfolio) in the framework of Turkish economy. The results found that for the Turkish economy push factors have a superior role in elucidating the behaviour of portfolio flows. Furthermore, there is a negative correlation between real interest rate and portfolio flows.

2.10 Concluding remarks

The literature study revealed factors that affect portfolio inflows as both pull and push factors. Furthermore, policies which can be helpful in dealing with the effects of capital flows have been outlined. Moving to the significant part, portfolio inflows have not been analyzed by employing machine learning techniques, however the current study showed the success of machine learning techniques in time series analysis. The literature of conventional econometric model of SVAR was also outlined. The study will employ machine learning techniques, SVR and ANN, and using SVAR to identify the drivers of portfolio inflows into South Africa. These ensure that a new model will be developed for modeling and forecasting portfolio inflows.

CHAPTER 3

METHODOLOGY

3.1 Introduction

Models which are used or employed in general to model and forecast portfolio inflows are performing to their best capabilities. These models are useful in determining the key drivers of portfolio inflows to or from emerging markets (EM). They reflect empirical and theoretical knowledge of how portfolio investors behave when trying to invest their bonds and equity into an economy. The field of time series has many useful techniques that are employed in modelling and forecasting. The machine learning models, over the years, have been gaining a lot of attention due to their excellent predictions and important properties. Furthermore, this current study is limited to using SVR, ANNs and SVAR modelling techniques. The study aims to find the likelihood of developing an empirical model(s) equipped for predicting portfolio inflows and its key determinants. The structured study objectives are as follows:

- To determine whether the underlying characteristics of the portfolio inflows are non-linear in nature.
- To determine the performance or efficiency of Support Vector Regression, Artificial Neural Networks and Structural VAR models.
- To evaluate the key drivers of portfolio inflows into South Africa.
- To compare the predictive efficiency/accuracy of Support Vector Regression, Artificial Neural Networks and Structural VAR models.

3.2 Data description and data sources

In address the research objectives, the study will use historic time series data of portfolio inflows which were sourced from the Rand Merchant Bank (RMB). A formal request was made for the purpose of obtaining the data. This data enabled the study to undertake the empirical study. The study used portfolio inflows as the dependent variable and exchange rate, inflation linked bonds, real GDP as the independent variables covering the period of 01 March 2004 to 01 February 2016 consisting of 3111 observations.

3.3 Preliminary data analysis

Preliminary data analysis is the basis of the analysis before the actual analysis is performed. The key features of the data are obtained from the preliminary analysis. Kline (2005) suggested that before actual analysis important issues such as normality must be assessed. Besides the stated ones, other significant descriptive statistics such as the median, mean and standard deviation are estimated. Furthermore, skewness-kurtosis measures are also estimated to check the normality of the actual data.

3.4 Nonlinearity assessment in the data

In academic research the assessment of linearity and stationarity are of key significance. This will appropriate the choices of the model(s) included in the study so as to achieve the research objectives. Xaba (2014) stated that nonlinearity can occur in different forms, thereby this means that there is no test that is superior in detecting nonlinearity. There are several tests which can be used to assess the series in terms of nonlinearity. Those tests amongst others are; the McLeod-Li test by McLeod and Li (1983); BDS test developed by Broock et al. (1996a); neural network test developed by White (1989); reset test developed by Ramsey (1969); Keenan's (1985) test and Tsay (1986) test. The study will employ both Brock-Dechert-Scheinkman (BDS) test and cumulative sum (CUSUM) test for detecting nonlinearity and stability in the series respectively. The reason for the choice of the tests is simply because they are popular and mostly used. Xaba (2014) employed both tests in his study.

3.4.1 The Brock-Dechert-Scheinkman (BDS) test

Time series data has an element of nonlinearity. Broock et al. (1996b) developed the BDS test of nonlinearity based on the idea that arises in the theory of chaos. Furthermore, chaos theory depends on the assumption that the underlying system is a nonlinear procedure, and the underlying system is the deterministic framework. The BDS test depends on the series integral correlation. The statistic of the BDS test is given by:

$$BDS_{m.M}(r) = \sqrt{M}\frac{C_m(r)-C_1^T(r)}{\sigma_{m.M}(r)} \quad 3.1$$

where M is the embedded point of the space with m dimension; r is the radius of a sphere centred on X_i, C is the constant and $\sigma_{m.M}(r)$ is the standard deviation of $\sqrt{M}C_m(r) - C_1^T(r)$. Moreover, the cumulative sum (CUSUM) test is used in accordance with the BDS test to assess the stability. Brock et al. (1996) showed that when the residuals under the null hypothesis are independent and identically distributed (IID) or the white noise process is being followed,

$$BDS_{m,n} \sim N(0,1). \quad 3.2$$

In the instance that the null hypothesis is rejected (linearity) the test statistic of the BDS will exceeds the critical value at a given significance level or if the probability value of $BDS_{m,n}$ is lower than α. If the latter is to happen then this means that there is presence of nonlinearity in the series.

3.4.2 Cumulative sum (CUSUM) test

Stability is another part of nonlinearity in data. CUSUM looks at data stability by testing for conceivable structural change in the series. Several studies have employed the test in the past empirical studies of time series amongst others are the studies of (Shao and Zhang, 2010, Talas et al., 2013, Halicioglu and Ugur, 2005). The other test that can be used to test stability is CUSUMSQ. In the condition that there is stability in the model, then there will be no change over time in the coefficient (**β**) and $\sigma^2{}_{\varepsilon}$. Then if the latter is achieved the matrix can be used to obtain the coefficient (Brown et al., 1975):

$$\hat{\beta} = (Y'_{t-1}Y_{t-1})^{-1}Y'_{t-1}Y_t \qquad 3.3$$

dependent variable is given by Y_t and $Y_{t-1} = \left(1\ Y_{t-1}\ Y_{t-2} \dots Y_{t-p}\right)'$ and $\varepsilon_t \sim iid(0, \sigma^2{}_{\varepsilon})$. Given that the model is unstable, then coefficient (**β**) and the $\sigma^2{}_{\varepsilon}$ possibly change over time. In such a case, then coefficient **β** is replaced by b_t and so

$$b_{t-1} = (Y'_{t-1}Y_{t-1})^{-1}Y'_{t-1}Y_{t-1} \qquad 3.4$$

Where $Y_{t-1} = \left(1\ Y_{t-1}\ Y_{t-2} \dots Y_{t-p}\right)'$ and $\varepsilon_t \sim iid\left(0, \sigma^2{}_{1,\varepsilon}\right)$. Should the AR(p) be stable, then there will be consistency in the parameters over time, this will show that there is no structural change in the series. Then hypotheses put forth to be tested are given as:

$$H_o: \beta_1 = \beta_2 = \cdots = \beta_p = \beta$$

3.5

Or $H_o: \sigma^2{}_{1,\varepsilon} = \sigma^2{}_{2,\varepsilon} = \cdots = \sigma^2{}_{n,\varepsilon} = \sigma^2{}_{\varepsilon}$

Then, the calculation of the $\sigma^2{}_{\varepsilon}$ is as follows:

$$var(\varepsilon_t) = E(\varepsilon'_t\varepsilon_t = var\{\varepsilon_t - Y'_t(b_{t-1} - \beta)\}$$

$$= \sigma^2{}_{\varepsilon} + Y'_t\sigma^2{}_{\varepsilon}(Y'_{t-1}Y_{t-1})^{-1}Y_t$$

$$= \sigma^2{}_{\varepsilon}\{1 + Y'_t(Y'_{t-1}Y_{t-1})^{-1}Y_t\} \qquad 3.6$$

The scaled recursive residuals, ω_t, may be defined as

$$\omega_t = \frac{\varepsilon_t}{\sqrt{\{1+Y'_t(Y'_{t-1}Y)^{-1}Y_t\}}} = \frac{\varepsilon_t}{var(\varepsilon_t)} = \frac{\varepsilon_t}{s.e(\varepsilon_t)} = \frac{\varepsilon_t}{\sigma_\omega}, \qquad 3.7$$

Under constant parameters, $\omega_t \sim iid(0, \sigma^2{}_\omega)$. Therefore, the CUSUM statistic will be given by:

$$W_t = \sum_{j=l+1}^{t} \omega_j, \qquad t = l+1, l+2, \dots n. \qquad 3.8$$

The statistic of CUSUMSQ (cumulative sum of squares) is given by mathematically:

$$S_t = \sum_{j=l+1}^{t} \omega_j / \sum_{j=l+1}^{n} \omega_j, \qquad t = l+1, l+2, \dots n. \qquad 3.9$$

The application of the two test is by plotting W_t and S_t against time t. The confidence bounds are found through plotting the two lines that join the points $[l, \pm a\sqrt{n-l}]$ and $[n, \pm 3al]$. At 5% level (95% confidence interval) a=0948 and at 1% level (99% confidence interval) a=1.143. The existence of structural break can be seen when the test statistic is outside the interval at a specific significance level, together with non-consistency in the parameters which leads to instability in the series. Furthermore, this will lead to failing to accept null hypothesis of stability.

3.5 Nonlinear unit root test of stationarity

The current study will be testing or assessing stationarity before utilizing the three models included in modelling and forecasting portfolio inflows. Kapetanois Shin Snell Nonlinear Augmented Dickey Fuller unit root test (KSS-NADF) and Bierens Nonlinear Augmented Dickey Fuller unit root test (B-NADF) will be employed to test for nonlinear stationarity. The above mentioned tests have been utilized by the empirical studies of (Liu and He, 2010, Xaba, 2014).

