The performance of Bayesian VAR Markov switching and logistic regression models with Monte Carlo simulated data

By

Katleho Makatjane

(23085738)

A dissertation submitted in fulfilment for the Degree **Master of Commerce in Statistics** to the Faculty of Commerce and Administration, School of Economic and Decision Sciences of the North-West University (Mafikeng Campus)

Supervisor : Prof N D Moroke

Co-supervisor: Mr L.D Xaba

April 2017

Declaration

I, Katleho Makatjane, hereby declare that this dissertation is the result of my own investigation except where otherwise stated. I also declare that it has never been submitted previously as a whole or in part for any other degree at North West University or any other institution.

Date

Acknowledgements

Undertaking this dissertation has been an inspiring and heartwarming task. Special thanks are due to my supervisors Professor N.D Moroke and Mr L.D Xaba. You have provided a meaningful guidance and support with your constant and unconditional patience and encouragement. To My fiancé, Hopolang Lenoesa, you never left my side and you have always given me that support that one ever needs. Even when it was difficult to go through my study, you always gave me encouraging words that I will be all right. Special thanks are due to the Lord all mighty, for giving me strength and power to do all this wonderful work and being with me for the entire master's program. A big thank you to my family, especially Professor T.J Makatjane and Mrs Makatjane, and all my friends. Thank you all.

Dedication

This piece of writing is dedicated to my family, and friends. A special feeling of gratitude goes to my loving parents Tiisetso and Makatleho Makatjane, my fiancé Hopolang Lenoesa, my nephew Matiisetso Makatjane. A special dedication goes to Professor N.D Moroke and Mr LD Xaba for giving all they have for me to attain my statistical skills. I am who I am today because of your unconditional and constant help throughout my whole career.

Table of Contents

List of Tables

Acronyms and abbreviations

AIC	Akaike information criterion
ANN	Artificial neural network
ANSR	Adjusted noise-to signal ratio
AR	Autoregressive
ARCH	Autoregressive conditional heteroscedasticity
ARMA	Autoregressive moving average
BDS	Brock-Dechert-Scheinkman
BVAR	Bayesian vector autoregressive
CDF	Cumulative density function
CUSUM	Cumulative sum
DGP	Data generating process
EM	Expectation maximisation
EWS	Early warning system
EXAR	Exponential autoregressive
GARCH	Generalized autoregressive conditional heteroscedasticity
GLM	Generalized linear model
HMM	Hidden Markov model
HQC	Hannan-Quinn criterion
IV	Input Variable
JB	Jarque-Bera
KSS-NADF	Kapetanios, Shinn-Shell nonlinear augmented Dickey-fuller
LA	Logistic analysis
LRM	Logistic regression model
MAE	Mean absolute error
MAPE	Means absolute percentage error
MCMC	Markov chain Monte Carlo
MDA	Multiple discriminant analysis
MLE	Maximum likelihood
MS-AR	Markov-switching autoregressive

MS-BVAR	Markov-switching Bayesian vector autoregressive
MSE	Mean square error
MS-GARCH	Markov-switching generalized autoregressive conditional heteroscedasticity
MSM	Markov-switching model
MSR	Markov-switching regression
MS-SVAR	Markov-switching structural vector autoregressive
MS-VAR	Markov -switching vector autoregressive
NCD	Normal cumulative distribution
OLS	Ordinary least square
PCCC	Percent of Crisis Correctly Called
PFA	Percent of False Alarm
PNCC	Percent of Non-Crisis Correctly Called
POCC	Percent of Observation Correctly Called
PRGNS	Probability of an Event of High Inflation Given No Signal
PRGS	Probability of an Event of High Inflation Given a Signal
RESET	Regression specification error test
RMSE	Root mean square error
RSA	Republic of South Africa
SA	South Africa
SARB	South African reserve bank
SBC	Schwarz Bayesian criterion
STAR	Smooth transition autoregressive
SVAR	Structural vector autoregressive

Abstract

In this study, the main intention is to build an early warning system (EWS) model for inflation in South Africa using the findings from the Markov-switching Bayesian vector autoregressive (MS-BVAR) on logistic regression model. Monte Carlo experimental methods are used to simulate both the inflation rate and repo rate of South Africa. In total, the procedure simulated 210 observations for the period January 1999 to June 2016. For this data generating process, the study followed a Gibbs sampling technique. Prior to model estimation, preliminary test of nonlinearity called the Brock Dechert Scheinkman (BDS) test was employed and the results confirmed the data to be nonlinear and suitable for MS-BVAR method. The Kapetanios-Shin-Snell nonlinear augmented Dickey-Fuller (KSS-NADF) also confirmed the presence of nonlinear unit root in the simulated series. Moreover, the RESET test, CUSUM and Bai Perron multiple break point tests were also calculated to determine if there is structural change in the data and that the model is correctly specified.

With the attempt to build an early warning system (EWS) model, the study estimates the $\mathrm{MS}-\mathrm{BVAR}(1)$ model of two regime shifts. This model serves as a primary tool in detecting regime shifts in inflation in terms of low and high regimes. The results of the $\mathrm{MS}(2)-\mathrm{BVAR}(1)$ indicates that the SA inflation might be in low inflation regime for the period of 11 years and 4 months. Furthermore, the results of the logistic regression revealed that the repo rate is not a good tool to predict inflation rate. The results of the marginal effects of the repo rate towards inflation rate implied that if everything held constant, a 1% increase in repo in a month increases inflation by 81%.

Similar results were also reported by several authors such as Mboweni et al. (2008); Gupta and Komen (2009); and Bonga-Bonga and Kabundi (2015). In predicting the possibility of inflation crisis in SA, the assessment of the EWS model confirmed that only 57% of the inflation crises are correctly called for by the in-sample model compared to the 45% of correctly called by out-of-sample model forecasts.

The study concluded that combating inflation rates in South Africa (SA) using variables such as repo rate might not be a good idea as this might also increase the likelihood of SA being be into inflationary. Finally, the study recommends the enhancement of error correction model to the MS-BVAR model when including other determinants of inflation rate in the analysis. The study might provide a clearer picture about both the long-term and short-term relationships between inflation and related variables. Such findings might be used by policy makers to embark on strategies to combat the anticipated inflationary crisis in South Africa.

Key words: Early warning system, Markov-switching Bayesian vector autoregressive, Monte Carlo Simulation, logistic regression analysis, inflation rates

CHAPTER 1

ORIENTATION OF THE STUDY

1.1 Introduction

The global monetary authorities have targets for smoothing inflation rates including high prices. South Africa is not an exception in striving to this accomplishment. Volatile inflation rates twist the judgement that consumers make about their living standards, and this is evident from past studies which reported about the importance of prices stability. The slow economic growth rates are subdued to markets failure which results from these distortions. Money circulation in the economy for buying goods and services slowly but surely wear off because of high inflation which in the long run harms the households specifically those with low incomes. Nevertheless, keeping a low inflation rate and stabilising it supports sustainable economic growth.

Since consumer inflation is the main indicator in determining the sustainability of economic growth, all trusts of the rate cresting underneath 10% in the first quarter of 2008 have now been surrendered. Inflation rate of South Africa is being driven by four fundamental powers such as food prices, up 70% comprehensively; oil prices (up 65%); the rand (down 15%) against an extremely feeble dollar so far this year Svensson (2005). Other powers are a solid domestic consumer demand during an era when output is obliged by bottlenecks and prominently power and skilled labour. Going ahead, the stress is that proposed power price treks of about 50-60% in 2008/09 guaranteed that inflation stays in twofold figures, particularly if food price stays high Hyvonen (2004).

To exceptionally combat inflation rate to low rates, Bernanke and Woodford (1997) indicated that policy instruments are changed by significant monetary policy lag. According to Mishkin and Schmidt-Hebbel (2007), the persistent increment of South African's (SA) repo rate caused the inflation rate to develop outside the 3%-6% interval since early 2007. However, the expectation was that the repo rate will sooth inflation rate. In order to achieve best approaches, Svensson (2010) suggested: (1) algebraic growth targets, (2) significant fiscal strategy that provides part of the expansion forecasts to be practiced; and lastly (3) selection of the short-run enthusiasm rate as the best instrument for fiscal strategy.

1.2 Problem statement

In 1994 the first democratic government of South Africa inherited a persistently high inflation above ten percent per annum. These high inflation rates caused a regressive effect on lower-income families and older people in society because prices for food and domestic utilities such as water and heating rose at a rapid rate Psaradakis and Sola (1998). However, the year 2000 was marked by the approval of an inflation targeting framework as the anchor of monetary policy in South Africa (Bonga-Bonga and Kabundi, 2015). In collaboration with the South African Reserve Bank (SARB), the minister of finance decided the target which was to achieve the average of 3%-6% interval by the year 2000. Previously the SARB was using the repo rate as the policy instrument to control the level of inflation within the chosen interval. However, the effectiveness of the repo rate as policy instrument to control the inflation rate has not been criticized in SA only, but also universally according to Bonga-Bonga and Kabundi (2015). The reason for repo rate being criticized is that altering the repo rate in the monetary sector, affects short-term liquidity in the monetary system, which quickly has an effect on all other rates.

The SA inflation rate went out of the interval in the early 2007 where it then increased from 3% to 8.6%. The recurrent upturn in the repo rate in order to curtail the inflation rate has speeded up its trend rather than subduing it. This is a period in which SA had encountered high production levels because it experienced far above the ground interest rates, increasing inflation, a prolonged fall in prices and trade of housing and vehicle markets and also a degrading of business and consumer firm trust indicators. These problems could have been avoided if they were detected earlier before inflation rates got out of control. It is clear, given these reasons, that there is still a gap with regards to this sector, especially when it comes to controlling it. Reasons may be studies done around warning systems in inflation are fragmented if at all they do not exist or that the methods used are not as effective as possible. This prompted the undertaking of this study where statistical methods such as logistic regression are explored in conjunction with the Monte Carlo simulated inflation rates and estimates Markov-switching model to develop an early warning system and determine the likelihood of future high inflation rate in South Africa. The findings could be useful in alerting the policy makers well in advance about the anticipated inflation rates and as a result, strategies to curb such problems could be devised beforehand.

1.3 The study aims and objectives

The overarching aim of this study is to explore MS-BVAR model with two regimes to estimate and forecast the inflation rate regimes within the country and finally use logistic regression model to quantify the possibility of the future occurrence of high inflation.
To help address the problem, the following secondary objectives are formulated:

- To simulate the inflation and repo rates data using Monte Carlo method.
- To estimate a Markov-Switching Bayesian vector autoregressive model using the inflation rate and repo rate of South Africa
- To estimate the logistic regression model as a classifier of inflation crises on the basis of repo rate.
- To formulate suggestions for policy and future studies.

1.4 Significance of the study

The study will contribute to literature of early warning system (EWS) by envisioning the probability of inflation crises in the Republic of South Africa (RSA). The expected duration of high and low inflation will be distinguished together with the transition probabilities of the high and low regimes. This monitoring tool so called EWS comprises a detailed definition of a crisis and a mechanism for causing likelihoods of crises (Edison, 2000). The upgrading of EWS for use in economic policy invention will transmit mainly to the extrapolation of financial crises and economic crises.

The warning signs that are driven by a logistic regression model (LRM) will also help in detecting the inflation turbulent for the following 5-years period. The use of the 5-year period will give a larger sample as the study is focused on the monthly simulated series and this also helps in protecting the normality assumption. Given these reasons, the study contributes to the methodology of EWS and fills the gap in early warning signs of inflation crisis. Both scholars and policy makers will benefit from this study.

From the findings of the study, suggestions will be given towards policies of the monetary policy framework. For the monetary policy committee (MPC), the study will develop the models that will help them to enrol into the EWS framework for inflation. To assess the inflation environment outlook risk, the South African reserve bank (SARB) may also use this EWS model to substitute the existing inflation toolkit.

1.5 Organization of the study

This study consists of five chapters which are presented as follows:

Chapter 1: The chapter provides the introduction to the study and it also provides a background that creates relevance for the study. In this section, the study objectives are outlined, significance of the study together with the limitations to the study are also explained.

Chapter 2: This chapter presents the review of concepts of the literature regarding the MS-BVAR models used to model the inflation regime episodes and the logistic regression model that will help in predicting the likelihood of occurrence of high and low inflation within the in-sample and out-of-sample forecasts.

Chapter 3: The chapter entails the methodology adopted for this study. Detailed theory of statistical tests that are used to analyses data in developing the EWS are discussed.

Chapter 4 This chapter gives an outline of empirical analysis and interpretation of results.