3.5.1 Kapetanois-Shin-Snell Nonlinear Augmented Dickey-Fuller (KSS-NADF) Unit root test

Most studies in the current literature tend to use the unit root test based on the linear assumption. Augmented Dickey Fuller (ADF) test being the widely used test to assess unit root which was proposed by Dickey and Fuller (1981). However, empirical studies pointed out that ADF unit root test gives poor performance in small sized samples (Phillips, 1987, Phillips and Perron, 1988) and nonlinearity (Bierens (1997); Leybourne et al. (1998)). This being the case it is significant that such tests which accommodate nonlinearity must be employed such as KSS and B-NADF tests respectively (Xaba, 2014). ADF was modified in order to develop KSS nonlinear unit root test. Kapetanios et al. (2003), a nonlinear univariate model of order 1 was considered, which has the stochastic process of:

$$y_t = \beta y_{t-1} + \gamma y_{t-1}\Theta(\theta; y_{t-d}) + \varepsilon_t, \quad t = 1, \dots, T, \qquad 3.10$$

given $\varepsilon_t \sim \text{iid}(0, \sigma^2)$, and β and γ are unknown parameters. Following the literature of the nonlinear model, the transition function adopted was of the exponential form, i.e.

$$\Theta(\theta; y_{t-d}) = 1 - \exp(-\theta {y^2}_{t-d}), \qquad 3.11$$

where $\theta \geq 0$, and $d \geq 1$ is the delay parameter. Kapetanios et al. (2003) using (3.10) and (3.11) obtained the nonlinear model of

$$y_t = \beta y_{t-1} + \gamma y_{t-1}[1 - exp(-\theta {y^2}_{t-d})] + \varepsilon_t, \qquad 3.12$$

Parameterized form is as follows:

$$\Delta y_t = \varphi y_{t-1} + \gamma y_{t-1}[1 - exp(-\theta {y^2}_{t-d})] + \varepsilon_t, \qquad 3.13$$

where $\varphi = \beta - 1$, γ, θ these parameters must be estimated and ε_t is the residual term. Setting $\varphi = 0$ and $d = 1$ gives the test to be specified as follows:

$$\Delta y_t = \gamma y_{t-1}[1 - exp(-\theta {y^2}_{t-1})] + \varepsilon_t \qquad 3.14$$

According to Kapetanios et al. (2003), the traditional ADF test might not be robust when the true process is stationary but nonlinear. They set the following hypothesis:

$$H_0: \theta = 0 \qquad 3.15$$

Against the alternative

$$H_1: \theta > 0. \qquad 3.16$$

However, Kapetanios et al. (2003) argue that although looking at test (3.15) directly won't be feasible since γ won't be identified in the null hypothesis . Luukkonen et al. (1988) in testing nonlinear stationarity in Y_t reformulated an estimable nonlinear specification using a first order Taylor series approximation.

$$\Delta Y_t = \Upsilon {Y^3}_{t-1} + \varepsilon_t. \qquad 3.17$$

To account for the possibility of serial correlation in the error term (3.17) is augmented with the lags of difference of y_t as:

$$\Delta Y_t = \Upsilon {Y^3}_{t-1} + \sum_{j=1}^{p} \delta_j . \Delta Y_{t-j} + \varepsilon_t \qquad 3.18$$

Where testing for unit root ϒ as the coefficient is employed to detect the existence of unit root. The KSS-NADF unit root test will have the following statistic which is based on the nonlinear stationarity specification:

$$t_{NL} = \frac{\hat{\delta}}{s.e.(\hat{\delta})} \quad 3.19$$

Where the standard error of ξ is given by $s.e.(\xi)$. From the t-statistic the obtained hypothesis are evident:

$$H_O: \xi = 0 \qquad \text{(Nonlinear nonstationary)}$$

3.20

$$\text{Vs.} \quad H_1: \xi < 0 \qquad \text{(nonlinear stationary)}$$

Based on the three nonlinear specification-raw, demeaned and de-trended data will construct the three critical values (Kapetanios et al., 2003). The following scenarios prevail:

- The raw data will be used if X_t has a zero mean, then the appropriate data to use is $Y_t = X_t$.
- If X_t has a non-zero mean and zero trend, then the appropriate data to use is

  $Y_t = X_t - \bar{X}$, the demeaned data, where $\bar{X}$ is the mean of the data.

  If X_t has a non-zero mean and non-zero trend, then the appropriate data to use is $Y_t = X_t - (\alpha_0 + \alpha_1 t)$, the de-trended data, where $(\alpha_0 + \alpha_1 t)$ is the trend-line obtained by regressing X_t on time point $t = 1,2,3,4,\dots,n$ with an intercept term.

The KSS-NLADF test is sensitive to the choice of lag length, p. The best way to selecting the lag length is by following the approach suggested by (Hall, 1994). This involves setting up an upper bound, Pmax, suggested by (Schwert, 2002).

$$P_{max} = integer\left[12.\left(\frac{n}{100}\right)^{\frac{1}{4}}\right] \quad 3.21$$

In the equation 3.21 n represents sample size and estimating the test regression with $p = p_{max}$. The current study will take lag length of 8 as it was used in the study by (Xaba, 2014). Xaba (2014) stipulated that if the lag included is not significant the *p* will be reduced by one lag until the last lag is significant. Furthermore, the current study will use the lag selection utilised by (Xaba, 2014). The following table represents the critical values of KSS-NADF test at 1%, 5% and 10%.

TABLE 3. 1: CRITICAL VALUES FOR KSS NONLINEAR UNIT ROOT TEST

Significance level (fractile)	Raw data	De-Meaned data	De-Trended data
1	-2.82	-3.48	-3.93
5	-2.22	-2.93	-3.40
10	-1.92	-2.66	-3.13

Source: Kapetanios et al. (2003)

3.5.2 The B-NADF unit root test

The Bierens Nonlinear ADF (B-NADF) is a further elaboration of the unit root test of (Dickey and Fuller, 1979, Dickey and Fuller, 1981). Chebishev polynomials are utilized to inexact a nonlinear deterministic time trend. The Chebishev polynomials have significant favorable circumstances over normal time polynomials which were utilized by Ouliaris et al. (1989) because they are orthogonal with a close form and are bounded (Bierens, 1997). In the B-NADF, the tested hypothesis is unit root with constant drift against the alternative of nonlinear trend stationary. Bierens (1997) changed the nonlinear Dickey-Fuller form by supplanting the conventional time polynomials with orthogonal Chebishev time polynomials because the test does not follow the standard F distribution. The advantage of utilizing the Chebishev polynomials is that they permit distinguishing between stationarity around a linear trend from stationarity around a nonlinear deterministic trend under the alternative hypothesis. According to Camarero et al. (2006) the ADF test under these polynomials will be:

$$\Delta X_t = \alpha X_{t-1} + \sum_{j=1}^{p} \varphi_j \Delta X_{t-j} + \theta^T {p^m}_{t,n} + \varepsilon_t \qquad 3.22$$

The three alternative hypotheses were considered by Bierens (1997) against the null hypothesis of unit root with drift. Those hypotheses were stationarity around a level; around a linear trend; or around a nonlinear trend. Bierens (1997) gives the distribution fractiles in view of Monte Carlo simulation. The model without unit root test of Bierens (1997) of B-NADF auxiliary regression is:

$$\Delta X_t = -\rho X_{t-1} + \lambda_0 + \rho\lambda_1 t + f(t) + \mu_t \qquad 3.23$$

where ρ lies in the interval $\{0,1\}$, $f(t)$ is a non-constant deterministic function of time such that $lim_{n\to\infty}\left(\frac{1}{n}\right)\sum_{t=1}^{n} f(t) = 0, lim_{n\to\infty}\left(\frac{1}{n}\right)\sum_{t=1}^{n} tf(t) = 0$, and μ_t follows a central limit theorem and is a zero mean process. The tested hypotheses are as follows:

$H_o: \rho = 0$ (Nonlinear unit root)

3.24

vs $H_1: \rho < 0,$ (No nonlinear unit root)

Bierens (1997) proposed three vital tests - $t(m), A(m)$ *and* $F(m)$ under the B-NADF test. The $t(m)$ is the t-statistic on the predictable coefficient, ρ. Under the null hypothesis, the $F(m)$ test is a joint F -test that the predictable coefficient, ρ, and the coefficients of the nonlinear Chebyshev polynomials are zero (not significant). The $A(m)$ test statistic is given by:

$$A(m) = \frac{n.\hat{\rho}}{|1-\sum_{t=1}^{p} \hat{\varphi}_i|} \qquad 3.25$$

where n is the sample size, is an alternative test for *t(m)* test and it can be utilized to check the robustness of outcomes of the t(m) test. As the tests are inclined to size distortion, critical values utilized depend on the Monte Carlo simulation with 1000, 2000, 5000 or 10000 replications of a Gaussian *AR(p)* process for the first-difference data, ΔX_t, where p is controlled by an information criterion such as AIC, SBC, BIC and HQC. The null hypothesis of a nonlinear unit root is rejected if a test statistic is not as much (less than) as its associated critical value at the 1%, 5% or 10% level.

3.6 Modelling and forecasting methods

The following sub-section presents the models which are employed in the study to model portfolio flows. The included models are econometric model of SVAR and machine learning models (SVR and ANN).

3.6.1 Support vector regression (SVR) model

Support vector machine is a newly developed machine learning classification paradigm, from which support vector regression (SVR) is an adaptation of this support vector machine. In the SVR concept, a typical regression problem is formulated. Let's ruminate a set of data $G = \{(x_i, q_i)\}_{i=1}^{n}$, given that x_i gives a model inputs in a vector form, q_i is actual value and n represents total number of data patterns.

Regression analysis has an objective of determining a function$f(x)$, in order to precisely forecast the desired output (q). Given that objective, the regression function can be given by $q_i = f(x) + \delta$, where δ is a random error with distribution of $N(0, \sigma^2)$. There are two kinds of regression issues, to be specific linear and nonlinear respectively. Nonlinear regression problems are somehow hard to manage. SVR was for the most part created for handling the nonlinear regression problems.

In SVR, taking care of nonlinear regression problem, the inputs are firstly nonlinear mapped into a high dimensional element space (F), wherein they are put into a linear relationship with the outputs. According to Lu et al. (2009) the SVR will have the following linear estimation function:

$$f(z) = \left(v \cdot \varphi(z)\right) + b \qquad 3.26$$

Given that v, b, $\varphi(z)$ and $\left(v \cdot \varphi(z)\right)$ denotes the weight vector, constant, mapping function from the feature space and the dot production in the feature space F respectively. In SVR, there is a transformation from a nonlinear regression problem to a linear regression problem from a lower dimension input space (z) to a higher dimension feature space (F). This means, the initial optimization problem including a nonlinear regression is recast as looking through the flatter function in the feature space and not in the input space.

There are a number of cost functions that can be used in the SVR formulation. These functions includes Laplacian, Huber's Gaussian and ε-insensitive loss function (l_ε). The one given below is the most commonly adopted (Lu et al., 2009).

$$l_\varepsilon(f(z), q) = \begin{Bmatrix} \{|f(z) - q| - \varepsilon & if\ |f(z) - q| \geq \varepsilon \\ 0 & otherwise \end{Bmatrix} \qquad 3.27$$

given ε denotes a radius of the tube situated in the regression function $f(z)$ and it is a precision parameter. Figure 3.1 present SVR with ε-insensitive loss function. In figure 3.1 the locale encased by the tube is known as "ε-insensitive" since the loss function assumes a zero figure in this locale and does not punish the forecast errors with extents smaller than ε (Lu et al., 2009).

According to (Lu et al., 2009) the weight (v) and constant (b) in (3.24), the subsequent risk function can be minimized when estimating those parameters (weight and constant):

$$R(C) = C\frac{1}{n}\sum_{i=1}^{n} L_e(f(x_i), q) + \frac{1}{2}|w|^2 \qquad 3.28$$

given that $L_e(f(x), q)$ is $\varepsilon - insensitive$ loss function in (3.25); $\frac{1}{2}|w|^2$ is the regularization term which controls the exchange between the complexity and the estimation exactness of the regression model to guarantee that the model has an improved generalization performance; C *is* the regularization constant used to indicate the exchange between empirical risk and regularization term.. C and ε parameters can be determined by the user.

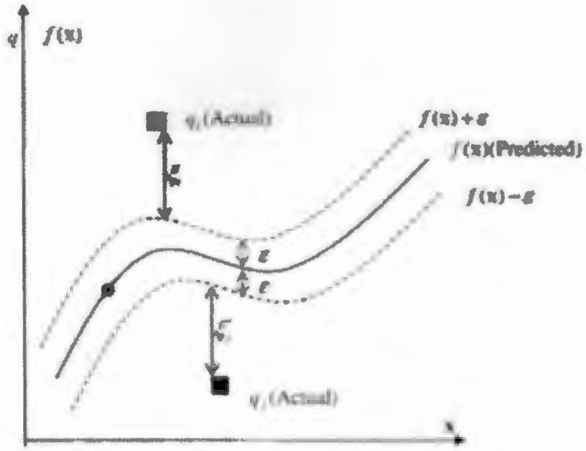

FIGURE 3. 1: A SCHEMATIC REPRESENTATION OF THE SVR E-INSENSITIVE LOSS FUNCTION

Two positive slack variables, $\check{c}_i \; and \; \check{c}_i^*$, $i = 1,2 \ldots \ldots, n$, are used to measure deviation $(q_i - f(x_i))$ from the borders of the $\varepsilon - insensitive$ zone. This means they denotes the separation or distance from the actual values to the conforming border value of $\varepsilon - insensitive$ zone as this is shown in figure 3.1. Equation (3.26) is transformed by using the slack variables into the subsequent constrained method:

Minimize: $R_{reg}(f) = \frac{1}{2}|w|^2 + C\sum_{i=1}^{n}(\check{c}_i + \check{c}_i^*)$ 3.29

subjected to:

$$\begin{Bmatrix} q_i - (w \cdot \vartheta(x_i)) - b \leq \varepsilon + \check{c}_i \\ (w \cdot \vartheta(x_i)) + b - q_i \leq \varepsilon + \check{c}_i^* \\ \check{c}_i, \check{c}_i^* \geq 0, \;\; for \; i = 1, \ldots, n \end{Bmatrix} \quad 3.30$$

By using Lagrangian multipliers and Karush-Kuhn-Tucker conditions to equation (3.27), this will yield the following dual Lagrangian form Lu, Maximize:

$$L_d(\alpha, \alpha^*) =$$

$$-\varepsilon\sum_{i=1}^{n}(\alpha_i^* + \alpha_i) + \sum_{i=1}^{n}(\alpha_i^* - \alpha_i)q_i - \frac{1}{2}_i\sum_{j=1}^{n}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)k(x_i, x_j) \quad 3.31$$

subject to the constraints:

$$\begin{Bmatrix} \sum_{i=1}^{n}(\alpha_i^* - \alpha_i) = 0 \\ 0 \leq \alpha_i \leq C, \;\; i = 1, \ldots, n \\ 0 \leq \alpha_i^* \leq C, \;\; i = 1, \ldots, n \end{Bmatrix} \quad 3.32$$

The equality of $\alpha_i \alpha_i^* = 0$ is satisfied by the lagrangian multipliers in (3.28). The Lagrangian multipliers, α_i and α_i^* are calculated and an optimal desired weight vector of the regression hyperplan is $v^* = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)k(x, x_j)$. SVR regression function can be written according to (Lu et al., 2009, Chen and Wang, 2007) as:

$$f(x, v) = f(x, \alpha, \alpha^*) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)k(x, x_i) + b \qquad 3.33$$

given that $k(x, x_i)$ is called kernel function. The product of the two vectors, x_i and x_i, in the feature space $\varphi(x_i)$ *and* $\varphi(x_j)$ will be equal to the kernel; that is, $k(x, x_i) = \varphi(x_i)\varphi(x_j)$. Any function that can be used to satisfy the Mercer's condition, it can be employed as a kernel function (Chen and Wang, 2007). The broadly utilized kernel function is the radial basis function, although several functions are available (Lu et al., 2009). The radial basis function is computed as follows:

$$K(x_i, x_j) = exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right) \qquad 3.34$$

Given that σ is the width of the RBF. In this manner, the current study will utilize the RBF as it was utilized in the study of (Lu et al., 2009).

3.6.2 Artificial neural networks (ANNs) model

Computational intelligence systems and particularly the artificial neural networks (ANNs) which are free of dynamics have been used in approximation function and forecasting (Khashei and Bijari, 2010). The ANN model has one significant advantage over other nonlinear models; ANNs are widespread approximates that can approximate a substantial class of functions with a high level of accuracy. Their capacity originates from the parallel processing of information from the data.

There are no prior assumptions required in the model building process. The characteristics of the series determines the model. Single hidden layer feed forward network has been widely applied in time series modelling and forecasting (Khashei and Bijari, 2010). Recently, the studies of Adebiyi et al. (2014) and Khashei and Bijari (2010) used the single hidden layer feed forward network. This model is made up of a network of three layers of simple processing units connected by acyclic links (figure 3.2). The output (y_t) and the inputs $(y_{t-1}, \ldots, y_{t-p})$ has a relationship that can be denoted as follows in a mathematical representation:

$$y_t = w_0 + \sum_{j=1}^{q} w_j \cdot g\left(w_{0j} + \sum_{i=1}^{p} w_{ij} \cdot y_{t-i}\right) + \varepsilon_t \qquad 3.35$$

given that $w_{ij}(i = 0,1,2, \ldots, p, j = 1,2, \ldots, q)$ and $w_j(j = 0,1,2, \ldots, q)$ are model parameters often called connection weights; p is the number of input nodes; and q is the number of hidden nodes.

There are several forms that activation function can take. The reason of the activation function is to prohibit outputs from achieving huge values which can 'incapacitate' neural networks and along these lines inhibit training (Kaastra and Boyd, 1996). For nonlinear mapping and classification, linear activation functions are not useful. According to Kao and Ma (1992), (Levich and Thomas III, 1993), Kaastra and Boyd (1996) they found that there is a nonlinearity in the financial markets series thereby nonlinear activation functions are more appropriate to be used. The logistic and tangent hyperbolic functions are used as the hidden layer activation function which are shown respectively in equations 3.36 and 3.37, respectively:

$$sig(y) = \frac{1}{1+exp(-y)}. \qquad 3.36$$

$$Tanh(y) = \frac{1-exp(-2y)}{1+exp(-2y)}. \qquad 3.37$$

Such that the ANN model in Equation 3.35, a nonlinear function mapping will be performed from the past observations to the future value y_t, i.e.

$$y_t = f(y_{t-1}, \ldots, y_{t-p}, w) + \varepsilon_t \qquad 3.38$$

given that w is a vector of all parameters and $f(\cdot)$ is a function determined by the network structure and connection weights. Thus, the neural network is equal to a nonlinear auto-regression model. The simple network given in equation 3.35 is amazingly powerful in that it is able to approximate the arbitrary function as the number of the hidden nodes when q is adequately large (Khashei and Bijari, 2010).

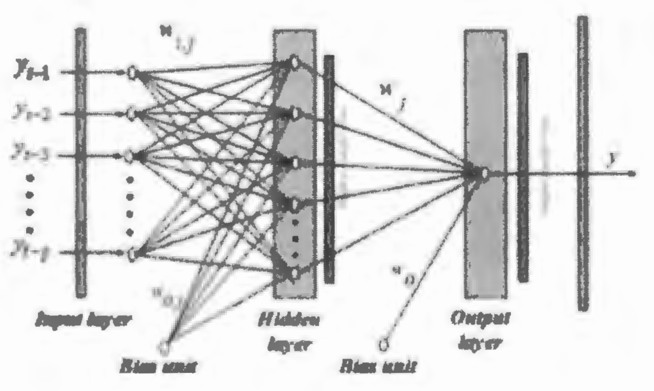

FIGURE 3.2: NEURAL NETWORK STRUCTURE $(N^{(p-q-1)})$

There is no method that can be used to choose parameter q as it is data-dependent. After appropriate number of hidden nodes is chosen, lagged observations, p, is another significant duty of the ANN modelling of time series. The nonlinear autocorrelation structure of the time series is determined by the lagged observations, p, which is estimated from ANN model.

Pruning algorithm, polynomial time algorithm, canonical decomposition method and the network information criteria can be used to find the optimal structure of the ANNs model (Khashei, 2005). Furthermore, there are many methods that can be employed in finding the optimal structure of the ANNs model. However, these methods are somehow very difficult to implement (Zhang et al., 1998). The shortcoming of these methods is that they can never give an optimal solution in real forecasting problems. There is no appropriate method on choosing parameters; in this way the method is to test various networks with different numbers of inputs and hidden nodes (p, q), estimate generalization error and select the network with the most minimal generalization error. The parameters are evaluated such that the cost function of neural network is limited. Cost function is the aggregate accuracy criterion, for example, mean squared error:

$$E = \frac{1}{N}\sum_{n=1}^{N}(e_i)^2$$

$$= \frac{1}{N}\sum_{n=1}^{N}\left(y_t - \left(w_0 + \sum_{j=1}^{q} w_j g\left(w_{0j} + \sum_{i=1}^{p} w_{ij} y_{t-i}\right)\right)\right)^2 \qquad 3.39$$

given that N is the number of error terms. An efficient nonlinear optimization algorithms are employed but not the basic back-propagation training algorithm (Khashei and Bijari, 2010), where neural network parameters, w_{ij}, are altered by an amount Δw_{ij}, according to the following formula:

$$\Delta w_{ij} = -\tau \frac{\partial E}{\partial w_{ij}} \qquad 3.40$$

Given that (τ) is the learning rate and $\frac{\partial E}{\partial w_{ij}}$ is the partial derivative of the function E with respect to the weight w_{ij}. This derivative is generally figured in two passes. In the forward pass, an input vector from the preparation set is connected to the input units of the network and is spread through the network, layer by layer, creating the last output. Amid the backward pass, the output of the network is compared with the optimal output and the subsequent error is then propagated in reverse through the network, modifying the network therefore. Rumelhart et al. (1986) presented a momentum term δ in equation 3.41 to accelerate the learning procedure, while keeping away from the instability of the algorithm.

$$\Delta w_{ij}(t+1) = -\tau \frac{\partial E}{\partial w_{ij}} + \delta \Delta w_{ij}(t) \qquad 3.41$$

The momentum term may likewise be useful in prohibiting the learning process from being trapped into poor local minima, and the study uses the interval of $[0,1]$ for training the neural network model.