Chapter 5: This chapter outlines the discussion of findings and provides the conclusion to the whole study and recommendations for future studies and policy.

1.6 Conclusion

The chapter introduced the study by providing a motivation for the study and defining the problem. The study objectives were outlined on the basis of the problem. Also listed were the study scope limitations and delimitations and further the significance of the study was explored. The next chapter discusses theoretical underpinnings adopted by the study and empirical literature on the subject.

CHAPTER 2

EMPIRICAL AND THEORETICAL LITERATURE

2.1 Introduction

The financial chaos that hit developing markets in the latest decades has initiated the need for precise country hazard assessment (Fuertes and Kalotychou, 2007). To explain and predict the crisis of the country including the currency crises, several models have been developed by a number of studies worldwide (Kumar et al., 2003). In observing the crises empirically, it is significant to be indistinct on how a crisis is defined. The purpose of the present study is to predict the possibility of inflation crisis in South Africa. The models used for determining the early warning signals of inflation are discussed in this chapter together with those used for obtaining regime switches of inflation rates.

The remaining part of this chapter is as follows: Section 2.2 gives an overview of the nonlinear time series models. Section 2.3 discuses Monte Carlo simulation. Section 2.4 presents an overview of regime switching models while section 2.5 discuses Markov-switching model and extensions. Section 2.6 discusses the empirical literature and finally section 2.7 presents concluding remarks for the chapter.

2.2 Nonlinear models

According to economic theory, a number of time series variables are expected to be nonlinearly related (Kleiber and Zeileis, 2008). Most business cycles experience a sharper recession than salvages in key macroeconomic variables. The variable of interest for the current study is inflation rate. Standard autoregressive moving average (ARMA) relies on linear difference equations, new dynamic area of time series econometrics seems to be growing.

Jonathan and Kung-Sik (2008) suggested that a linear ARMA model should conform to normal distribution standards. However, this linear, normal process suffers some limitations because the ARMA models are stationarised before estimation, they are therefore characterised by their mean and autocovariance function, hence the process reversed has the same distribution as the original process. The latter is known as time reversibility. Conversely, nonlinear time series models generally display rich dynamical structure. Indeed Jonathan and Kung-Sik (2008) showed that a very simple nonlinear deterministic difference equation may admit chaotic solutions in the sense that its time series solutions are sensitive to the initial values which may appear to be distinguishable from a white noise sequence based on correlation analysis.

Nonlinear time series analysts thus may provide more accurate predictions which can be very substantial in certain parts of the state space and shed novel insights on the underlying dynamics of the data. Therefore, the analysis of nonlinear time series was earnestly initiated in the late 1970s in which the need for modelling the nonlinear dynamics shown in the real data was prompted by (Tong, 2012). Makridakis and Hibon (2000) warned that linear models are not suitable to epitomize abundant nonlinear patterns; perhaps, asymmetry, high moment structures, time varying, asymmetric cycles, and jumps or breaks in a time series.

Due to unexpected constraints, some researchers more often than not, change the problem of nonlinearity to suit the linear models for the purpose of their studies (Kantz and Schreiber, 2004). While linear models on the one hand are helpful for much research, nonlinearity swarms our consistent life and ought not to be overlooked on the other hand. The motivation behind this is that, nonlinear models are now being given attention specifically business cycle models such as Markov-Switching models and many more.

Since, there exist a number of nonlinear time series models, it is customary to first test the linear hypothesis against the alternative of nonlinear before any modelling can be done (Kantz and Schreiber, 2004). Two nonlinear models such as Markov-Switching autoregressive (MS-AR) and Logistic Regression model have been considered by Cruz and Mapa (2013) with the aim of developing an early warning system model. The forecasts were combined by the regime switching of inflation and the likelihood of the occurrence of the inflation crisis.

Because Zhang (2003) has indicated the importance of combining linear models together with nonlinear models, by following the combination style of Zhang, the study combines the Bayesian Vector Autoregressive (BVAR) with Markov Switching model (MSM). This approach helps in addressing the complexity of serially correlated structures of the data set and dynamic changes in the same given series such as structural changes.

The combination for linear models together with some nonlinear models has gained some popularity in recent methodologies. However, this idea has been implemented decades ago. Terui and Van Dijk (2002) have shown that a combination of a Threshold autoregressive model and exponential autoregressive (ExpAR) have complete each other in their performances, and lastly that the combined forecasts from the models can be based locally on linear or nonlinear model which is far much important for time series that exhibits structural changes.

Aside from the MSM and logistic regression models, there are some nonlinear parametric models.; these include autoregressive Conditional heteroscedasticity (ARCH) and general autoregressive conditional heteroscedasticity (GARCH), artificial neural network (ANN), threshold autoregressive and Smooth transition autoregressive (STAR) which have been used for forecasting for some time. In any case, the greater part of the nonlinear statistical procedures require that the nonlinear model must be determined before the estimation of the parameters is done (Xaba et al., 2015).

According to Asteriou and Hall (2015), this pretesting for nonlinearity can help one to be protected from overfitting the data. Recursive estimation and the CUSUM test are frequently used for detecting nonlinearities. A number of additional procedures that have been developed to determine if the data seem to be nonlinear are used in the current study which are the RESET test and BDS test. In which the reset test was developed by Ramsey (1969) to test for the specification errors in classical linear models. in which the null hypothesis is that the model is correctly specified as a linear model. On the other hand, the BDS test was developed by Brock et al. (2001) to test for the independence based on the correlation dimension.

2.3 Monte Carlo Simulation

Monte Carlo simulations are used to model the probability of different outcomes in a process that cannot easily be predicted due to the intervention of random variables. These contain the dynamic panel group and time specific effects. Smith et al. (2013) have shown that the data generating process has 4 steps. These steps are the initialisation, importance sampling step, selection step and

Markov transition step. Since this is a sequential method of Monte Carlo, the initialisation step is to initialize the random variable X to some value and then the variable is picked randomly and resampled.

The ultimate assumption is that all evidence about the data generating process (DGP) contained in the original sample of data is also confined in the distribution of these simulated samples. Resampling from one sample is corresponding to generating completely some new random samples from the population. Another way to think about this is that if the sample of data at hand is a reasonable representation of the population, then the distribution of parameter estimates produced from running a model on a series of resampled data sets will provide a good approximation of the distribution of that statistics in the population (Doucet et al., 2001).

The role of Monte Carlo methods has increased in importance during the past several years. According to Gentle (2013), many advances in the field of random number generation and Monte Carlo methods have been made. These methods assume a focal part in the rapidly developing sub disciplines of the computational physical sciences, the computational life sciences, and the other computational sciences. The developing force of computers and the developing simulation methodology have prompted the acknowledgment of computation as a third approach for propelling the characteristic sciences, together with theory and customary experimentation.

Generation of random numbers is also at the heart of many standard statistical methods. The random sampling required in most analyses is usually done. The computations required in Bayesian analysis have become viable because of Monte Carlo methods. This has led to much wider applications of Bayesian statistics, which, in turn, has led to development of new Monte Carlo methods and to refinement of existing procedures for random number generation (Zio, 2013).

Hammersley (2013) has indicated that Monte Carlo methods represents the solution of a problem as a parameter of the hypothetical population and by using random numbers as a sequence. The sample is drawn from the population from which statistical estimates of the parameter can be obtained. The standards for Monte Carlo experiments in statistics were set by Sawilowsky and Fahoome (2003) and Sawilowsky (2003) with the aim of improving the randomization and permutation test.

Diebold and Inoue (2001) used Monte Carlo experiments to show that the stochastic regime switching is easily confused with long memory even asymptotically as long as a small amount of regime occurs. For their study, Diebold and Inoue, simulated 10,000 realisation from various stochastic regimes switching. They further characterised the finite sample inference with a standard estimator of long memory parameter. The current study does simulation of data through the Gibbs sampling.

2.4 Overview of regime switching models

These types of models can be usefully divided into two categories. The Threshold models, which are modified by Tong (2012) were firstly introduced by Tong (1978) with the assumption that regime shifts are triggered by the level of observed variables in relation to an unobserved threshold. Markov switching models (MSM) which were introduced to econometric modelling by Goldfeld and Quandt (1973), Cosslett and Lee (1985) and Hamilton (1989), with the assumption that the regime shifts evolve according to a Markov Chain.

Piger (2009) accentuates that there is substantial interest in modelling the dynamic behaviour of macroeconomic and financial quantities that are observed over time. The greatest challenge is that time series data likely undergo changes in their behaviour over reasonably long sampled periods. Because of the potential shifts of economic time series, constant parameter time series models are becoming inadequate for describing their evolution hence there was a need to design parameter variation models.

MSM is a regime-switching model in which the shifts between regimes evolve according to an unobserved Markov Chain(MC). According to Piger (2009), regime switching models are time series models in which parameters are allowed to take different values in each of some fixed number known as regimes. A stochastic process assumed to have generated the regime shifts is included as part of the model, which then allows for model-based forecasts that incorporate the possibility of future regime shift.

Simple regime switching models have never found their statistical significance in both empirical and theoretical research in earlier research except their alternative models such as AR models.

However, scholars such as Kim and Nelson (2001), Kim et al. (2005) and Hamilton (2005) had found some strong statistical significance for both empirical and theoretical research. With that note, Hamilton (2005) focused on the alternative measures of the economic activity, while Kim and Nelson (2001) extended the univariate Markov switching to the multivariate model.

Another class of regime switching models is a Threshold autoregressive (TAR) model. This model was developed by Tong (1978) in time series settings. TAR depends on a few nonlinear elements regularly experienced practically, for example, increasing or decreasing asymmetry designs in a given time series. Ordinarily, the TAR model can be portrayed as a set of various linear AR models, with regime switches happening because of the development of threshold variable(s) with respect to fixed threshold(s). More particularly, in parts, the TAR model utilizes linear models to get a favoured estimation of the conditional mean. In spite of the fact that the TAR model is mostly linear, the likelihood of regime switching suggests a general nonlinear conduct for a given time series (Xaba et al., 2015).

According to Brooks (2001), TAR models have been less widely used than conditional variance models in the arena of economics and finance despite that these models are becoming more popular. The models are clearly of importance when the data may be drawn from one AR model in one regime, but an entirely different autoregressive model in another. Enders (2008) defines a TAR model as a regime switching model that allows the behaviour of a time series say (X_t) to depend on the state of the system. The TAR model parameters can be estimated using the ordinary least square (OLS) approach. In addition, one side of the threshold (X_t) sequence is governed by one AR process and on the other side there is a different AR process. Although (X_t) is linear in each regime, the likelihood of regime switching means that the entire (X_t) is nonlinear.Jonathan and Kung-Sik (2008) had also indicated that the value of the threshold is unknown and it must be estimated along with the other parameters of the TAR model.

Another family of regime switching models is the Smooth Transition Autoregressive (STAR) model which was developed by (Chan and Tong, 1986). The STAR model can be thought of in terms of the extension of AR model, allowing for changes in the model parameters according to the value of weakly exogenous transition variable Z_t. The model comprises of two AR parts connected by the transition function. The model is normally alluded to as a STAR(p) with the latter depicting the transition function. In particular, p is the order of the AR part. The most well-known transition function incorporates the exponential function and first and second-order logistic functions which in turn offer ascent to logistic STAR (LSTAR) and Exponential STAR (ESTAR) models (Tong, 2012).

2.5 Markov switching model and extensions

This section provides a description and discussion of MS model and the extensions.

2.5.1 AR enhanced Markov-switching model

Because many time series occasionally exhibit dramatic breaks in their behaviour, Hamilton (2010) has indicated that MSM are quite amenable to theoretical calculations of how these abrupt changes in fundamentals show up especially in financial time series. To describe the consequence of a dramatic change in the behaviour of a single series say Y_t, Ang and Bekaert (2002) and Dai et al. (2007) have discovered that the behaviour of the past can be described by the first order autoregressive denoted by AR(1). Due to the failure of the AR(1) to account for the change in the parameters, the current study establish a larger model encompassing the change in the parameter and the model must be estimated as:

$$Y_t = C_{st} + \Phi Y_{t-1} + \varepsilon_t \tag{2.1}$$

where C_{st} is the random variable that has happened as a result of institutional changes with values starting from $s_t = 1$ for $t = 1,2, \ldots, t_0$ and $s_t = 2$ for t=$t_0 + 1, t_0 + 2, \ldots$. A full description of the dynamics of Y_t could be obtained if a probabilistic description of how the economy changes from one regime to another is available. According to Hamilton and Raj (2013), the simplest model would be an MC written as:

$$\Pr(S_t = j | S_{t-1} = i, S_{t-2} = k, \ldots., Y_{t-1}, Y_{t-2}, \ldots) = \Pr(S_t = j | S_{t-1} = i) = p_{ij}. \tag{2.2}$$

With the assumption that S_t is directly unobservable, its operation can be inferred through the observed behaviour of Y_t. According to Timmermann (2000), the probability law governing the parameters it fully follows the Gaussian innovation σ^2, the coefficient of an autoregressive Φ, the two intercepts C_1 and C_2 and finally the two state transition probabilities p_{11} and p_{22} that follow homogenous MC.

An attractive feature of the model is that no prior information regarding the dates when the economy was in each regime, or the size of the two growth rates is required. This is in contrast with models such as probit and logit models that require and depends heavily upon the exact dates of all the regimes in the history of the series. Instead, the probability of being in a particular regime is inferred from the data (Moolman, 2005).

It should be noted that the way things are, the model needs a confinement to uniquely characterize the states and the state specific parameters. Generally, economic instinct or the purpose of the analysis itself yields such a confinement. Thinking of restrictions over time, a natural identification will be associated with the first state of periods of low inflation rate and second state with periods of high inflation, i.e. ordering the state specific parameters according to some element of Φ such that $\Phi_{1i} < \Phi_{2i}$ of which i is either a value out of $1, \dots,$ R. Kaufmann (2002) has shown that there is a problem of choosing the parameters as for which the states are recognized. Possibly, the states may even be ineffectively separable in terms of Φ, but well separable in terms of the persistence parameters $\eta_{ii}, i = 1,2$, in which η_{ij} is defined in (2.2) and a more generalisation is:

$$\eta_{ij} = p(S_t = j | S_{t-1} = i) \tag{2.3}$$

Restricting, η such that $\eta_{11} < \eta_{22}$ this would then help in identifying the state specific parameters. Sometimes, even a combination of the two might be appropriate see (Kaufmann, 2000).

In practice, if the process is not irreducible, all states are visited with non-zero probability in the steady state. This means that the moment analysis can simply be conducted on the subset of states occurring with non-zero stationary probability, *i.e* an analysis of the unconditional moments starting from the steady state need not assume that the Markov process is irreducible. This is so as either a single state or a block of states in absorbing all other states and therefore it will have zero steady state probabilities (Timmermann, 2000). In this case, MC (2.2) act as if the shift from C_1 to C_2 is a deterministic event and therefore the permanence of shift would be represented by $p_{22} = 1$ though the Markov formulation which invites a more general possibility that $p_{22} < 1$.

A model of the form of (2.1)-(2.2) with no AR elements, *i.e* $\Phi = 0$ was first invented by Baum et al. (1970), while Hamilton (2010) incorporated the AR elements and described such a process as a “Hidden Markov models”(HMM). The formulation of the problem described here, in which all the objects of interest are calculated as a by-product of an iterative algorithm similar to Kalman filter is due to (Hamilton, 1989). In instances where Y_t is observed directly, inferences about the S_t values takes the form of two probabilities such that:

$$\xi_{jt} = \Pr(S_t = j|\Omega_t; \theta), \tag{2.4}$$

for j=1,2, and the sum of these probabilities is at unity. Ω_t denotes the set of observations obtained at t and θ is a vector of population parameters which the general presentation is $\theta = (\sigma, \Phi, C_1, C_2, p_{11}, p_{22})^{`}$. Francq and Zakoıan (2001) indicated that the inference is performed iteratively for $t = 1,2, \ldots, T$ with step t accepted as input values:

$$\xi_{i,t-1} = \Pr(S_{t-1} = i|\Omega_{t-1}; \theta) \tag{2.5}$$

for, $i = 1,2$ and this produce the same output as in (2.2). The key magnitudes one needs in order to perform this iteration are the densities under the two regimes which are calculated like:

$$\eta_{jt} = f(Y_t|S_t = j, \Omega_{t-1}; \theta) = \frac{1}{\sqrt{2\pi\sigma}} e^{\left[-\frac{\left(Y_t - C_j - \Phi Y_{t-1}\right)^2}{2\sigma^2}\right]} \tag{2.6}$$

These industriousness parameters are essential in determining the higher order snapshots of the MS process. Moreover, autoregressive parameters are brought into the procedure as in the second and third switching models and extended to vector autoregressive form. This offers ascend to cross-product terms that upgrade the arrangement of third and fourth order moments and the patterns in serial correlation and volatility dynamics that these models can produce.

At the point when the MS models are considered as data producing forms, Yang (2000) demonstrates that it is alluring to clarify the generated MS processes by the conventional stationary-nonstationary basis and to describe their autocovariance structure. Economic theories frequently propose that disparities in economic harmony relationships ought to be stationary after some time. The known possibility for such stationary inconsistencies incorporates stationary

ARMA and fractional ARMA process. Compared with these stationary procedures, the MS process seem more adaptable as a structural shifts and short-run asymmetric responses can be portrayed efficiently (Hamilton, 2010). In the event of stationarity, the MS procedures will give an adaptable option system to model the disparities in economic equilibrium relationships. Accordingly, finding and describing stationarity conditions for the MS models seem imperative (Yang, 2000).

2.5.2 VAR enhanced Markov-Switching model

The extension of a univariate MSM to multivariate models was pioneered by many scholars which among them include Kim and Nelson (2001) and Droumaguet (2012) the new extended model is known as Markov-Switching Vector autoregressive (MS-VAR) which is the extension of (2.2-2.3) respectively. The observed time series is of a vector $Y_t = (Y_{1t}, \dots, Y_T)'$ whose parameters are unconditionally time varying but constant when conditioned on an unobservable discrete regime variable $S_t \in \{1, \dots, M\}$. A P^{th} order M-state MS-VAR of K-dimensional time series vector is denoted by $MS - VAR(p)$. Which therefore yield:

$$Y_t = \mu_{St} + \sum_{i=1}^{P} \Phi_{St}^{(i)} Y_{t-1} + \varepsilon_t \tag{2.7}$$

The error term of the MS-VAR follows the Gaussian distribution that is conditioned on S_t: $\varepsilon_t | S_t \sim NID(0, \sum(S_t))$. As per Francq and Zakoıan (2001), the parameter shift functions such as $\mu(S_t), \Phi_1(S_t), \dots, \Phi_p(S_t)$ and $\sum(S_t)$ describes the dependence of the vector autoregressive (VAR) parameters on the regime variable S_t as:

$$\begin{cases} \mu_1 = (\mu_{11}, \dots, \mu_{k1})` & \text{if } S_t = 1 \\ \vdots & \\ \mu_M = (\mu_{1M}, \dots, \mu_{kM})` & \text{if } S_t = 2 \end{cases} \tag{2.8}$$

The decisive characteristic of the MS model is that unobservable realisations of the regime such that $S_t \in \{1, \dots, M\}$ are generated by a discrete time, discrete state and Markov state stochastic process defined by the following transition probabilities:

$$p_{ij} = \Pr(S_{t+1} = j | S_t = i), \sum_{j=1}^{M} p_{ij} = 1 \tag{2.9}$$

As normalization, the regimes are ordered with increasing mean, *i.e* $\|\mu_1\| < \|\mu_2\|$. Identification requires that for all $m \in \{1, \dots, M\}$, there exist at least one $k \in \{1, \dots, K\}$ such that $\mu_{km} \neq \mu_{1i}$ for $i \neq m$. Bayesian methods are incorporated in this study as to compute the value of N implying the largest value for the marginal likelihood and the highest Bayes factor and adopted by Krolzig (2003) who enhanced MS-VAR model and introduced Bayesian priors. In addition, he used the model to explore the regime switches of inflation rates of South Africa. This model is basically used as a precursor to the logistic model for the current study. The intention is to obtain the regime switches and factor them into a logistic regression framework which is later used as a predictor of inflation crisis in South Africa.

The MS-VAR has two conditional assumptions which characterize it. (1) The first order MC where its development is autonomous of the past series is expected to be a series type of $\{S_t\}$ with the conditional distribution of latent series given the estimation of $\{S_t\}t' < t$ and it just relies upon the latent series with one lag. (2) The inflation rate is an AR process of order $P > 0$ with the coefficients advancing in time with the sequence of the inflation type of $\{X_t\}t' < t$ and $\{S_t\}t' < t$ is the conditional spreading of Y_t.

Zhou et al. (2014) constructed MS-VAR model to measure the nonlinear correlation between stock returns in Shanghai, Hong Kong and America, finding differing characteristics in the correlations among markets and various dynamic causal relationships. The MS-VAR approach adopted in this paper then also takes inspiration from the work of Rodriguez (2007), Zhou et al. (2014) and Troug and Murray (2015).

The advancement of Hamilton (1989, 1990) MSM offered ascent exploration of the exchange rate dynamics movements in the studies of currency crises. The modelling of EWS for currencies through the implementation of Markov-Switching Regression (MSR) with two considered regimes together with stable and volatility as a mixture of two normal distributions was first modelled by (Engel and Hakkio, 1996). Nevertheless, time-varying transition probability of the MSR model demonstrated an impermeable of pollution in Asian financial crisis.

2.6 Empirical literature

This section of the study evaluates the empirical literature as part of the selected models for the study.

2.6.1 Empirical literature on Markov-switching vector autoregressive model

The studies of financial models have gained more practice in recent years. Nonlinear models such as Markov-Switching have twisted out to be increasingly the mainstream of industrial economic and financial studies. Breaking it down into pieces, this includes among them industrial production, business cycle issues, interest rate, unemployment rates and stock prices among others. Because MSM are often adopted by researchers with the aim to account for specific features of economic time series such as the asymmetry of economic activity over the business cycle, Timmermann (2000) has indicated that these features translate into the higher order moments and serial correlation of the data generating process, so a characterization of the moments and autocorrelation function generated by MS will allow researchers to better understand when to make use of this class of models.

On the other hand, Ailliot and Monbet (2012) indicated that the Hamilton's Markov-Switching is an algorithm of drawing the probabilistic inference of discrete shifts of the mean growth rate of a nonstationary series in the form of a nonlinear interactive filter. The estimation of population parameters by a maximum likelihood method provides the foundation for forecasting future values of the series through the filter permission.

Furthermore, the stochastic instability segment of heterogeneous durations is been joined by the assets returns of the MSM as stated by (Calvet and Fisher, 2004). Lux (2008) has introduced a MS multifractal model for which the model allows the estimation of the parameters through the maximum likelihood estimation (MLE) and Bayesian forecasting of volatility. In any case, the appropriateness of MLE is confined to cases with a discrete distribution of volatility segments. From a handy perspective, MLE, likewise, turns out to be computationally unfeasible for huge quantities of segments regardless of the fact that they are drawn from a discrete distribution, therefore the contribution of the study too advance MLE for parameter estimation to expectation maximum (EM).

Furthermore, the inflation crises series instability of standard models can be determined using the MSM (Droumaguet, 2012). Studies proved that forecasting volatility with models such as fractionally integrated generalized autoregressive conditional heteroscedasticity (FIGARCH) gives biased results due to its unstableness. Researchers further used MSM for financial industries with the aim to model and forecast volatility of the financial sector and also compute the risk and price derivatives because of the shortcomings of the FIGARCH and other volatility models which cannot perform the task.

Engel and Hakkio (1996) used the MSM model while modelling the European exchange rate volatility. Firstly, the authors extended Hamilton's model by allowing the probability of switching from one state to another to depend on position of the exchange rate within its European Monetary system (EMS) as opposed to Hamilton's assumption of constant switching probabilities. This model of Engel and Hakkio was then propagated in the early warning system studies such as of Cruz and Mapa (2013) to identify episodes of high and low inflation in which the outcome of the regime classification appeared to be erratic with the regime lasting for a month.

Abiad (2007) used MS-VAR to identify and characterise the crisis period endogenously. In terms of the Asian countries currency, crises and potential determinants of exiting the tranquil state was tested and a number of variables with significant medians across the panel were found. By using the panelised maximum likelihood methodology, Arias and Erlandsson (2004) in their study of regime switching as an alternative of early warning system of currency crises found that the method allowed them to extract smoother transition probabilities than in the standard case, reflecting the need of policy makers to have advance warning in the medium to long term rather than the short term. See also Brunetti et al. (2008); Abiad (2003) and Mariano et al. (2002).