3.6.3 Structural vector autoregressive (SVAR) model

To evaluate the possible drivers of portfolio inflows into emerging markets, the current study applies the structural identification methodology of vector autoregressive models (SVAR) developed by the purported AB-model of (Amisano and Giannini, 1997). SVAR model possess the benefit of allowing the researchers to impose limitations on structural relationships by using the theoretical assumptions on the model of which unrestricted vector autoregressive model has a shortcoming on imposing limitations on the relationships (structural). Such a case can be realized by presenting a theoretical and furthermore some auxiliary limitations to achieve econometric identification issue. Furthermore, assuming that $\sum = E[\varepsilon_t \varepsilon_t]$ presents the covariance matrix of the residuals. Thereby, the structural analysis uses the reduced form of the model given by:

$$A\varepsilon_t = B\mu_t \qquad 3.42$$

given that the disturbance vector in a given form is given by ε_t, whereas a structural innovation vector in an unobserved form is denoted by μ_t, both with a length *k*. Thus in equation 3.43 are taken into accounts the reduced form disturbance and underlying structural shocks. Both A and B need some limitations with a dimension in the SVAR analysis *kxk* to be added. Furthermore, noting that covariance matrix are present in the structural innovations given by $E[\mu_t \mu_t] = I$ where the identity matrix is given by I so that μ_t can enforce the following limitations on A and B.

$$A \textstyle\sum A^{\cdot} = BB^{\cdot} \qquad 3.43$$

For the recognizable proof of the AB model, at least $k^2 + \frac{k(k-1)}{2} = k(3k-1)/2$ limitations are required. On the off chance that the model is over-identified, which is the case in the empirical application in chapter four; the statistic of a likelihood ratio (LR) will be reported.

We ought to consider that the variables used as a part of a vector autoregressive procedure to execute innovative accounting strategies, for instance, impulse responses require not be stationary. Sims (1980) yielding a spearheading paper on the VAR procedure contends against differencing regardless of whether the time series utilized takes after a unit root process. Moreover, Sims et al. (1990) demonstrate that parameters that can be composed as coefficients on mean zero, non-integrated regressors, have together normal asymptotic distributions and propose that the basic practice with regards to endeavoring to transform models to stationary form by difference operators whenever it appears likely that the series are of integrated form is unnecessary. Otherwise, some vital knowledge contained in the series would perhaps not be used by the researcher.

The log-likelihood function of the SVAR model can be measured by way of a function of Π *and* Σ. Sims (1986), and assuming that there are no cross limitations on **Π** and **Σ** or on the other hand, in more broad terms, that there are no limitations at all on **Π** meanwhile some form of limitations are enforced on **Σ**, the identification and the F.I.M.L. the analysis of the likelihood function can help to estimate the parameters of models K, C and AB respectively:

$$L = c - \frac{T}{2} log|\Sigma| - \frac{T}{2} tr(\Sigma^{-1}\hat{\Sigma}) \qquad 3.44$$

given $\hat{\Sigma} = T^{-1}\hat{V}\hat{V}'$

which is the log-likelihood concentrated with respect to **Π**. The estimation of **Π** comparing to the concentration of the log likelihood unmistakably concurs with the OLS estimator when the log likelihood is moulded on the principal *p* observations of the sample. Other reliable estimators would yield asymptotically identical results with respect to the resulting estimation of the **Σ** matrix.

Following Amisano and Giannini (1997), impulse response functions for structural VARs can be calculated by:

$$\Theta_0 = K^{-1} = (B^{-1}A)^{-1} = A^{-1}B,\ \Theta_i = JM^iJ'\Theta_0,\ i = 1,2,3 \ldots \qquad 3.45$$

given that:

$$M = \begin{bmatrix} A_1 & A_2 & \cdots & A_{k-1} & A_k \\ I_p & 0 & \ldots & 0 & 0 \\ 0 & I_p & \ldots & 0 & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & \ldots & I_p & 0 \end{bmatrix} \qquad 3.46$$

M is a $(pk * pk)$ matrix , and J is a $(p * pk)$ matrix, or by:

$$\Theta_i = \Theta_i.\Theta_0, \Theta_0 = I_p,\ \Theta_i = \sum_{j=1}^{i} \Theta_{i-j}A_j,\ \ i = 1,2,3 \ldots. \qquad 3.47$$

where $A_i = 0$ for $i > k$. The impulse responses are predicted by substituting the theoretical variables by the respective estimators. The estimated impulse response that is stored up to horizon H in vector $[\Theta_1, \Theta_2, \ldots., \Theta_H]$ is unbiased and asymptotically normally independently distributed with covariance matrix $\frac{1}{T}\Sigma_\Theta(H)$.

3.7 Modelling evaluation

The assessment of models is necessary. This is to test if the resulting residuals from the models comply with the assumptions. Various tests will be utilized to assess the relevancy of the model(s) to the series. The tests include normality, autocorrelation and misspecification.

3.7.1 Normality test

Normality assumption is of paramount significance in statistical procedures. This is of the view that if the normality assumption is violated then forecasting with the estimated model may be biased and also inference will be biased. Xaba (2014) stated that a certain series can be assumed to follow a normal distribution based on the parametric statistical analysis. Therefore, normality assumption must be assessed prior to predicting with the estimated model. There are several ways to test for normality; the study will use the kurtosis and skewness for the assessment of normality. The resulting residuals will be assessed using other tests of normality such as Shapiro-Wilk test and Kolmogorov-Smirnoff test.

3.7.2 Autocorrelation test

Resulting residual term from the estimated models can at times be with autocorrelation. There are possible numbers of tests for assessing autocorrelation, however the most commonly used are the Durbin-Watson (DW) test and the Breusch-Godfrey (BG) test as these tests were also utilized by (Xaba, 2014). The current study will adopt the same tests in assessing autocorrelation.

Durbin-Watson test

Autocorrelation is one of the assumptions made in most models. A violation of this assumption leads to the error term to be correlated with its immediate precursor ($\varepsilon_t\ related\ to\ \varepsilon_{t-1}$). A commonly used test to detect autocorrelation is Durbin-Watson (DW) test. If first order autocorrelation is present in the error term, then they will follow the following relation:

$$\varepsilon_t = \rho\varepsilon_{t-1} + \mu_t \qquad 3.48$$

where μ_t values are expected to be independent $\mathrm{N}(0, {\sigma^2}_{\mu t})$. The hypotheses tested in the Durbin-Watson test are as follows:

$$H_0: \rho = 0$$

3.49

$$H_1: \rho \neq 0$$

The test statistic for DW test is:

$$DW = \frac{\sum_{t=2}^{n}(\varepsilon_t - \varepsilon_{t-1})^2}{\sum_{t=1}^{n}\varepsilon^2{}_t} \qquad 3.50$$

where $\varepsilon_t = x_t - \hat{x}_t$, x_t and $\hat{x}_t$ are both the actual and estimated values of the response variables respectively. The d_U and d_L which are upper and lower critical values have been tabled for different values of k (the number of explanatory variables) and n which is the sample size. The decision rule will be based on the following scenarios: if $DW < d_L$ null hypothesis would be rejected and conclude that error terms exhibit positive autocorrelation; if $DW > d_U$ then null hypothesis would not be rejected and conclude that there is no autocorrelation; and if $d_L \leq DW \leq d_U$the test would be inconclusive.

Breusch-Godfrey test

Gurajati (2003) states that in case of the Durbin-Watson test having a short coming in detecting autocorrelation then Breusch-Godfrey (BG) test can be utilized to detect autocorrelation. It involves running the regression model, store residuals, ε_t, and running auxiliary regression $AR(m)$:

$$\varepsilon_t = \rho_1\varepsilon_{t-1} + \rho_2\varepsilon_{t-2} + \rho_3\varepsilon_{t-3} + \cdots + \rho_r\varepsilon_{t-m} + v_t, \qquad 3.51$$

given that $v_t \sim iid(0, \sigma^2{}_v)$ is the disturbance term possessing white noise with zero as the mean and constant variance. Then there will be a statement of no autocorrelation under the null hypothesis:

$$H_0: \rho_1 = \rho_2 = \rho_3 = \cdots = \rho_m = 0 \qquad 3.52$$

$H_1: \rho_i \neq 0$ for at least one i

The statistic of the joint F-test for the significance of the residuals $\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-m}$ is given by:

$$F^* = \frac{\sum_{t=1}^{n}(\hat{\varepsilon}_t - \hat{\varepsilon})/(m-1)}{\sum_{t=1}^{n}(\varepsilon_t - \hat{\varepsilon}_t)/(n-m)} \sim F_\alpha(m-1), (n-m) \qquad 3.53$$

Then the statement of no autocorrelation under the null hypothesis for ε_t is not accepted (rejected) when $F^* > F_\alpha(m-1), (n-m)$.

3.8 Model selection criteria

Schwarz (1978) developed Schwarz Bayesian Criterion (SBC) which was developed from Bayesian modification of AIC criterion. Then the basic thinking of utilizing the criteria is to select the model with the minimum statistic of the criteria as the preferred model. SBC is given as the number of observations, n, SSE the number of independent variables $p \leq m + 1$ where p includes the intercept, it is computed as:

$$SBC = n ln\left(\frac{SSE}{n}\right) + p \ln(n) \quad 3.54$$

The punishment term for SBC is like AIC, yet utilizes a multiplier of $ln\, n$ for p rather than a constant by fusing the sample size n.

3.9 Comparison of model performance

In a comparative research several models are used in modelling and forecasting a specific time series data. These models will differ in terms of accuracy, performance and reliability. In this case various performance measures (or performance metrics) are proposed in literature for model selection in terms of accuracy and reliability. For the purpose of selecting the appropriate models which are namely; SVR, ANN and SVAR the following performance measures will be used in assessing the performance of the stated models MSE, RMSE, MAE, MASE and RMSLE. Each of the stated performance measures are as actual value (X_t) and predicted values $(\hat{X}_t)$ of the data, $\varepsilon_t = X_t - \hat{X}_t$ and n being the sample size.

$$MSE = \frac{1}{n}\sum_{t=1}^{n} \varepsilon_t^{2} \quad 3.55$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} \varepsilon_t^{2}} \quad 3.56$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|\varepsilon_t| \quad 3.57$$

$$MASE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{|\varepsilon_t|}{\frac{1}{n-1}\sum_{t=2}^{n}|y_t - y_{t-1}|}\right) = \frac{\sum_{t=1}^{n}|\varepsilon_t|}{\frac{n}{n-1}\sum_{t=2}^{n}|y_t - y_{t-1}|} \quad 3.58$$

$$RMSLE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} \log \varepsilon_t^{2}} \quad 3.59$$

where in mean absolute scaled error, the naive predicting method is used to compute the mean absolute error which will be used as the denominator from the training set and it gets the predicted value from the actual value of the prior period. The forecast will be obtained as $F_t = y_{t-1}$.