Two primary issues have been faced by past analysts. Firstly, much research has been developed around the significance of precision in deciding the timing and duration of crisis periods. Furthermore, there has been a significant debate by researchers endeavouring to decide the most ideal approach to analyse correlation dynamics before, during and after these crisis stages (Troug and Murray, 2015). Scholars like Forbes and Rigobon (2002), Boyer et al. (2006) and Rodriguez (2007) had problem in accurately determining the crisis. These authors utilized different methods such as exogenous and endogenous approach but all found different results. Rodriguez (2007) found evidence of changing dependence structures during periods of financial turmoil. Increased tail dependence and asymmetry in times of high volatility characterize the Asian countries, while symmetry and tail independence describe better the Latin-American case. Baur (2012) notes that the length of the crisis periods, when determined endogenously, far exceeds those determined using exogenous methods.

In order to reduce the selection bias of the crises, the study adopts Rodriguez (2007) method of using an MS model to endogenously predict an inflation crisis period of several months, which is same with that of (Cruz and Mapa, 2013). The approach utilized as a part of the exploration in the study includes consolidating the MS techniques utilized by Rodriguez (2007) with the VAR methodologies of Forbes and Rigobon (2002) empowering more accurate modelling of the crisis period, in view of lagged values of inflation and repo rate. This MS-VAR approach has beforehand been actualized effectively by Brandt et al. (2012) to determine crisis periods inside datasets for Israel and Palestine.

Moysiadis and Fokianos (2014) noted that a MC algorithm has given the future states and its significance while the categorical response variable is lagged. Two reasons arise for the problem caused by a clear categorical time series when it is modelled by Markovian methods. (1) There is a positive nonlinear relationship between the order of MC and free parameters. i.e., as the order of the MC accumulates, so does the free parameters. Nonetheless, these free parameters increase exponentially. However, the study incorporates the Bayesian approach to restrict these free parameters to increase exponentially but remain constant over time with non-constant regime switching probabilities (2). The response variable and the covariates which are observed jointly must be a Joint flow between them. Of course, this type of determination might be impossible in the stochastic processes of higher time series frequencies.

With the point of depicting and forecasting financial time series volatility from one day to one month skyline, Marcucci (2005) thought about various generalised autoregressive conditional heteroscedasticity models. The unreasonable tirelessness which is typically found in generalised autoregressive conditional heteroscedasticity (GARCH) models are been modelled by Markov-switching GARCH (MS-GARCH) where the parameters are permitted to switch between the low and high volatility regime. Nonetheless, the final results of Marcucci (2005) signposted that MS-

GARCH models do truly beat all standard GARCH models in estimating volatility at shorter skylines as indicated by broad set of statistical loss functions but models do really outperform all standard GARCH models in forecasting volatility at shorter horizons. At longer skylines standard deviated GARCH models fare the best.

Sims and Zha (2006) used regime switching within a structural vector autoregressive (SVAR) to assess the impact of changes in the US monetary policy. Their model allowed the time variation in disturbance variances only. With coefficients allowed to change, the model is with change only in the monetary policy rule with estimating the three regimes which are corresponding roughly to periods when most observers believe that monetary policy actually differed. But the differences among regimes are not large enough to account for the rise, then decline, in inflation rate. Droumaguet (2012) extended the model of Hamilton (2008b)

Hamilton (2008a) extended a univariate modelling to multivariate with up to 20 equations. MS-VAR models considered for stage Monte Carlo experiment are the models with switching intercepts. Droumaguet (2012) scrutinized three classes of models which are models with regime switching in intercepts only, models with regime switching in the variance only and model with regime switching in all the parameters that is, switching in intercept vector, autoregressive coefficients matrix and variance-covariance matrix. Ang and Bekaert (2002) showed that incorporating more series in the model provides better regime classification than in the univariate case. This study hence estimates the latent regime in a multivariate case in the current study.

Sims et al. (2008) present the Bayesian methodology for handling general Markov Switching Structural Vector Autoregressive (MS-SVAR) models. These models were found to be useful in business cycles for instance. Thus they are potentially suited in many cases where SVAR models are traditionally used. Kilian (2006) on the other hand introduced Bayesian impulse response analysis for MS-VAR model. The obtained regime separated the sample into two periods over the periods of 1986. The structural changes that occurred in time transformed the oil market into more competitive as highlighted within the regime dynamics.

Krolzig (2000) focused on the predictability of MS-VAR processes as the property of a stochastic process in relation to an information set. They derive the optimal predictor, and show that its properties depend on (i) the significance of regime movements, (ii) the tirelessness of the regime generating process, (iii) the asymmetry of the regime generating process and (iv) the interaction with the AR elements. The outcomes obtained permit to infer parametric conditions under which the optimal predictor shrinks to a linear forecast prediction rule.

To investigate the inference and volatility forecasting, Chen et al. (2009) used a Markov-Switching generalized autoregressive heteroscedastic (MS-GARCH) model with a fat-tailed error distribution. This was done to allow the analysis of asymmetric effect on both the conditional mean and conditional volatility for the financial time series. The motivation of extending the model to MS-GARCH model is that the switching variable is said to follow unobserved first-order Markov process and this simultaneously incorporates a MS in variance and mean of the model. Furthermore, these inference and estimation of parameters are executed through the MCMC scheme which follows a Bayesian framework. In addition to that, Chen et al. (2009) used Bayesian forecasting in their comparative study of value-at-risk and all the proposed methods were demonstrated via simulations and eight international stock market return series. The findings of the study indicated that a double MS-GARCH model with an exogenous variable outperformed all other proposed models.

Moolman (2005) applies a Markov regime-switching model to assess the relationship between stock returns and macroeconomic variables in South Africa. The author finds that the degree to which stock returns depend on macroeconomic variables, depends on the state of the business cycle in South Africa. Apart from being used to capture cyclical asymmetry in the stock market, the MSM can also be used to identify turning points in the economy and to model economic growth.

2.6.2 Empirical literature on Logistic regression model

This study attempts to predict the likelihood of inflation crisis in South Africa. In doing so, the logistic regression model is estimated. According to Edison (2000), the model known as an early warning system (EWS) is engaged for the prediction of crises mainly the financial crises. There are various types of crises of which the 2008 United States (US) financial crises typically studied by Kenourgios et al. (2011), including currency crises which were studied by Jeanne and Masson (2000), banking crises by Borio and Drehmann (2009), sovereign debt crises and private sector debt crises Schimmelpfennig et al. (2003), and equity market crises by (Bekaert et al., 2011). Therefore, the study extends the current focus of crises to the prediction of inflation crises.

When finding signs and likelihood of classification for the high and low inflation episodes in South Africa, the study proposes the logistic regression. Logistic regression is a model where the dependent variable (DV) is categorical (Freedman, 2009). While fitting the logit model, James et al. (2013) viewed the maximum likelihood estimate (MLE) as an optimal technique in fitting the best logistic model.

In developing an EWS for inflation crisis, there are three methodologies that emphasizes. These are the bottom-up methodology, the aggregate methodology and the macroeconomic methodology. The odds of inflation crisis are addressed and the systemic volatility is being activated and signed if the odds become significant. For the second method, the model is applied to data other than individual banking data. On the third method, the focal point is centered in building a relationship between economic variables with the review that various macroeconomic variables are required to affect the financial system and reflect their own condition.

To describe the conditional log-odds of the conditional variances, the time series that trails a categorical setting is been pushed by an inactive procedure as Moysiadis and Fokianos (2014) emphasised in their study of binary time series modelling. Here, the problem of ergodicity, stationarity and MLE were studied with the estimation of a multinomial logistic models which include latent process.

The application of logistic regression analysis in the prediction of bankruptcy has been pioneered by Ohlson (1980). The logit methodology Joins together the nonlinear changes and makes use of the cumulative distribution function from the logistic to maximize the Joint likelihood of default for the firms' upset and also, the non-failure likelihood for the sound organizations in a sample. A great part of the early research in the region of financial suffering, concentrated on Multiple Discriminant Analysis (MDA) and after that in later years on logistic analysis (LA).

Davis and Karim (2008) used a multivariate logit model in their comparison study of an early warning system with the aim of relating the likelihood of occurrence or non-occurrence of a crisis to a vector of n explanatory variables. The probability that the dummy variable takes a value of one (crisis occurs) at a point in time was given by the value of the logistic cumulative distribution evaluated for the data and parameters at that point in time. Their results showed that the logit model they estimated maybe the best model for globally detecting the banking crisis.

Although models have been developed to allow banking crisis prediction, their comparative performance is difficult to evaluate. Current models have been derived from various historic datasets and more importantly, by using different dependent variables and overall methodologies. Consequently, leading indicators may appear inconsistent and in-sample and out-of-sample results differ. The study contribution includes the following: (1) The study makes a follow-up of both Davis and Karim (2008) and Cruz and Mapa (2013), by estimating the logistic regression to predict the inflation crises in South Africa. (2) The cross-country and time-series coverage is more extensive than most previous studies. Hence consideration of refinements to the current EWS by considering how all other classified crisis theory together with the monetary transmission mechanism theory could help to improve specification and variable choice.

Moreover, Gunsel (2005) indicated that the financial ratios and failure of banks in North Cyprus have some sort of relationship which has been linked by a multivariate logit model. The main point of using a multivariate logit model is to compute the probability of bank failure as a vector explanatory variables. Basically, financial ratios are designed to measure information for the six categories which the natural potential risk within the financial institutions is emphasized. In spite of the potentiality to predict the sign of the crisis, binary time series models have been considered for this purpose Further than that, financial indicators are mostly used as bank indicators.

Due to the small samples and the need to keep the degrees of freedom, Kolari et al. (2002) added to the work of EWS by estimating the stepwise logistic regression in order to identify the subset of the covariates that are needed in the model through their power to discriminate. The predefined significance level was set at 10% and the impact of this was that few variables were chosen in the model, hence the need to increase the significance level to 30 which now was used as a threshold to add variables in the model. The main problem that caused the lack of significance of the variables in entering the model is due to the fact that the error term in the regression model followed a cumulative distribution which does not accurately estimates a logit function.

2.7 Concluding remarks

This chapter has reviewed both theoretical and empirical literature of the Markov-Switching model and Logistic regression model. Both models have been indicated as good models for EWS as Markov-Switching model is identified as a best model for abrupt change modelling in the macroeconomic and financial time series data. Past researchers have been using the MS model for modelling financial returns volatility. However, the current study uses the MS to estimate the periods of high inflation. The MS model is used to cater again for the differences in the equilibrium of inflation rate and repo rate. For model estimations procedure, literature has emphasized that MLE has some deficiency of feasibility while estimating a large series with discrete modelling such as MSM therefore the best approach is through migrating from MLE to EM.

There are two methods of estimating the switching which are identified as constant switching probabilities and varying switching probabilities. The varying switching probabilities allow the researcher to establish better smooth transition probabilities as opposed to the constant switching probabilities. Furthermore, in determining inflation crises in the current study, the variables are set to be endogenous as this is identified as an optimal way of predicting the crises and correctly classifying them.

While building an early warning system, some studies such as of Fuertes and Kalotychou (2007), used K-means clustering while the model for EWS in this study is motivated by the methodology of Cruz and Mapa (2013) who used the univariate logistic regression model to classify the episodes of high inflation accordingly. Again, the literature has highlighted Monte-Carlo experiments plays a vital role in the empirical analysis of econometric modelling when especially the properties of the original data, or models at study are well known and properly predefined.

CHAPTER 3

METHODOLOGY

3.1 Introduction

Time series analysis contains procedures for analysing time series data keeping in mind the end goal to separate important measurements and different attributes of the data. According to Jonathan and Kung-Sik (2008), the motivation behind time series analysis is by and large twofold: (1) To comprehend or demonstrate the stochastic mechanism that offers ascend to an observed series. (2) To predict or forecast the future values of a series in light of the historical backdrop of that series and perhaps, other related series or variables. The present study delineates diverse methods prepared to help out for the perception of the issue.

Using proper models and doing analysis is the key aspect that is discussed in this chapter. The study integrates two modelling methods for building an early warning system for inflation. An R programing 3.2.4 revised software Matlab and Oxmetrics 6 are used to execute the analysis. The results are presented in tables and figures. The analysis of data is geared to achieve the following objectives which are to:

- Simulate the inflation and repo rates data using Monte Carlo method,
- Estimate a Markov-Switching Bayesian vector autoregressive model using the inflation rate and repo rate of South Africa,
- Estimate the logistic regression model as a classifier of inflation crises on the basis of repo rate,
- Formulate suggestions for policy and future studies.

The rest of this chapter is organised in the following chronological order: Section 3.2 presents preliminary data analysis methods where nonlinear tests, descriptive statistics of the data and normality test are addressed. Section 3.3 presents prior tests and the discussion of information criterions used for maximum lag length. Section 3.4 discusses the proposed methods used to address the study objectives. Section 3.5 presents model diagnostic checking. Section 3.6 discusses the forecasting procedure using the selected MS-BVAR model together with the forecasting performance error metrics. And lastly section 3.7 presents the concluding remarks for the chapter.

3.2 Data simulation

The process used for generating the data used in this study follows a nonlinear VAR mechanism of order 1 to 2 (Smith et al., 2013). Here, $\mu_t \sim \mathrm{i.i.d}\ N(0,1)$ random variables. Again, S_t is a two-state standardised, irreducible and periodic MC. In these experiment, the study generates 50+T data points for both the inflation and repo rate with the starting values being set to zero and S_0=1 for both the series. In order to attenuate the effect of the initial values, the last $T = 1$ is in the Monte Carlo replication. It is worth noting that random deviations are a product of the algorithm of (Kinderman and Ramage, 1976).

The sample is chosen based on the three criterions or selection methods. Firstly, the parameters and biases in standard error are less than 10% for any parameter estimated. Secondly the standard error bias for the parameter whose power is being evaluated is less than 5%. In the last step, the coverage should be in the range of 0.91 and 0.98. Provided the three steps are covered, the sample size is chosen to keep power close to 0.80 (Dell et al., 2002). According to the authors, 0.80 is a generally conventional value for sufficient power. Muthén and Muthén (2002) also suggested 0.8 as the best threshold for sample size and model power determination.

The generated sample start at 1 to n and following Dendukuri et al. (2004); Mustafa (2006), the chosen sample converges when $\varepsilon \geq |\bar{x} - \mu|$ with confidence interval constructed as $1 - \alpha = \mathrm{pr}\left(|\bar{x} - \mu| < z\alpha_{/2} \frac{\sigma}{\sqrt{n}}\right)$ where $z\alpha_{/2}$is the upper $100(1 - \alpha_2)^{\mathrm{th}}$ percentile of the standard normal distribution. Relying on the confidence interval, the deterministic sizes are determined by:

$$n_{\mathrm{CLT}}^{a} = (\varepsilon, \alpha, \sigma^2 < \infty) = \left[\left(z\alpha_{/2} \frac{\sigma}{\varepsilon}\right)^2\right]. \tag{3.1}$$

Here, ε is the margin error of estimation of the sample.

The application of Monte Carlo methods and simulation has rapidly increased especially in science related studies. These methods are also of ut-most importance in growing sub-disciplines such as those of computational physical sciences and the computational sciences. Recent technological advances and the surfacing replication procedures motivated the appreciation of computation as a third methodology for progressing the natural sciences, together with theory and traditional research(Zio, 2013). At the central of Monte Carlo simulation is random number generation (Gentle, 2013). The sampling unit with the confidence interval presented in 3.1 follows the following measure:

$$\mathrm{P}\left(\mathrm{x_i}|\mathrm{X_{i\neq j}}\right) \tag{3.2}$$

Hammersley (2013) has indicated the following (a) proof of validity. (b) Metropolis-Hasting's proposal. Nevertheless, in (a), detailed balance for component update is checked and then the Metropolis-Hastings proposal as indicated in (3.2) is accepted with the probability of 1. This is known as a Gibbs sampler. The conditionals with few discrete settings can be explicitly normalized as:

$$\mathrm{P}\left(\mathrm{x_i}|\mathrm{X_{i\neq j}}\right) \propto \mathrm{P}\left(\mathrm{x_i}, \mathrm{X_{i\neq j}}\right) = \frac{\mathrm{P}\left(\mathrm{x_i}, \mathrm{X_{i\neq j}}\right)}{\sum_{\mathrm{x_i'}} \mathrm{P}\left(\mathrm{x_i'}, \mathrm{X_{i\neq j}}\right)} \tag{3.3}$$

Following the Markov Chain Monte Carlo (MCMC), the sample is processed by:

$$\mathrm{I} = \sum_{\mathrm{x}} \mathrm{f}(\mathrm{x_i})\mathrm{P}\left(\mathrm{x_i}|\,{}^{\mathrm{X}}\!/_{\mathrm{i}}\right) = \sum \mathrm{x}_{/_{\mathrm{i}}} \left(\sum_{\mathrm{x_i}} \mathrm{f}(\mathrm{x_i})\, \mathrm{P}\left(\mathrm{x_i}|\,{}^{\mathrm{X}}\!/_{\mathrm{i}}\right)\right) \mathrm{P}\left({}^{\mathrm{X}}\!/_{\mathrm{i}}\right) \tag{3.4}$$

Therefore, (3.4) simplifies to

$$\frac{1}{\mathrm{S}} \sum_{\mathrm{s}=1}^{\mathrm{S}} \left(\sum_{\mathrm{x_i}} \mathrm{f}(\mathrm{x_i})\mathrm{P}\left(\mathrm{P}\left(\mathrm{x_i}|\mathrm{X}_{/\mathrm{i}}^{(\mathrm{s})}\right)\right)\right) \tag{3.5}$$

where, $\mathrm{X}_{/\mathrm{i}}^{(\mathrm{S})} \sim \mathrm{P}\left(\mathrm{X}_{/\mathrm{i}}\right)$. Monte Carlo methods, are sometimes referred to as stochastic simulations which include stochastic integration, where simulation is used based on the method for evaluating a fundamental Monte Carlo tests. Simulation is preferred when computing the p-value, and MCMC, where MC are constructed with the hope to converge to the distribution of interest.

3.2.1 Preliminary data analysis

In this section the preliminary data analyses are conducted with the purpose of describing the behaviour of the data set. The implementation of the descriptive statistics is employed to provide a sound understanding of the data within the study. Time series plots are also generated in this section to show the preliminary data analyses are conducted with the kind of properties in the series. Because the study is based on the nonlinear modelling, the nonlinear tests such as BDS test, Ramsey Rest test, and Cumulative sum (CUMSUM) graphs are utilized. Pertinent issues governing the MS-BVAR and logistic regression models are also discussed.

3.2.2 Nonlinear test and nonlinear unit root test

The key question is whether the slope of the series can be expected to vary with time or not. Because the linear time series modelling had remained the forefront of academic and applied research, it has often been found that simple linear time series models usually leave certain aspects of economic and financial data unexplained. Hence there is the need to test for linear hypothesis that the given data series is linear against its nonlinear (Stollenwerk et al., 2001). The following discussion looks at both the nonlinear test and nonlinear unit root testing.

3.2.3 Nonlinear unit root test

Most of the time series are not stationary over time (Gujarati, 2010). See also, (Box et al., 2015). In addition, if the time series is non-stationary, this imposes more variance in the series. Xaba et al. (2016) in their study of modelling South African banks closing stock prices utilized a MS-AR model and indicated that the unit root test is the basic assumption in this case and the MS-AR model becomes more effective on nonlinear unit root data. In order to address the unit root in the nonlinear time series, the study uses the Kapetanios, Shin- Shell Nonlinear Augmented Dickey Fuller (KSS-NADF). According to Kapetanios et al. (2003), the KSS is a modified test of the Augmented Dickey-Fuller (ADF) test which is grounded on the following nonlinear model:

$$Y_t = \beta Y_{t-1} + \gamma Y_{t-1}\left[1 - e^{-\vartheta Y_{t-k}^3}\right] + \varepsilon_t, \tag{3.6}$$

where its parametrization yields:

$$\Delta Y_t = \varphi Y_{t-1} + \gamma Y_{t-1}\left[1 - e^{-\vartheta Y_{t-k}^3}\right] + \varepsilon_t, \tag{3.7}$$

in which the parameters to be estimated are $\varphi = \beta - 1,\ \gamma,\ \vartheta$ and ε_t is the error term and therefore, $\left[1 - e^{-\vartheta Y_{t-k}^3}\right]$ is the exponential transition function adopted in the test to presents the nonlinear adjustment. To have a reduced constant form model, the KSS then sets the φ to zero where the decay parameter k is set to 1 giving rise to a modified (3.6) as:

$$\Delta Y_t = \gamma Y_{t-1}\left[1 - e^{-\vartheta Y_{t-k}^3}\right] + \varepsilon_t \tag{3.8}$$

The KSS test the following null hypothesis of linear stationarity:

$$H_0: \gamma = 0$$
$$H_1: \gamma > 0$$

Since the speed of reversion is unknown, Kapetanios et al. (2003) argued that it is unbearable to directly test the null hypothesis. Therefore, using the Taylor Series expansion, the model is then estimated as a nonlinear specification for testing the nonlinear stationarity of the series. To account for a deemed for serial correlation in the error term, by augmenting equation 3.8 by the first order lag differencing and estimated as:

$$\Delta y_t = \delta y_{t-1}^3 + \sum_{k=1}^{q} \rho \Delta y_{t-k} + \varepsilon_t, \tag{3.9}$$

where the coefficient for testing the presence of the unit root is δ, and ρ is the number of augmentations that can be specified using lag length selection criteria. The KSS-NADF unit root test statistics is presented as:

$$\tau_{NL} = \hat{\delta} \big/ se(\hat{\delta}). \tag{3.10}$$

where, $\hat{\delta}$ is the OLS estimate of δ and $se(\hat{\delta})$ is the standard error $\hat{\delta}$. According to Liu and He (2010), τ_{NL} statistics does not obey an asymptotic standard normal distribution.

Here, the null hypothesis to be tested is

$$H_0: \delta = 0 \text{ (Nonlinear nonstationarity)}$$
$$H_1: \delta < 0 \quad \text{(Nonlinear stationarity)} .$$

The decision is ruled to reject the null hypothesis if the calculated probability value or if the calculated value of τ_{NL} exceeds the observed critical value.

Table 3.1 Critical values of KSS Unit Root test

Significance Level	Raw	No mean	No Trended
1	-2.82	-3.48	-3.93
5	-2.22	-2.93	-3.4
10	-1.92	-2.66	-3.13

Source: Kapetanios *et al.* (2003)

3.2.4 Nonlinearity testing

Numerous parts of economic conduct may not be linear. Experimental proof and easy-going thoughtfulness propose that financial specialists' dispositions towards hazard and expected returns are nonlinear. The terms of numerous financial contracts, for example, alternatives and other subordinate securities are nonlinear. Also, the key collaborations among market participants, the procedure by which information is consolidated into security prices and the progression of extensive changes are all characteristically nonlinear. Along these lines, a characteristic outskirt for financial econometrics is the modelling of nonlinear wonders (Kyrtsou and Serletis, 2006).

Lee et al. (2001) demonstrated that large portions of algorithms from nonlinear flow and theories of nonstochastic confusion are found to be constantly inconsistent. As a result, nonlinearity tests are based on the dimension of correlation with spatial embedding. The discriminating statistic that is used here is the dimension of the spatial correlation. Nonetheless, the study adopts Wang et al. (2006) procedure who used the nonparametric method known as Brock-Dechert-Scheinkman (BDS) for testing serially independent series and nonlinear plan in a time series. The current study proposes the same nonparametric test to test the nonlinear of the both simulated series. The test is based on the series integral correlation described as:

$$\mathrm{BDS}_{\mathrm{m.M}}(\mathrm{r}) = \sqrt{\mathrm{M}}\,\frac{\mathrm{C}_{\mathrm{m}}(\mathrm{r}) - \mathrm{C}_1^{\mathrm{r}}(\mathrm{r})}{\sigma_{\mathrm{m.M}}(\mathrm{r})} \tag{3.11}$$

where M is the embedded points of the space with m dimension; r is the radius of a sphere centred on $\mathrm{X_i}$, C is the constant and $\sigma_{\mathrm{m.M}}(\mathrm{r})$ is the standard deviation of $\sqrt{\mathrm{M}}\mathrm{C}_{\mathrm{m}}(\mathrm{r}) - \mathrm{C}_1^{\mathrm{r}}(\mathrm{r})$ which is the correctional integral. Reject the null hypothesis of linearity in favour of the nonlinearity when the calculated probability value is less than the suggested significance level. The choice of the BDS test is based on the methodology of Ismail and Isa (2006). This test is derived to test the null hypothesis of independently and identically distributed (iid) in data and determining the non-random chaotic dynamics. Because the study simulated a large sample of 210 cases, Ismail and Isa (2006) showed that the distribution of the BDS does not depart from asymptotic normal distribution as in small samples.

3.3 Prior tests

This part of the study presents prior test for model estimation. Information criterions are discussed for the purpose of maximum lag length selection and the number of structural breaks that may be identified within the analysis. Some nonlinear tests are such as RESET test, CUSUM are also addressed.