3.10 Diebold-Mariano (DM) test

In empirical applications usually the case that at least two time-series models are accessible for predicting a specific variable of interest. Many statistical methods exhibit different performances in terms of forecasting ability. Comparing these methods or models is a way to tell the difference if any these models possess in terms of their forecasting abilities. Although, the standard is that the little the error the accurate the model, it is not always the case because the difference between error matrices from different models may not be statistically different form zero. Diebold-Mariano test is utilized to compare models in terms of their predicting accuracy, in which the two models are assessed in pairs to detect which model is superior than the other one in forecasting a particular data set. If $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are equivalent in terms of predicting accuracy, then the mean square differences,

$$\bar{d} = E(d_t) = E\left({\varepsilon^2}_{1,t} - {\varepsilon^2}_{2,t}\right) \qquad 3.60$$

must be approaching zero, that is $\bar{d} = \frac{1}{n}\sum_{t=1}^{n} d_t = 0$. The following hypotheses are constructed for Diebold-Mariano test:

$H_o: \bar{d} = 0$ (equal forecasting accuracy of a pair(s) of models)

3.61

$H_1: \bar{d} \neq 0$ (no equality of forecasting accuracy of a pair(s) of models)

When assessing the null hypothesis of the models having the equivalent predicting accuracy, then the statistic of the Diebold-Mariano test will be computed as:

$$DM\ test = \frac{\bar{d}}{\sqrt{\frac{2\pi \hat{t}_d(0)}{T}}} \qquad 3.62$$

where that $\hat{t}_d(0)$ is a reliable estimate of $t_d(0)$ defined by:

$$\hat{t}_d(0) = \frac{1}{2\pi}\sum_{k=-(T-1)}^{T-1} I\left(\frac{k}{h-1}\right)\hat{\gamma}_d(k) \qquad 3.63$$

given that:

$$\hat{\gamma}_d(k) = \frac{1}{T}\sum_{t=|k|+1}^{T}\left(d_t - \bar{d}\right)\left(d_{t-|k|} - \bar{d}\right) \qquad 3.64$$

and

$$I\left(\frac{k}{h-1}\right) = \begin{Bmatrix} 1 & for \left|\frac{k}{h-1}\right| \leq 1 \\ 0 & otherwise \end{Bmatrix} \qquad 3.65$$

When the DM test statistic is greater than the associated critical value then the null hypothesis of model 1 and model 2 having the equivalent predicting accuracy is rejected, or if the probability value of the DM test is less than the appropriate significance level either 1%, 5% or 10% the null hypothesis is rejected. In case that the null hypothesis is rejected then t-statistic with a higher positive value for model 1 than model 2 will depict that model 2 have the superior predicting accuracy than model 1. The following figure summarises the methodology of the dissertation:

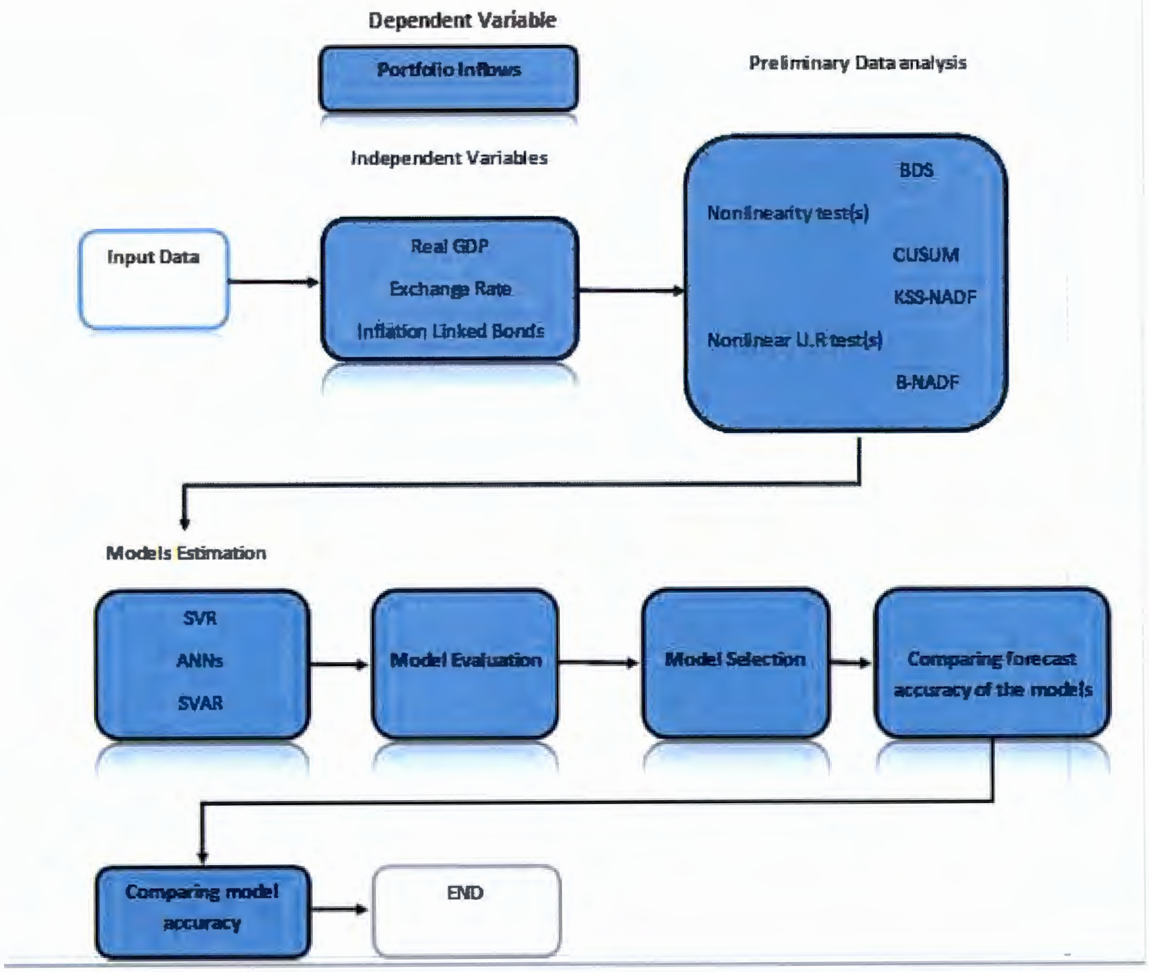

FIGURE 3.3: METHODOLOGY DIAGRAM

3.11 Concluding remarks

This chapter has outlined the various statistical tests in conjunction with the methods that will be employed to analyse the portfolio flows. The criterions used to identify the best model(s) was also discussed. This method and tests are described fully in the subsequent chapter.

CHAPTER 4

EMPERICAL ANALYSIS AND RESULTS

4.1 Introduction

This chapter outlines the empirical analysis and results of the series using chapter 3 as a guideline in undertaking the proper analysis of the current study. The objectives of the study are to be addressed in the current chapter. The analyses are presented in terms of figures and graphs. Furthermore, the analyses are done using the statistical software of Eviews, easy reg international and R studio.

4.2 Explanatory data analysis results

This section is one of the significant sections, in a sense that it gives the characteristics of the measured variable(s) which are analysed. These characteristics includes type of data used, graphical methods of analysis and other basic descriptive statistics, for instance mean, median, standard deviation, skewness and kurtosis. Moreover, nonlinearity and nonlinear unit root tests are assessed respectively.

4.2.1 Descriptive statistics

TABLE 4.1: DESCRIPTIVE STATISTICS

Variable	Portfolio flows	Exchange rate	Real GDP	Inflation-linked bonds
Mean	9.425058	6.704596	13.15178	11.73551
Median	9.641215	6.637533	13.16707	11.76145
Std. dev.	1.390921	0.227674	0.129336	0.762516
Skewness	-5.922360	0.858337	-0.694901	-0.005083
Kurtosis	39.31928	3.044956	2.470845	1.534455
Jarqua Bera	189173.1	382.2633	286.6726	278.4249
Probability value	0.000000	0.000000	0.000000	0.000000

Schumacker and Lomax (2004) and Kline (2005) as highlighted in the study of Xaba (2014) suggested that prior to doing the actual analysis of the study, important issues must be addressed such as normality. Besides the one mentioned (normality) other descriptive statistics are discussed such as the mean and standard deviation of the series. The statistics of these measures are summarized in table 4.1. The variable(s) in question have a multimodal distribution as is depicted in the histogram of the series. Theoretical values of skewness and kurtosis based on the normality assumption must assume values of 0.00 and 3.00 respectively. However, the values of the two measures have deviated from the theoretical values of both skewness and kurtosis respectively; thereby the normality assumption is violated due to the empirical fact that the series is nonlinear. This results were quantified by employing the test of JB and its probability value is 0.000, which rejects the null hypothesis of normality at all levels of significance 1%, 5% and 10% for all the included series. In terms of the normality test, with assumption being violated, Cziraky and Čumpek (2002) believe that by applying transformation such as the normal scores the series can be normally distributed. However, with the current study all the series still violates the normality assumption even after the appropriate transformation and this can be because all the variables are nonlinear in nature.

Knowing the characteristics of the series is of the paramount significant. For this purpose, the plot of the series is normally the one used to show any movements of the series from the start date to the end date of the series. This is so that in financial time series, many factors affect these series and fluctuations may be apparent amongst other characteristics and must be taken into account if they exist to obtain unbiased results. Figure 4.1 shows the series plot of portfolio inflows into South Africa together with its key drivers covering the period of 01-March-2004 to 01-February-2016 consisting of 3111 observations.

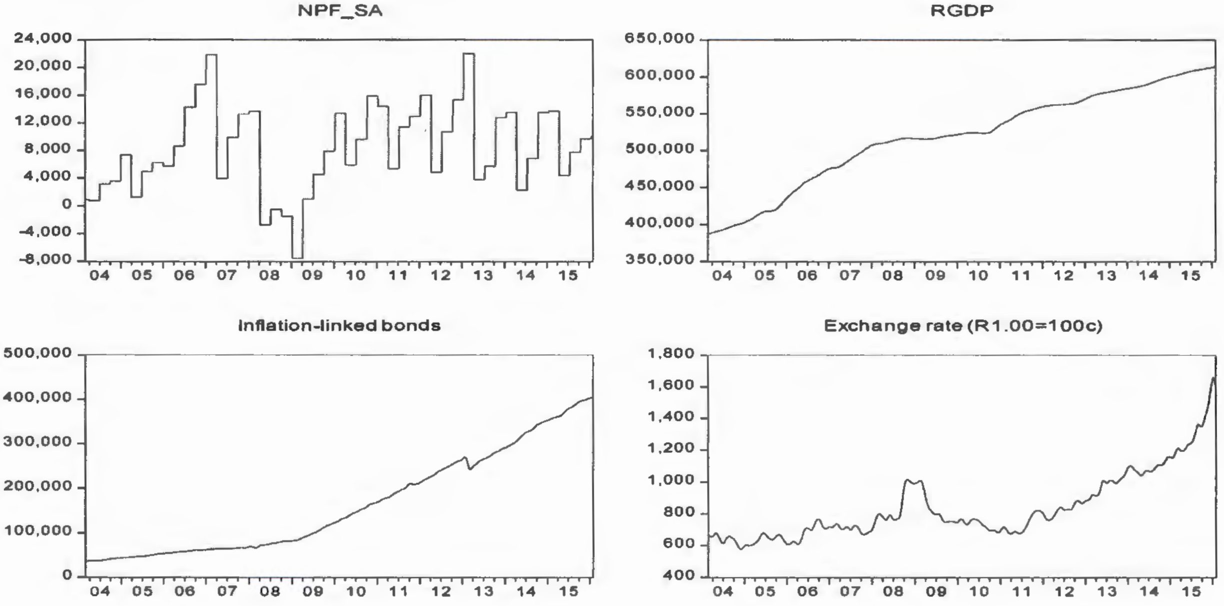

FIGURE 4.1: GRAPHICAL REPRESENTATION OF THE PORTFOLIO FLOWS INTO SOUTH AFRICA AND ITS KEY DRIVERS

A visual examination of the series plot shows that there are those periods in which South Africa received more portfolio flows in their balance of payments. These periods are made up of those spikes in the data, which show volatility of the series. The series has had several volatility periods. This being the case, it shows that the series is stationary in nature meaning appropriate test will not be taken or employed to stationarize the series, however in some cases nonlinear unit root tests of KSS and BNADF will be employed to assess the unit root of the series. The following sub-section will test the nonlinearity of the series. There are also apparent trends and fluctuations in the plots of the drivers of portfolio flows for South Africa.