3.3.1 Information criterion for lag length selection and Structural break point test

Model selection is a huge issue in practical data analysis (Makatjane and Moroke, 2016). Despite the fact that the model can have a high coefficient of determination (R^2), there is still a plausibility that the reported results are spurious. This suggests that the coefficient of determination ought not to be the main paradigm depended on with regards to selecting the model most appropriate for the data. Consequently, information criteria, for example, the Akaike information criterion (AIC), by Akaike (1974), Schwarz Bayesian information criterion (SBC) by Schwarz (1978)and Hanna Quin (HQ) by Hannan and Quinn (1979) are the most ordinarily utilized and proposed as a part of most empirical analysis.

According to Bozdogan (2000), the need for presenting the idea of model assessment has been perceived as one of the authoritative specialized zones. The method for estimating models aims to minimize the model estimation error. For the model with least error which in other terms is considered to be the best model, the SBC and AIC have the smallest values that correspond to the estimated model. This implies that the model with the least AIC, and SBC are chosen. The contrast comes with the LR model selection criterion, where the largest LR value is considered to be the one to select the best model. Nevertheless, the current study suggests the use of the three-information criterion for model selection to avoid issue of biasness. The SBC measure is estimated as follows:

$$\mathrm{SBC} = -2[\ln \widehat{\varphi} + \mathrm{k} * \ln(\mathrm{n})], \tag{3.12}$$

where n is the sample size, k is the number of parameters to be estimated, $\widehat{\varphi}$ is the likelihood function of the estimated model (M) which is $\widehat{\varphi} = \mathrm{p}\left(\mathrm{x}|\hat{\theta}, \mathrm{M}\right)$, x is the observed data and θ is the parameter of the estimated model.

The study further uses the AIC for the purpose of model selection. According to Pan (2001), AIC is most powerful widely used by most researchers:

$$\mathrm{AIC} = \mathrm{nlog}\left(\frac{\mathrm{RSS}}{\mathrm{n}}\right) + 2\mathrm{k}, \tag{3.13}$$

where n is the sample size, RSS is the estimated residual of fitted model and 2k is the variance. In this case, the model with least AIC is the one selected to be the best model.

The Hanan Quin (HQ) like BIC, but unlike AIC, is not asymptotically efficient, and whatever method is being used for fine-tuning the criterion will be more important in practice than the term $loglog(n)$, since this its value is small even for very large *n* (Hjort, 2008). Then the procedure is as follows:

$$\mathrm{HQ} = -2\mathrm{log}\tilde{\mathrm{L}}_{\mathrm{n}}(\theta_{\mathrm{n}}) + 2\mathrm{ck}_0\mathrm{loglogn}, \mathrm{c} > 1, \tag{3.14}$$

where k_0 is number of estimated parameters of the model, n is the sample size and $\tilde{\mathrm{L}}_{\mathrm{n}}(\theta_{\mathrm{n}})$ is the likelihood function.

3.3.2 The reset test

Most nonlinear related studies employ the RESET test to confirm the specification of linear regression analysis. The RESET test uses a univariate AR (p). Ramsey (1969) describes a linear regression model as follows:

$$\mathrm{Y}_{\mathrm{t}} = \beta_0 + \sum_{\mathrm{j}=1}^{\mathrm{p}} \beta_{\mathrm{j}} \mathrm{Y}_{\mathrm{t-p}} + \varepsilon_{\mathrm{t},} \tag{3.15}$$

where $\beta_0, \beta_1, \ldots, \beta_{\mathrm{p}}$ are the estimated parameters of the regression model and $\varepsilon_{\mathrm{t}} \sim \mathrm{i.i.d}(\mu = 0, \sigma_\varepsilon^2 = 1)$. The selection of AR order, p, is to reduce the error denoted as ε_t in (3.15). In order to practically achieve a minimum error, Franses and Van Dijk (2000) stated that the value of p musts be selected in such a way that it minimizes information criterions such as Schwarz Bayesian Criterion (SBC), Akaike information Criterion (AIC), Hannan-Quinn Criterion (HQC) etc. But the study only uses SBC. If then, $Y_t = (Y_{t-1}, Y_{t-2}, \dots, Y_{t-p})'$ then (3.15) becomes:

$$Y_t = Y_{t-1}\beta + \varepsilon_t. \tag{3.16}$$

Because the study is based on the Bayesian modelling, then (3.16), can be generalised in the following manner as Shumway and Stoffer (2010) has indicated

$$Y_t = \Phi(\Phi T_{t-2} + \varepsilon_{t-1}) + \varepsilon_t \tag{3.17}$$

where, Φ is an autoregressive(AR) parameter estimated and T_{t-2} is a time depended parameter that is imposed by the researcher to tighten the AR parameter of the model and ε_t is an error term of the estimated model and $\varepsilon_t \sim \mathrm{i.i.d}(\mu = 0, \sigma_\varepsilon^2 = 1)$. Therefore (3.17) simplifies to:

$$Y_t = \varepsilon_t + \Phi\varepsilon_{t-1}\Phi^2 Y_{t-2} \tag{3.18}$$

Which then repeated $K - 1$ times, (3.18) becomes:

$$Y_t = \varepsilon_t + \Phi\varepsilon_{t-1} + \Phi^2\varepsilon_{t-2} + \cdots + \Phi^{k-1}\varepsilon_{t-k+1} + \Phi^k Y_{t-k} \tag{3.19}$$

Assuming that $|\Phi| < 1$, Barnett et al. (1996) has now incorporated the Bayesian modelling by imposing the prior in (3.19) by letting $J_{1j} = 0$ if $\Phi_j = 0$ and let $J_{1j} = 1$ otherwise, $J = 1, \dots, p$. Note that the prior that $J = 1, J = 1, \dots, p$ is prescribed by the researcher. Furthermore, the prior for μ is flat and the prior for σ^2 is $f\left(\sigma^2 \propto {}^{1}/_{\sigma^2}\right)$.

Having done all this, instead of modelling the errors as a heavily tailed using a discrete mixture normal, it possible to use a continuous mixture such as t-distribution. The procedure to calculate a RESET test is firstly to obtain the OLS estimate, β, in equation (3.19), the residual $\hat{\varepsilon}_t = Y_t - \hat{Y}_t$, and the sum squared residuals:

$$SSR_0 = \sum_{t=p+1}^{n} \hat{\varepsilon}_t^2 \tag{3.20}$$

The second step is estimating the following regression:

$$\hat{\varepsilon}_t = Y_{t-1}^{`}\lambda_1 + M_{t-1}^{`}\lambda_2 + e_t, \qquad (3.21)$$

where $M'_{t-1} = \left(\widehat{Y}_t^2 Y_t^3 \ldots Y_t^{s+1}\right)$ for $s > 1$, $e_t \sim \mathrm{i.i.d}(\mu = 0, \sigma_\varepsilon^2 = 1)$. The sum of squared residuals from the estimated residuals of $\hat{\varepsilon}_t = \hat{\varepsilon}_t - \hat{\hat{\varepsilon}}_t$ is computed as:

$$SSR_1 = \sum_{t=p+1}^{n} \hat{e}_t^2. \qquad (3.22)$$

Note that if the underlying AR(p) is adequate, the RESET test asserts that λ_1 and λ_2 are zero hence, the following hypothesis is tested:

$$H_0: \lambda_{ij} = 0$$
$$H_a: \lambda_{ij} \neq 0$$

The test statistics is the usual regression F statistic given as:

$$F = \frac{SSR/_{p-1}}{SSE/_{n-p}} \sim F_{\alpha,p-1,n-p} \qquad (3.23)$$

In this case, the null hypothesis of linearity is rejected if the calculated probability value of F statistic is less than the observed probability value. This implies that the true model specification is nonlinear.

3.3.3 CUSUM test

To test the stability of the estimated BAR(p) model as part of testing the nonlinear effects on the data set, Grigg et al. (2003) sowed that the CUSUM can be used to test any occurrence of structural change in the AR(p) model parameters. If the estimated model is stable, then the coefficients ϕ_{ij} and σ_ε^2 are constant over time. In that situation, the coefficients from 3.16 are obtained from the matrix developed by Brown et al. (1975) as:

$$\widehat{\phi} = (Y'_{t-1}Y_{t-1})'Y'_{t-1}Y_t \qquad (3.24)$$

where Y_t is the response variable in equation 3.12 and $Y_{t-1} = \left(1\, Y_{t-1}\, Y_{t-2} \ldots Y_{t-p}\right)'$ with $\varepsilon_t \sim \mathrm{i.i.d}(\mu = 0, \sigma_\varepsilon^2 = 1)$. The null hypothesis is:

$$H_0: \phi_{ij} = 0$$
$$H_a: \phi_{ij} \neq 0$$

The recursive residuals are estimated as:

$$\omega_t = \frac{Y_t - \widehat{\Phi}_{t-1} Y_t}{\sqrt{\hat{\sigma}^2 \left[1 - Y_t^{`} \left(Y_t^{`} Y_t\right)^{-1} Y_t\right]}}. \tag{3.25}$$

Therefore, the CUSUM of square test statistic is given by:

$$\mathrm{CUSUMSQ}_t = \frac{\sum_{j=k+1}^{t} \widehat{w}_j^2}{\sum_{j=k+1}^{n} \widehat{w}_j^2}. \tag{3.26}$$

where, $W_t = \sum_{j=k+1}^{t} \omega_j$ t=k+1,k+2,…,n

The decision rule is, reject the null hypothesis if the observed probability is greater than the expected probability. Nevertheless, the $\mathrm{CUSUMSQ}_t$ can also be performed by plotting it against time t with confidence bands obtained in the following manner as defined by Montgomery (2007):

$$\begin{aligned} C_i^+ &= \max[0, x_i - (\mu + k) + C_{i-1}^+] \\ C_i^- &= \max[0, (\mu - k) - x_i + C_{i-1}^-] \end{aligned} \tag{3.27}$$

The starting values are $C_0^+ = C_0^- = 0$. And k is the reference value and it is usually chosen halfway between the target μ_0 and out of the control value of mean μ_1.

Reject the null hypothesis if the plotted CUSUMSQ graph is beyond either the C_i^+ and C_i^- where, C_i^- and C_i^+ are the lower and the upper control bands of the CUSUMSQ graph.

3.4 Primary data analysis

This section gives a brief review of the models to be used in the building of an early warning system. MS-BVAR model is used to detect the episodes of high inflation and low inflation which are driven by the interest rate episodes. Logistic regression model is utilized for developing warning system.

3.4.1 Theoretical framework

This study follows a Markov-Switching framework to determine the classification of the inflation rate into high inflation regime (inflation crisis) and low inflation regime (non-inflation). This model is based on its ability to represent the business cycles where the conditional mean of the growth rate in regime one gives an annualized expansion and the second regime which is known as recession reflects annualized mean contraction. Moreover, the model is nested within the class of autoregressive models. Also, the regime duration is consistent with traditional description of the length of recession and recoveries.

This study extends the univariate model of Frühwirth-Schnatter (2006) to the multivariate level. By considering the change points to be those time points which divide a dataset into distinct homogeneous segments, the number of change points will not be known. Barber et al. (2011) noted that the capability to spot change points is imperative for both methodological and practical reasons. This includes (1) the authentication of an untested scientific hypothesis; (2) monitoring and assessment of safety critical processes; and (3) the authentication of modelling assumptions.

The first step is executed by constructing a Markov Switching (MS) by enhancing it with the Bayesian Vector autoregressive (BVAR). Troug and Murray (2015) recommended a MS model when the researcher intends to describe data exhibiting the discrete dynamic configurations over different periods of time. In essence, the MS-BVAR model aims at establishing the dynamic processes of observed time series Y_t and a discrete state variable $\mathrm{S_t}$ for t=1,…,T. This is done by computing the joint probability $\Pr(\mathrm{Y_t}, \mathrm{S_t})$ and also by unravelling the information of the conditional probabilities $\Pr(\mathrm{Y_t}|S_t)$ and $\Pr(S_t|\mathrm{Y_t})$ (Brandt and Davis, 2014).

Because of this abrupt changes in fundamentals, Hamilton (2010) emphasised that fixing the significant change in the average level of the series by fixing the changing value of the intercept from intercept 1 to intercept 2 i.e. $(\mathrm{C_1} \text{ to } \mathrm{C_2})$ which instead have some imperfectly predictable forces that produced the change, there is some larger model encompassing them both which is a Markov Switching Autoregressive.