4.2.2 Nonlinearity test results

Several tests have been developed in testing for nonlinearity in the series as this was highlighted in the previous chapter which is chapter 3. However, for the current study the BDS test will be employed to test for nonlinearity which was incepted by (Broock et al., 1996a) together with the CUSUM test of stability. Originally the BDS test was developed to test for independence and identical distribution *(i.i.d)*, however it became popular for testing nonlinearity in the series (Bisaglia and Gerolimetto, 2014). The results of the BDS test is presented in table 4.2 together with the CUSUM test results shown in figure 4.2.

TABLE 4.2: BDS TEST RESULTS

Variable(s)	Dimension	BDS Statistic	Std. Error	Z-statistic	P-value
Portfolio flows	2	0.205356	0.000794	258.5316	0.0000
	3	0.348782	0.001256	277.6763	0.0000
	4	0.448666	0.001488	301.6065	0.0000
	5	0.517933	0.001542	335.9499	0.0000
	6	0.565674	0.001478	382.6946	0.0000
Real GDP	2	0.208568	0.001094	190.7141	0.0000
	3	0.355180	0.001731	205.2321	0.0000
	4	0.458269	0.002051	223.4017	0.0000
	5	0.530777	0.002128	249.4462	0.0000
	6	0.581791	0.002042	284.9178	0.0000
Exchange rate	2	0.206652	0.001505	137.2934	0.0000
	3	0.351737	0.002392	147.0623	0.0000
	4	0.453641	0.002848	159.3021	0.0000
	5	0.525224	0.002968	176.9860	0.0000
	6	0.575494	0.002861	201.1239	0.0000
Inflation-linked bonds	2	0.208844	0.000952	219.4497	0.0000
	3	0.355196	0.001502	236.5584	0.0000

	4	0.457813	0.001774	258.0323	0.0000
	5	0.529800	0.001835	288.7783	0.0000
	6	0.580320	0.001755	330.6671	0.0000

BDS test results are shown in table 4.2, based on the results the null hypothesis of linearity is rejected in favour of alternative of nonlinearity at all significance level since the probability values of BDS test are less than the specified significance level at all dimensions. Furthermore, the CUSUM test of stability is employed to support the results of BDS test. The results of CUSUM test of stability shows that the series is unstable since the blue line of the graph goes outside the critical red lines of the graph, this confirms the results of the BDS test that the series is nonlinear. Therefore, testing for unit root, nonlinear unit root test(s) of KSS-NADF and B-NADF were intended to be employed. However, since there is limitation of KSS-NADF test with the appropriate software codes, the study will employ only B-NADF to test for nonlinear unit root.

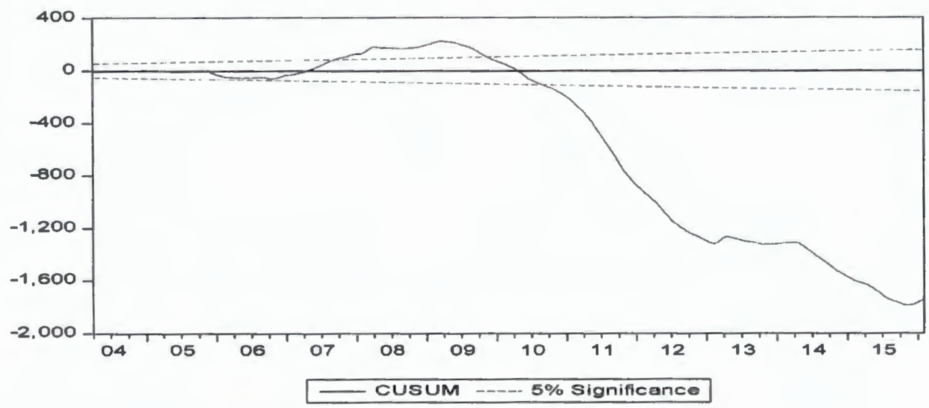

FIGURE 4.2: RESULTS OF CUSUM STABILITY TEST

4.2.3 Nonlinear unit root test results

Testing for unit root in the data has being assessed by employing the standard ADF test. However, it has shortcomings in a sense that it assumes linearity. The time series data used in the study is nonlinear in nature, hence it would be inappropriate to test unit root using ADF. The study intended to use KSS test together with B-NADF for testing nonlinear unit root in the series. These tests have been employed and gained a lot of attention. Due to the limitation of finding the syntax for KSS-NADF the study will only employ B-NADF. However, Su et al. (2013) advised that for optimal lag selection modified AIC-based KSS must be used. B-NADF test results are presented in Table 4.3.

TABLE 4.3: BIERENS NONLINEAR UNIT ROOT TEST RESULTS

VARIABLES	M	T-TEST		AM		F-TEST	
		STATISTIC	5% CRITICAL VALUE	STATISTIC	5% CRITICAL VALUE	STATISTIC	5% CRITICAL VALUE
PORTFOLIO FLOWS	2	-3.834	-3.97	-28.984	-27.20	4.924	1.08
	5	-4.296	-5.16	-37.028	-48.70	3.207	1.83
	10	-5.272	-6.67	-54.928	-80.30	2.801	2.15
	15	-5.443	-7.89	-59.565	-112.40	2.100	2.36
	20	-5.849	-9.00	-67.303	-145.70	1.899	2.52
EXCHANGE RATE	2	0.195	-3.97	0.477	-27.20	4.865	1.08
	5	-1.324	-5.16	-4.803	-48.70	4.198	1.83
	10	-1.571	-6.67	-7.213	-80.30	4.288	2.15
	15	-3.284	-7.89	-19.487	-112.40	4.775	2.36
	20	-1.572	-9.00	-11.774	-145.70	5.032	2.52
INFLATION LINKED BONDS	2	-1.406	-3.97	-1.668	-27.20	7.791	1.08
	5	-3.455	-5.16	-20.226	-48.70	6.514	1.83
	10	-5.102	-6.67	-59.842	-80.30	5.437	2.15
	15	-6.596	-7.89	-102.007	-112.40	5.150	2.36
	20	-7.271	-9.00	-143.204	-145.70	4.643	2.52

REAL GDP	2	-2.387	-3.97	-6.433	-27.20	3.074	1.08
	5	-3.773	-5.16	-30.197	-48.70	4.381	1.83
	10	-4.503	-6.67	-44.128	-80.30	4.400	2.15
	15	-3.845	-7.89	-52.833	-112.40	5.261	2.36
	20	-5.644	-9.00	-60.270	-145.70	6.061	2.52

B-NADF test results are presented in the above table on various Chebyshev polynomial orders. The process of selecting the optimal lag length for each variable on this study is the same as that used in the study of Xaba (2014), where the SBC is employed to select the optimal lag length and the test statistic is also obtained using 2000 replications of a Gaussian $AR(m)$ process. Based on the results it is shown that the null hypothesis of nonlinear unit root cannot be rejected using 0.05 significance level for all four variables. The statistic of the $t - test$, Am and Fm are all greater than their respective critical values. Moreover, this means that all four variables are non-stationary at levels.

4.3 Model estimation and results

This section outlines the estimation of the models in the study and results of SVR, ANN and SVAR models are presented. The analysis will be done based on the outline of methods and tests in chapter 3.

4.3.1 Support vector regression (SVR) model

For building support vector regression forecasting model, the $e1071\, r\, package$ proposed by Meyer et al. (2015) is adopted. The time series data is firstly scaled into the interval of $[0,1]$ using $e1071\, r\, package$. It is for the reason to avoid large input variables to affect the smaller input variables which may results in biased results.

In searching for the optimal parameters in the model of SVR. The study set an interval of the cost (C) and epsilon (ϵ) to be $(1{:}100)$ and $seq(0{,}1{,}0.1)$ respectively. Thus the optimal parameters chosen by the model are 100 and 0.4 for both the cost and epsilon parameters respectively. These model parameters give the best forecasting results (minimum testing MSE) with the best value of

0.01848077 and are set as the model parameters in forecasting portfolio inflows. The other model parameters which are of significance are the coefficients of the equation 3.24 in chapter 3. Those parameters are estimated so that they can be coefficients of the mentioned equation in chapter three. Equation 4.1 presents the coefficients of the estimated model function of the support vector regression:

$$w = [1, 1:3] \begin{Bmatrix} -6.0605 & 10.5350 & -22.6916 \\ RGDP & exchange\ rate & inflation\ linked \end{Bmatrix}$$

$$b = 0.738 \tag{4.1}$$

The following figure, 4.3, presents the two sets of parameters namely the cost parameter and the epsilon of the model respectively. The model has the best performance in the darker blue area were the best performing parameters are (epsilon and cost parameters).

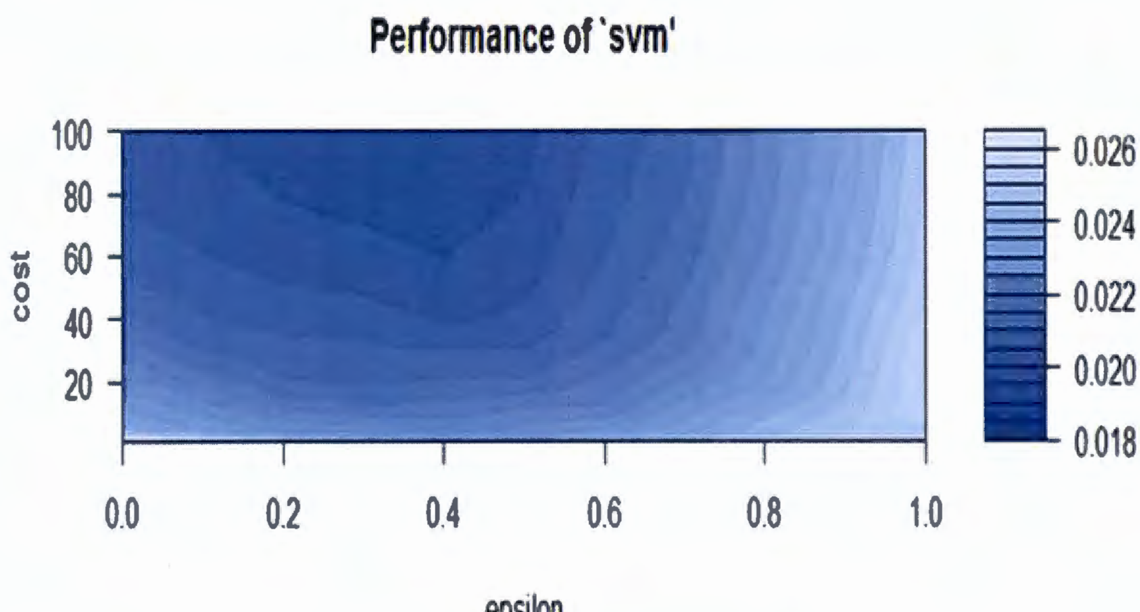

FIGURE 4.3: PERFORMANCE OF THE SVM REGRESSION MODEL

The support vector regression model was estimated for portfolio inflows and the diagnostic tests conducted to evaluate the appropriateness of this model. The results are presented in the following table 4.6. Based on the results of the Durban-Watson test and Breusch-Godfrey tests residuals obtained from the support vector regression model depict that the residuals are auto-correlated. The results are obtained using the $R - studio$ environment.

TABLE 4. 4: DURBAN-WATSON AND BREUSCH-GODFREY TEST ON RESIDUALS FROM SVR MODEL

RESIDUAL VARIABLE	AUTOCORRELATION TEST(S)	T-STATISTIC	P-VALUE
PORTFOLIO FLOWS	DURBIN-WATSON	0.078233267	0.00000000000000022204
	BREUSCH-GODFREY	861.07354	0.00000000000000022204

4.3.2 Artificial neural networks (ANNs) model

In building artificial neural network (ANNs) model the *neuralnet r package* of Fritsch et al. (2016) was used in the study. In the artificial neural network model, the data set was scaled based on the interval of $[0,1]$ so that the widely used activation function of logistic function could be used. Backpropagation algorithm is employed in training the neural network model. Since the response variable is numeric in nature the sum of squared error was used as the measuring error of the network. The threshold used was of the default of 0.01. The results of neural network are presented in the following matrix.

TABLE 4. 5: THE ANN MATRIX

ERROR	25.7554
REACHED THRESHOLD	0.0097
STEPS	13488
INTERCEPT TO 1LAYHID1	4.6054
RGDP TO 1LAYHID1	-16.9177
EXCHANGE RATE TO 1LAYHID1	-5.4977
INFLATION LINKED BONDS TO 1LAYHID1	15.7947
INTERCEPT TO 1LAYHID2	-4.2122
RGDP TO 1LAYHID2	8.7387
EXCHANGE RATE TO 1LAYHID2	2.5802
INFLATION LINKED BONDS TO 1LAYHID2	-7.4104
INTERCEPT TO PORTFOLIO FLOWS	1.4089
1LAYHID.1 TO PORTFOLIO FLOWS	-1.0273
1LAYHID.2 TO PORTFOLIO FLOWS	-1.8104

In reaching absolute partial derivative, it took the training process 13488 steps and that obtained smaller error function which is smaller than 0.01 (which is the default value of the threshold). The predicted weights had an interval of -16.92 to 15.79. For instance, the intercept of the first hidden layer were 4.605 and -4.212 and the three weights leading to the first hidden neuron are estimated as -16.918, -5.498 and -7.410 for the covariates of RGDP, exchange rate and inflation linked. The following figure presents the architecture of the neural network model estimated for the current study and is made up of four input layer, 2 hidden layers and one output layer.

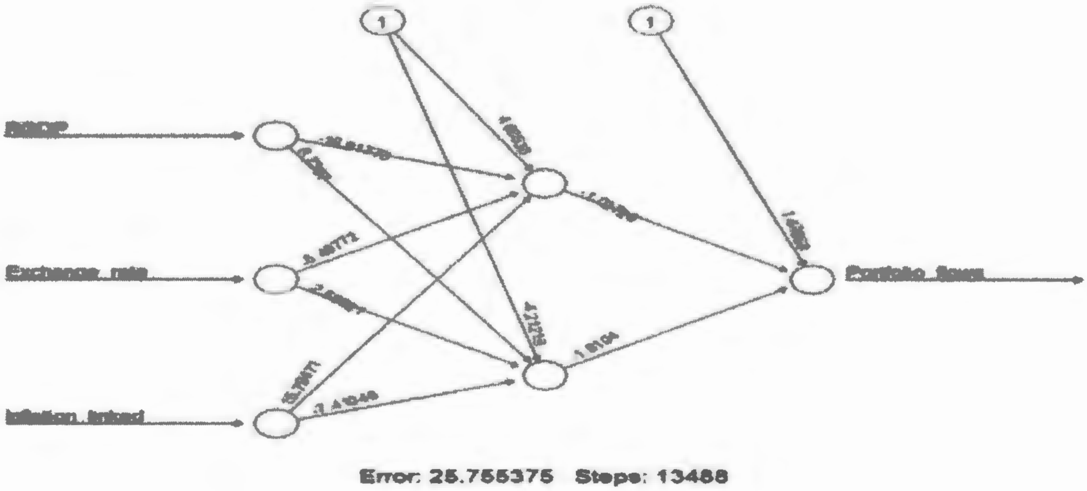

FIGURE 4. 4: ANN ARCHITECTURAL STRUCTURE

Many empirical studies have employed artificial neural networks (ANNs) for time-series modelling and forecasting. This model is a non-parametric model and does not assume any distribution, model evaluation in the current study is not undertaken. The studies which have employed this model are those of (Khashei and Bijari, 2010, Adebiyi et al., 2012, Bing et al., 2012, Ramani and Murarka, 2013, Adebiyi et al., 2014, Benkachcha et al., 2015) and model evaluations were not undertaken.

Lu et al. (2009) stated that neural networks, unlike traditional statistical models, are data driven and non-parametric. Adebiyi et al. (2014) stated that there are fewer prior assumption needed for ANNs because the model is self-adaptive and data driven.

4.3.3 Structural vector autoregressive (SVAR) model

Estimation of SVAR model is undertaken and results presented in this section. Upon estimation of the SVAR model, the unrestricted VAR model is estimated on the four stationary variables. The unrestricted VAR (8) model is initially estimated as AIC, SBC and HQC selected lag length of 8 for the model. AIC and SBC were both used in the study of (Korap, 2010) for lag length selection. Thus the unrestricted VAR (8) model is selected.

There are certain assumptions which are put forth in the study as this was the case with Çulha (2006) and Korap (2010). The study applies structural restrictions. It is assumed that portfolio flows are affected by all the shocks on the other variables. It is also assumed that exchange rate is responsive to shocks on the real gross domestic product. Inflation is also assumed to be responsive to shocks on both exchange rate and real gross domestic product. Thus the study used the following AB model in equation 4.2.

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ c(1) & 1 & 0 & 0 \\ c(2) & 0 & 1 & 0 \\ c(3) & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_t npf\_sa \\ \mu_t rgdp \\ \mu_t \inf lation \\ \mu_t exchangerde \end{bmatrix} = A$$

(4.2)

$$\begin{bmatrix} c(4) & 0 & 0 & 0 \\ 0 & c(5) & 0 & 0 \\ 0 & 0 & c(6) & 0 \\ 0 & 0 & 0 & c(7) \end{bmatrix} \begin{bmatrix} \varepsilon_t npf - sa \\ \varepsilon_t rgdp \\ \varepsilon_t \inf lation \\ \varepsilon_t exchangerde \end{bmatrix} = B$$

SVAR estimated model is presented in Appendix A and according to the results the model is over identified with 3 degrees of freedom. The LR test statistic estimated for the system identification restrictions under the null hypothesis is $\chi^2(3) = 8.39E + 09$ with a probability value of 0.0000. The structural parameters are estimated by a method of scoring (analytic derivatives). Furthermore, the SVAR impulse response function is represented in figure 4.5 with periods of 10 days using 95% confidence interval.

Figure 4.3 highlights the impulse response function (IRF) of the SVAR model which shows the 95% confidence interval of the four variables included in the study. Since there are no large margins or the confidence intervals are not large, this gives a margin of certainty that the results estimated can, at some instance, be reliable and unbiased. As can be expected, the portfolio inflows have a positive and negative response to its own shocks for the first period of the shock. According to figure 4.3 it is seen that the 'push' factors that affect portfolio inflows are the real gross domestic product together with pull factor of exchange rate. The response of portfolio inflows due to shocks on inflation is along the zero line, thereby there is a positive shock to portfolio inflows that has been brought by inflation as a push factor. After taking into consideration the structural factorization of the impulse responses, table 4.5 presents the results of the variance decomposition of SVAR model.

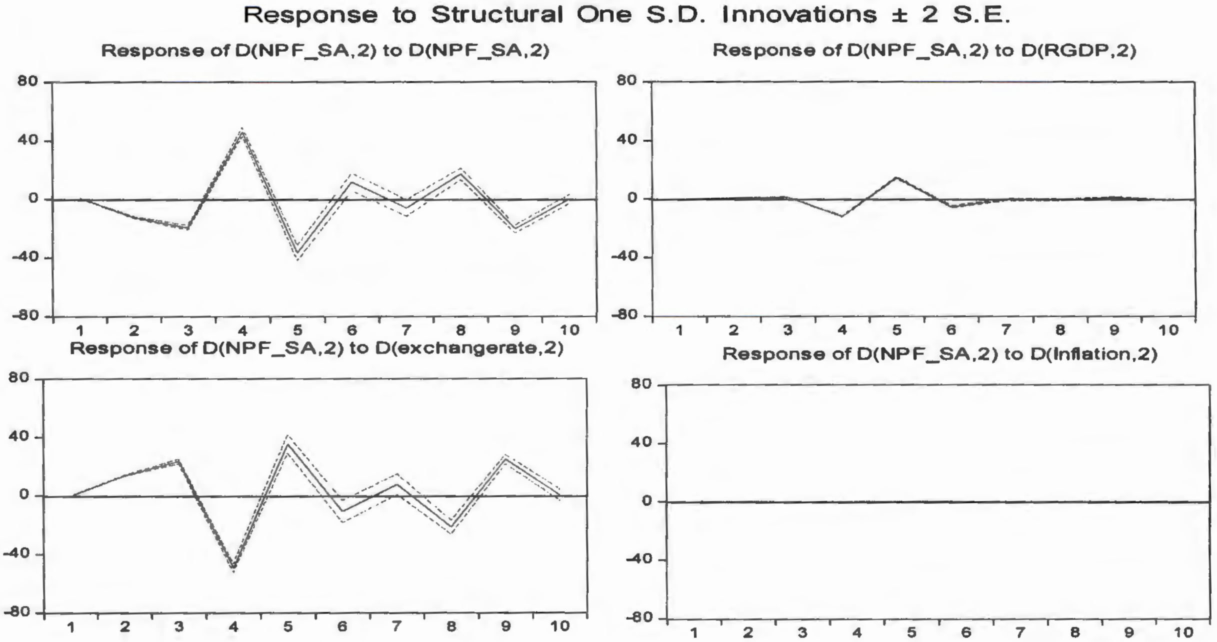

FIGURE 4.5: SVAR IMPULSE RESPONSE FUNCTION

TABLE 4. 6 SVAR VARIANCE DECOMPOSITION

VARIANCE PERIOD	PORTFOLIO FLOWS	RGDP	INFLATION-LINKED BONDS	EXCHANGE RATE
1	100.0000	0.000000	0.000000	0.000000
2	99.93822	0.000747	0.057904	0.003133
3	99.85827	0.003058	0.126535	0.012141
4	99.61583	0.202605	0.130053	0.051513
5	99.28494	0.510752	0.132892	0.071419
6	99.23974	0.550461	0.136562	0.073234
7	99.23805	0.550547	0.137191	0.074209
8	99.22872	0.550732	0.138911	0.081636
9	99.21513	0.552498	0.140840	0.091535
10	99.21462	0.552880	0.141001	0.091503