Bayesian Vector autoregressive with Markov-Switching parameters (MS-BVAR) fit the data better than their constant parameter predecessors (Krolzig, 2013). However, Bayesian inference for MS-VAR with existing algorithms remains challenging because the invention of the statistical models using Bayesian statistics has the sole feature of demanding the specification of the prior distribution for any unknown parameters. According to Krolzig (1998), these preceding distributions are as integral to Bayesian approach and can be either hyper-parameters or hyper-preceding distributions.

MS-VAR model is proposed as an alternative to the constant-parameter of linear time-series models of Box et al. (2015) traditional modelling so as to allow changes in regimes of the process generating time series. The general idea behind this class of regime-switching models is that the parameters of say K-dimensional vector time series process $\{Y_t\}$ depends upon an unobservable regime variable $S_t \in \{1, \dots, M\}$ and presents the probability of being in a particular state.

For model estimation, Ailliot et al. (2006) indicated that the maximum likelihood estimation (MLE) gives more robust results as recommended by Leroux (1992). Furthermore, the mathematical computation of the MLE in model with hidden variables is been addressed. Nonetheless, the most popular method for optimising the parameter estimation of the model that allows the convergences in its parameters is the expectation maximization (EM) algorithm which has first been familiarized by (Baum et al., 1970). In this study, EM algorithm is proposed.

Following Ailliot et al. (2006), the likelihood of high and low regimes was examined exhaustively as to determine the accuracy of prediction for the possible upcoming inflation crisis. When the system is subject to regime shifts, Krolzig (2013) indicated that the parameters say ϕ of the VAR process become time-varying. But, the process might be time-invariant conditional on an unobservable regime variable S_t which indicates the regime prevailing at time t.

According to Krolzig (2013), MS-BVAR can be considered as generalizations of the basic finite order Bayesian VAR (BVAR) model of order p. Consider the P^{th} order autoregressive for the $K-$ dimensional time series vector, $Y_t = (y_{1t}, y_{2t}, \dots, y_{kt})', t = 1,2, \dots, T$, then,

$$Y_t = \Phi_{c1} + \Phi_{11} Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{1t-p} + \varepsilon_t;\ \varepsilon_t \sim \text{iid.}(\mu = 0, \sigma_\varepsilon^2 = 1), \qquad (3.28)$$

where, $t = 1, 2,3, \dots, T$. Each equation has $M = NxP + P$ regressors. By grouping the coefficients matrix to the form $M \times N$, then, $\Phi = [\Phi_c\ \ \Phi_1\ \dots \Phi_p\ ]$. Because the errors are assumed to be normally distributed, that is, $\varepsilon_t \sim \mathrm{i.i.d}(\mu = 0, \sigma_\varepsilon^2 = 1)$ then (3.28) is branded as the intercept form of a stable Gaussian VAR(p) model. When reparametrizing by adjusting the mean from the VAR model, Krolzig (2013) simplified the model to:

$$Y = X\Phi + \epsilon. \tag{3.29}$$

In this case, $Y = [y_1, \dots, y_T]'$, $X = [x_1, \dots, x_T]'$ and, $E = [\varepsilon_1, \dots, \varepsilon_T]'$ are respectively $T \times N$, $T \times M$ and $T \times N$ matrices.

Following Carriero et al. (2015) procedure, the following Normal-Inverted Wishart (N-IW) prior conjugate is used:

$$\Phi | \sigma_\varepsilon^2 \sim N(\Phi_0, \sigma_\varepsilon^2 \otimes \Omega_0), \sigma_\varepsilon^2 \sim IW(S_0, \upsilon_0). \tag{3.30}$$

As the N-IW is the conjugate, the conditional posterior distribution of this model is also N-IW Greenberg (2012):

$$\Phi | \sigma_\varepsilon^2, Y \sim N(\overline{\Phi}, \sigma_\varepsilon^2 \otimes \overline{\Omega}), \sigma_\varepsilon^2 | Y \sim IW(\overline{S}, \overline{\upsilon}.) \tag{3.31}$$

The general thought behind this class of models is that the parameters of the principal data making the procedure of the observed time series vector Y_t depend on the unnoticeable regime variable S_t, which addresses the probability of being in an alternate condition. Since the MSM has a particular trademark that the undetectable acknowledgment of the regime is administered by a discrete state Markov stochastic procedure, then the transition probabilities are characterized as follows:

$$P_{ij} = pr(S_{t+1} = j | S_t = i), \textstyle\sum_{j=1}^{q} P_{ij} = 1 \ \forall_{ij} \in \{1,2, \dots, q\}. \tag{3.32}$$

More precisely, it is expected that S_t takes after an irreducible ergodic q state Markov process with the transition matrix:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1q} \\ \vdots & & \ddots & \vdots \\ p_{11} & p_{12} & \cdots & p_{1q} \end{bmatrix}, \tag{3.33}$$

where $p_i q = 1 - p_{i1} - \cdots - p_{i,q-1}$ for $i = 1,2,3, \dots, q$ and are estimated from the regime $Ms(q) - BVAR(p)$ model. The underlying $Ms(q) - BVAR(p)$ model is then given by:

$$Y_t - \mu(S_t) = \phi_1(S_t)\big(Y_{t-1} - \mu(S_{t-1})\big) + \cdots + \phi_p(S_t)\left(Y_{t-p} - \mu\big(S_{t-p}\big)\right) + \varepsilon_t, \qquad (3.34)$$

where $\varepsilon_t \sim \mathrm{i.i.d}\; N(0, \sum S_t)$ and $\mu(S_t), \phi_1 S_t, \ldots, \phi_p(S_t), \sum S_t$ are parameter shift functions describing the dependence of the parameters.

The $\mathrm{Ms}(q) - \mathrm{BVAR}(p)$ allows one to make inference about the observed regime value S_t, through the conduct of the exogenous Y_t. This inference takes after the filtered probabilities, which when assessed, the basic iterative algorithm is utilized to compute both the likelihood function more than once and the conditional filtered likelihood on the going with set of observation $\xi_t = \big(X_{t,} X_{t-1}, \ldots, X_0\big)$ till to time t which are characterized as $P(S_t = i|\xi_t)$.

The most critical information which is extricated from the transition matrix is the expected duration of the i^{th}regime and also the ordinary duration of thei^{th} regime. Once more, $\frac{1}{P_{ij}}$ is a proportional of the expected duration of the process to stay in i^{th} regime. In the event that the estimation of P_{ij} for $i \neq j$ turns out to be small, it uncovers that the process takes a more drawn out time in regime i while the comparing, $\frac{1}{P_{ij}}$ uncovers the term in which the process stays in the regime.

3.4.2 The expectation maximum (EM) algorithm

While estimating the parameters of a model, diverse estimation methods are being utilized by various analysts. Jonathan and Jonathan and Kung-Sik (2008) demonstrate that these methods incorporate into them, the method of moments (MM), least square estimation (LSE), maximum likelihood estimation(MLE), unconditional least square (UCL), expectation maximum (EM) and many more. For the present study, while estimating the parameters of $\mathrm{MS}(q) - \mathrm{BVAR}(p)$, the EM is adopted.

The EM algorithm is an iterative technique for discovering maximum likelihood estimates of parameters in statistical models, where the model depends on upon imperceptibly latent variables. As indicated by McLachlan and Krishnan (2007), the EM emphasis interchanges between performing a desired(E) step, which builds up a function for the desire of the log-likelihood evaluated using the present appraisal for the parameters, and an intensification (M) step, which processes parameters by augmenting the expected log-likelihood found on the E step. These parameter-estimates are then used to choose the distribution of the latent variables in the accompanying E step. The algorithm was built up by Dempster et al. (1977) as:

Given the statistical model that generates X of observed data, a set of unobserved latent values Z and a vector of unknown parameters θ along with the likelihood function

$$\ell(\theta) = \sum_{Z} \log p(x, z|\theta) \tag{3.35}$$

using the slope method for example, slope ascent, conjugate slope, quasi-Newton, (3.35) is being maximised as indicated by Ng et al. (2012):

$$\begin{aligned} \ell(\theta) &= \log p(x|\theta) = \log \textstyle\sum_{z} p(x, z|\theta) \\ &= \log \textstyle\sum_{z} q(z|x, \theta) \frac{p(x,z|\theta)}{q(z|x,\theta)} \\ &\geq \textstyle\sum_{z} q(z|x, \theta) \log \left(\frac{p(x,z|\theta)}{q(z|x,\theta)}\right) \equiv F(q, \theta) \end{aligned} \tag{3.36}$$

where, $q(z|x, \theta)$ is a random density over z. Note that this inequality is known as a Gibbs inequality. Instead of maximising $\ell(\theta)$ directly, EM maximizes the lower bound $F(q, \theta)$ via coordinate ascent:

$$\text{E} - \text{step: } q^{(t+1)} = \underset{q}{\operatorname{argmax}} F(q, \theta^{t}) \tag{3.37}$$

$$\text{M} - \text{step: } \theta^{(t+1)} = \underset{\theta}{\operatorname{argmax}} F\left(q^{(t+1)}, \theta\right) \tag{3.38}$$

Commencing with some initial value of the parameters $\theta^{(0)}$, one cycle between the E and M-steps until θ^{t} converges to local maxima. Computing equation 3.36 directly involves fixing $\theta = \theta^{t}$ and optimizing over the space of distributions. For it can be shown that $q^{(t+1)} = p(z|x, \theta^{t})$, then equation 3.35 fix q as:

$$\begin{aligned} \ell(\theta) &\geq F(q, \theta) \\ &= \textstyle\sum_{z} q(z|x, \theta) \log \left(\frac{p(x,z|\theta)}{q(z|x,\theta)}\right) \\ &= \textstyle\sum_{z} q(z|x, \theta) \log p(z|x, \theta) - \textstyle\sum_{z} q(x|z, \theta) \log q(z|x, \theta) \end{aligned} \tag{3.39}$$

So then equation 3.36. is simplified to:

$$\ell(\theta) = Q(\theta|\theta^{(t)}) + H(\theta|\theta^{t}) \tag{3.40}$$

where, $H(\theta|\theta^{t})$ is demarcated by the negated sum it is replacing. In this instance, exploiting $F(q, \theta)$ is equivalent in exploiting the expected complete log-likelihood and equation 3.33 and 3.36 are re-estimated as:

$$\mathrm{E-step: Compute}Q(\theta|\theta^{(t)}) = E_{p(z|,\theta^{t})}[\log p(x, z|\theta)] \tag{3.41}$$

$$\begin{aligned} &\mathrm{E-step: Compute}Q(\theta|\theta^{(t)}) = E_{p(z|,\theta^{t})}[\log p(x, z|\theta)] \\ &\mathrm{M-Step:}\ \theta^{t+1} = \underset{\theta}{\mathrm{argmax}} E_{p(z|x,\theta^{t})}[\log p(x, z|\theta)] \end{aligned} \tag{3.42}$$

3.4.3 Logistic regression

The logistic model is utilized as a part of this study to determine an early warning system (EWS). This method is utilized as a development from the MS-BVAR model. The regimes are utilized as binary response variables. These incorporate the high and low inflation regime. As indicated by Cruz and Mapa (2013), the practicality of the inflation crisis has a reason appraisal that is been given by the probabilities which are extracted from the logistic regression model.

Taking after Tong (2012)'s discussion, the binary series is premeditated with the values of 0 or 1 signifying the low inflation and high inflation regimes respectively. These regimes are resulting from the simulated MS-BVAR model. The past covariates say $t = 1,2,3 \dots, T$ originates from a set of series clearly expressed by $W_{t-1} = (W_{(t-1)1}, \dots, W_{(t-l)p})$ with their equivalent P dimensional vector and denotes the process as W_t. The mean series being expressed by $\mu_t = E[Y_t|S_{t-1}]$, is assumed to be the conditional expectation of the response given earlier values. Therefore, the condition likelihood estimation considered in the preceding study is being presented by:

$$P_{\beta}(Y_t = 1|S_{t-1}), \tag{3.43}$$

where β is a p-dimensional vector, and S_{t-1} indicates the observed components to the researcher at time $t-1$ of the time series and the covariates information.

In the case where the response random time covariate has a unit root, then the, vector $\{W_{t-1}\}$ might designate a single or multiple time series and thereof the functions which impact the principal ongoing inventions of the series of interest (Kedem and Fokianos, 2005). In declaring that $P_\beta(Y_t = 1|S_{t-1})$ produce precise likelihood estimates, a suitable inverse link h ≡ F is chosen and engaged in such a way that it maps both real line and the interval $[0,1]$. Finally, designating the probability of success F_{t-1} as Π_t, the model is then established as:

$$\prod_t(\beta) = \mu_t(\beta) = P_\beta(Y_t = 1|S_{t-1}) = F(\beta^{`} Z_{t-1}) \tag{3.44}$$

F is continuous and strictly an increasing function, and returns values ranging between 0 and 1. From that point, the choice of F that has a standard combined logistic function determines the logit model that prompts the speculation of the logistic regression model as:

$$\prod_t(\beta) = P_\beta(Y_t = 1|S_{t-1}) = \frac{1}{1+e^{\left(-\beta^{`} Z_{t-1}\right)}}, \tag{3.45}$$

where β presents the P −dimension of the covariates process. W_{t-1} and the inverse link is well-defined by $F \equiv \Phi$, the cumulative function which form the standard normal distribution specified by Φ (Nyberg, 2010).