Variance decomposition analysis indicates that over the 10 periods of variation, forecast error variance of portfolio inflows of 99% can be attributed to its own shocks. The results also show that the variable which shows the best explanation (forecast error variance) is the real gross domestic product. A shock to the variable explains nearly 55% of the variation to portfolio inflows. A shock to the inflation variable explains nearly 14% of variation to portfolio inflows. The least variable which explains the minimum variation of 9% is the exchange rate to portfolio inflows. In the overall analysis the pull factors in the study explains nearly 69% of variation to portfolio inflows and only 9% of variation is explained by the only one push factor included in the study. All the estimation results indicate that the pull factors are indeed dominant over the push factors in acquiring the portfolio inflows as a form of investment into the South African economy one which is considered as an emerging market economy.

4.4 Performance criterion

According to study objectives forecasting accuracy of the two machine learning (SVR and ANNs) models are to be compared. Forecasting of the future value of any economic variable(s) is of the greatest importance to the academia, potential investors, decision making and policy formulation individuals. These models (SVR and ANNs) have never been used to model and forecast portfolio inflows together with its determinants or drivers. As such, the current study sought to determine whether these models could be of use to financial forecasting of economic variable in terms of portfolio inflows. In terms of measuring the accuracy of the included models the study used the five criteria to assess the accuracy of the models. The five criteria are MSE, RMSE, MAE, MASE and RMSLE as these measuring error matrices as discussed in chapter 3 of the study. Table 4.7 summarizes the results of these error matrices in measuring the forecasting accuracy of the models for portfolio inflows.

TABLE 4.7: FORECAST ACCURACY OF SVR, ANN AND SVAR

Performance criterion	SVAR	SVR	ANN (3-2-1) model
MSE	N/A	0.0174	0.2637
RMSE	N/A	0.1561	0.5135
MAE	N/A	0.1028	0.2637
MASE	N/A	14.3975	12.9335
RMSLE	N/A	0.0851	0.3559

From the results, four of the five criterions select the SVR model for having the highest accuracy as compared to the other model. One criterion of mean absolute squared error chooses the artificial neural networks model. Thereby it can be concluded that the support vector regression model simulates and forecasts portfolio inflows better than the ANNs model.

4.5 Comparing predictive accuracy of the models

According to Diebold (2015) the question that DM test is answering is whether one model is truly superior to another model or is it mere luck. Lower error matrices do not necessarily mean that the forecasting ability of one model is superior to another one, as the difference between the error matrices may not be statistically significant (Xaba, 2014). The need to assess the predictive accuracy of the models is apparent and the Diebold-Mariano test was employed in the current study to measure the predictive accuracy of the models. The summary of the results of the test are presented in table 4.8.

TABLE 4. 8: COMPARISON OF MODEL ACCURACY: DIEBOLD-MARIANO TEST

Variable	Hypothesis	Forecast horizon	Loss function power	t-statistic	Probability value
Portfolio flows	ANN vs. SVR	1	2	8.5086376	0.00000000000000022204

According to the results reported in table 4.8, the null hypothesis of equal predictive accuracy of the models ANN and SVR is rejected since the respective probability value (0.00000000000000022204) reported is less than the default significant level of 5% or 0.05. The alternative hypothesis state(s) that there is no equality of forecasting accuracy of pair(s) of models, furthermore model two (SVR) have a superior predicting accuracy than model one (ANNs). Therefore, since the t-statistics (8.5086376) is positive it can be concluded that the estimated SVR model is more accurate than the estimated ANN model for portfolio flows.

4.6 Concluding remarks

The current chapter presented the empirical analysis of portfolio inflows using three models made up of two machine learning models (SVR and ANNs) and one conventional econometric model (SVAR). This chapter was undertaken in-line with addressing the objectives of the study which were presented in chapter one. The results reveal the true nature of portfolio inflows and provided the best model for modelling and forecasting portfolio inflows. A fully detailed summary of findings and recommendations for future studies are presented in the next chapter.

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

5.1 Introduction

The current study aimed at developing an empirical model for portfolio inflows using machine learning techniques. The daunting reason for this is for a fact that most time-series are modelled as a linear process whereas the nature of the series is nonlinear. Machine learning are thought to be prominent in terms of being self-adoptive and data driven and based also on the fact that they are nonlinear, and also for their exceptional modelling characteristics. The current chapter will outline the summary of the findings together with the recommendations for future work.

5.2 Summary of the findings

In the current dissertation explanatory data analysis was taken. Descriptive statistics were conducted and portfolio inflows, real GDP, inflation-linked bonds and exchange rate had the mean and median scores of more than 6.00 after the logarithm of the series was employed. The first objective of the study assessed the possibility of the variables in terms of nonlinearity. BDS test and cumulative sum test are conducted. The results of the BDS test showed that the series of the variables are nonlinear in nature. This was also supported by the results of the CUSUM test which revealed that these series are unstable. Using the Bierens (B-NADF) nonlinear unit root tests, all the variables in the study are nonlinear non-stationary.

Second objective assess the forecasting performance of the models in terms of modelling and forecasting portfolio inflows. According to UVAR model the lag length of 8 was selected by the SBC. Based on the SVAR model, the results showed that the model was over identified by the 3 degrees of freedom. The impulse response function of the SVAR model showed a 95% confidence interval for the four variables included in the study. Since the SVAR impulse response function shows that the confidence interval is not large, this gives a margin of certainty that the results obtained from the estimation of the model can, at some instance, be reliable and unbiased. In the SVR model, the study employed $e1071\, r\, package$ for building the SVR model. The two parameters of the best model which were the cost (C) and epsilon (ϵ) were set in the interval of $(1{:}100)$ and $seq(0,1,0.1)$ respectively. Thus the best model of support vector regression chose the values of *100* and *0.4* for both the cost function and epsilon respectively. These model parameters give the best forecasting results (minimum testing MSE) with the best value of 0.01848077 and are set as the model parameters in forecasting portfolio inflows. In the artificial neural networks (ANNs) model, the study used the $neuralnet\, r\, package$ for building the neural network model. As is the case in the SVR model, the study scaled the variables to an interval of

{0,1} and the logistic activation function was used in the hidden layer as the activation function of the network together with the back propagation algorithm. Since the response variable is numeric in nature the sum of squared error was used as the measuring error of the network.

In assessing the modelling and forecasting performance of the models included in the data, the following error metrics were utilized: MSE, RMSE, MAE, MASE and RMSLE. The results showed that the support vector regression (SVR) model has the best modelling performance in modelling and forecasting portfolio inflows. In case of determining the factors that affect the allocation of portfolio inflows into South Africa based on the SVAR model, it is shown that *69%* of variation in the portfolio inflows is explained by pull factors (real gross domestic product and inflation linked bonds) included in the study and only *9%* is explained by push factor (exchange rate) and *99%* of variation in the portfolio inflows is attributed to its own shocks. From the discussion of the results the following conclusions can be drawn:

- ➢ All the four variables in the study are nonlinear in nature.
- ➢ The support vector regression (SVR) model has the best modelling performance of the portfolio inflows using error metrics of MSE, RMSE, MAE, MASE and RMSLE.
- ➢ The structural vector autoregressive (SVAR) model shows that *69%* of variation in the portfolio inflows can be explained by both real gross domestic product and inflation linked bonds, whereas exchange rate can only explain *9%*. The shocks of portfolio inflows explain *99%* of variation to the portfolio inflows. Furthermore, the results show that pull factors are the key drivers of portfolio inflows into South Africa.
- ➢ Based on the B-NADF unit root test, all four variables are nonlinear unit root.
- ➢ Based on the Diebold-Mariano test of predictive accuracy the support vector regression (SVR) model is more accurate than its counterpart in artificial neural network (ANNs).

5.3 Recommendations for future work

The current study showed that machine learning techniques can model portfolio inflows better than the econometric conventional model. The study would like the banking sector particularly the RMB bank to use these machine learning techniques in modelling portfolio inflows when embarking on their research. There are other machine learning techniques that can be used in modelling portfolio inflows. These can be used to signify the modelling capabilities of the machine learning techniques.

5.4 Area of further studies

Machine learning models have been prominent when it comes to time series modelling and forecasting. These methods have better understanding of the distribution of the series because of their exceptional properties. In the current study machine learning models were employed in modelling and forecasting portfolio flows. For the purpose of further research, it is advisable to employ other types of artificial neural network e.g. recurrent networks, ridgelet networks etc. Support vector machines also have their other functions e.g. dynamic least square SVM and least square SVM. These models are powerful and they can approximate any function. Although there are other parameters that the researcher should consider the most important is the selection of the threshold function, therefore it is important that for future study the researcher should also be equipped in selecting the proper threshold function. Since artificial intelligence has certain branches, the other important branch is the use of hybrid models. Hybrid models combine two or more models with different properties so that all the characteristics of the series are taken into account, thereby the use of hybrid models can be used in further research or studies. Testing for nonlinearity is of the utmost importance as these will cement the choices of the models used in modelling and forecasting the series. This dissertation employed both the BDS test and CUSUM test for testing nonlinearity, there are other tests that can be used to test for nonlinearity and these are McLeod-Li test, neural network test, Reset, Keenan's and Tsay test. These tests can be employed for further research or studies.

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APPENDICE(S)

APPENDIX A

Structural VAR estimation results

Method of scoring estimation

Log likelihood = -4.19E+09

Structural VAR is over-identified with 3 degrees of freedom

LR test: $\chi^2(3) = 8.39E+09$ probability (0.0000)

Estimated matrix A

1.000	0.000	0.000	0.000
0.092587	1.000	0.000	0.000
0.219628	0.000	1.000	0.000
0.356944	0.000	0.000	1.000

Estimated matrix B

0.591921	0.000	0.000	0.000
0.000	0.706829	0.000	0.000
0.000	0.000	0.692805	0.000
0.000	0.000	0.000	0.459003