3.4.4 Computation of marginal effects

Marginal effects are the partial derivatives of the event probability with respect to the predictor of interest. A more direct measure is the change in predicted probability for a unit change in the predictor. For the purpose of the study, the marginal effects are computed to quantify the likelihood of the occurrence of inflation crises. Norton et al. (2004) have emphasised that the intuition from linear models, however, does not extend to nonlinear models. The authors showed that the conditional mean of the response variable is:

$$\begin{aligned} E[y|x_1, x_2, X] &= \Phi(\beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + X\beta) \\ &= \Phi(u) \end{aligned} \tag{3.46}$$

where, Φ is the standard normal cumulative distribution and u denotes the index $\beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + X\beta$. Supposing that x_1 and x_2 are continuous, then marginal effect of just the interaction term $x_1 x_2$is:

$$\frac{\partial \Phi(u)}{\partial x_1 x_2} = \beta_{12} \Phi'(u) \tag{3.47}$$

Most researchers interpret this as the interaction effect and the full interaction effect is the cross-partial derivative of the expected value of y.

3.5 Model diagnostics checks

Box et al. (2013) caution of the drawbacks that might affect the quality of conclusions drawn from fitted models. These drawbacks might even lead to uninterpretable results. Some of these drawbacks are considered to be important especially in applied econometrics. Among the most pertinent are heteroscedasticity or serial correlation of the error terms, structural changes in the regression coefficients, nonlinearities, utilitarian misspecification or overlooked variables. For the purpose of the current study, issues pertaining to heteroscedasticity, serial correlation and normality of the error term are discussed.

Because the model with serially correlated residuals have some problem of minimum variance among the estimators, Maas and Hox (2004) argue that it is best to test for the correlations as the correlation introduces bias into the standard variance estimates. While in the normality assumption, the normality test is established to test whether the model coefficients are significantly different from zero and for calculating confidence intervals for forecasts if this assumption is violated, then this creates some problems because sometimes the error distribution is skewed by the presence of a few large outliers (Maas and Hox, 2004).

3.5.1 Normality

Jarque-Bera (JB) test is used in this study to test the assumption that a given sample X_s originates from a normal distribution and also the estimated residuals for each model are normally distributed. The JB test of normality does better when used on samples of more than 50 observations. From the power calculations, the JB test is found to have a large empirical alpha test of normality for both small and large samples hence it is the best over the other normality tests. The JB test is calculated using the following formula:

$$\mathrm{JB} = \frac{\mathrm{n-k}}{6}\left(\mathrm{S}^2 + \frac{1}{4}(\mathrm{K}-3)^2\right) \sim \chi^2, \mathrm{df}, \quad (3.48)$$

where S is the skewness, K is the number of regressors from the regression model, n is the sample size and df is the degrees of freedom. The test follows a chi-square distribution with 3 degrees of freedom for sample size of 2000 and above. But when the sample is less than 2000, the JB test follows a normal cumulative distribution (NCD). The tested hypothesis is:

$$\begin{gathered} H_0 : E(\varepsilon_t = 0) \\ H_a : E(\varepsilon_t \neq 0) \end{gathered}$$

The null hypothesis is rejected if the calculated probability value of the JB static is less than an observed probability value or if the calculated JB statistic is greater than the critical value obtained from chi-square distribution with two degrees of freedom. The rejection of the null hypothesis implies that the series does not conform to normal distribution standards suggesting imposition of necessary transformation.

3.5.2 Serial correlation

The purpose behind testing the serial correlation of the estimated model is that the error term which are serially correlated makes the model estimates and standard errors to be biased; additionally, bringing about the less efficient results (Drukker, 2003). While the Durbin-Watson test is formulated with the AR(1) alternative hypothesis error, it should have some power in detecting other forms of serial correlation provided $E[\varepsilon_t \varepsilon_{t-1}] \neq 0$ under the alternative hypothesis. Still, there are more powerful tests for high-order serial correlation that involves high-order autocorrelation estimators. For high order test, the Breusch-Godfrey test is used in this study. Assume that the error term follows an $AR(p)$ for $p > 1$, i.e:

$$\varepsilon_t = +\rho_1 \epsilon_{t-1} + \cdots + \rho_p \varepsilon_{t-p} + \nu_t, \tag{3.49}$$

and $\nu_t \sim i.i.d(\mu = 0, \sigma_\varepsilon^2 = 1)$ then the hypothesis is defined as:

$$\begin{gathered} H_0 : \rho_1 = \cdots = \rho_m \\ H_a : \rho_m \neq 0 \end{gathered} ,$$

Then equation (3.49) is expanded to be a Q-statistic from squared residuals presented by:

$$Q_m = n(n+2) \sum_{k=1}^{p} \frac{\rho_k^2}{n-k} \sim \chi_{\alpha,}^2, m - p. \tag{3.50}$$

Here, n is the sample size and k and p is number of the estimated model parameters. The null hypothesis is not rejected if the calculated probability is greater than the observed probability value implying that the estimated residuals are not correlated to each other over time.

3.5.3 Heteroscedasticity

Since the estimated model needs stable estimates, the test for homogeneity of the variance is found to be a crucial aspect (Box et al., 2013). If the estimated model has a varying variance in the error terms, three conditions in the model are being observed such as, (1) the coefficients of the estimated model are unbiased, (2) the R^2 and adj R^2 are unbiased and (3) the variance of the estimated coefficients increases in the presence of heteroscedasticity. This causes the estimates of the model not to be best linear unbiased estimators (BLUE) hence the standard errors become biased. This in turn leads to biasness in test statistics and confidence intervals (Asteriou and Hall, 2015).

Denoting the autocorrelations of the residuals of the estimated model by $\rho_1, \ldots, \rho_m$ with $m = \frac{n}{4}$, the independence of the residual ε_t is tested on the hypothesis that was established by Engle (1982) as:

$\begin{matrix} H_0: \rho_{ij} = 0 \\ H_a: \rho_{ij} \neq 0 \end{matrix}$ meaning the residual are independent against residuals are not independent.

The above hypothesis is tested by a test statistic known as Q-statistic of squared residuals which is given by:

$$Q_m = n(n+2)\sum_{k=1}^{m} \frac{\rho_k^2}{n-k} \sim \chi_\alpha^2, n-p \tag{3.51}$$

The rejection rule is that reject the null hypothesis in favour of the alternative if the observed probability value is greater than the calculated probability value of the test statistic. Because the Q statistic is closely related, the Lagrange multiplier test for autoregressive conditional heteroscedasticity (ARCH), then Engle (1982) showed that the test is based on the linear regression as:

$$\hat{\varepsilon}_t^2 = \eta_0 + \sum_{i=0}^{m} \eta_i \varepsilon_{t-i}^2 + \upsilon_t \tag{3.52}$$

where, $\eta_0, \ldots, \eta_m$ are the parameter estimates and $\upsilon_t \sim \text{i.i.d}(\mu = 0, \sigma_\varepsilon^2 = 1)$. Hence the tested hypothesis is:

$$H_0: \text{Var}(\varepsilon_t) = \sigma_t^2$$
$$H_1: \text{Var}(\varepsilon_t) \neq \sigma_t^2$$

The test statistic is the usual F-statistic:

$$F^* = \frac{R^2/m}{1-R^2/n-m-1} \sim F_{\alpha,(m,n-2m-1)} \tag{3.53}$$

Reject the null hypothesis if the F test is greater than critical value of $F_{\alpha,(m,n-2m-1)}$ and conclude that the error term is not constant over time this implies that the estimated model has estimates which are not BLUE.

3.6 Forecasting with $\mathbf{MS(q) - BVAR(p)}$

Primarily, time series model building necessitates projecting into the future the values of a variable of interest. It is prominent to assess the precision of the projections as noted by(Chen, 2009). In order to come up with the early warning signal model, the forecasts of the simulated MS-BVAR are established. Denoting the forecast as $\widehat{Y}_{T+\tau}(T)$, Montgomery et al. (2015) recommended the mean squared error as one of the forecast error metrics. This criterion uses the following equation: expected value of the squared forecast errors, which is calculated as $E\left[\left(Y_{t+\tau} - \widehat{Y}_{T+\tau}(T)\right)^2\right] = E[e_T(t)^2]$ is being minized. Carriero et al. (2015) showed that the h-step ahead forecasts are obtained by the following iteration:

$$\widehat{Y}_{t+h} = \overline{\Phi}_c + \overline{\Phi}_1 \widehat{Y}_{t+h} + \overline{\Phi}_2 \widehat{Y}_{t+h} + \cdots + \overline{\Phi}_p \widehat{Y}_{t+h-p} \tag{3.54}$$

where $\widehat{Y}_{t+h} = \widehat{Y}_{t+h-p}$ for $h \leq p$ and $\overline{\Phi}_1, \ldots, \overline{\Phi}_p$ are the estimated parameters of the forecasting model.

3.6.1 Evaluating the Performance of MS(q)-BVAR(p)

The forecasting exercise is performed in Pseudo real time, $i.e$ the information which is not accessible is never utilized at the time the forecast is made. For all models, Carriero et al. (2015) utilized the recursive estimation window and assessed their outcomes with root mean squared forecast error (RMSFE). By and by, Makatjane and Moroke (2016) demonstrated that forecasting performance is checked upon as to discover the best performing model and utilized the three error measurements to be specific; mean square error (MSE), mean absolute error (MAE) and mean absolute percentage error(MAPE). In any case, the present study tails these methods for Carriero et al. (2015) and Makatjane and Moroke (2016) for forecasting performance of the MS-BVAR and uses the root mean square error (RMSE), MAPE and MAE.

Given the time series $\mathrm{Y_t}$ and the estimated $\widehat{\mathrm{Y}}_\mathrm{t}$, Makatjane and Moroke (2016) defined the MAE and MAPE as:

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{t}=1}^{\mathrm{n}}\left[\mathrm{Y_t} - \widehat{\mathrm{Y}}_\mathrm{t}\right]^2 \tag{3.55}$$

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{t}=1}^{\mathrm{n}}\left|\mathrm{Y_t} - \widehat{\mathrm{Y}}_\mathrm{t}\right| * 100 \tag{3.56}$$

where, n is the sample size, Y_t is the original time series data and finally $\hat{Y}_t$ is the forecasted time series. While Carriero et al. (2015) specified RMSE as:

$$\mathrm{RMSE} = \sqrt{\sum_{\mathrm{t}=1}^{\mathrm{n}}\left[\mathrm{Y_t} - \widehat{\mathrm{Y}}_\mathrm{t}\right]^2} \tag{3.57}$$

3.7 Concluding remarks

This chapter introduced an overview of two statistical models for building an early warning system for inflation in South Africa. The preliminary analysis included in the Monte Carlo experiment in assessing the properties of the sample used and it convergence. The behaviour of the data set is assessed by the descriptive statistics and the Jarque-Bera test for normality. Prior model estimation, the nonlinear tests are used together with the nonlinear unit root test to check whether the data is ready for nonlinear model estimation. The tests used here are the KSS-NADF for nonlinear unit root test, followed by the BDS test for testing the presence of linearity in the series. Then the study continues by the estimation of the Ramsey RESET test to the independence of the estimated residuals of the linear model and finally used the CUSUM of square to support the RESET test. Upon realization that the data is ready for nonlinear modelling, the MS-BVAR and logistic regression models are estimated.

For the robustness of the $\mathrm{MS(q) - BVAR(p)}$, the model is diagnosed for the normality assumption, the serial correlation and heteroscedasticity in the error term. For a model to be robust, all the mentioned assumptions are met where all the calculated probability values of the test are found to be greater than the observed probability values. And lastly for forecasting performance of the $\mathrm{MS(q) - BVAR(p)}$, the three-error metrics are employed and these are the MAE, MAPE and RMSE. Furthermore, these tests and routines are utilized in the next section of the study.

CHAPTER 4

DATA ANALYSIS AND RESULTS

4.1 Introduction

Data analysis is a process of investigating, cleaning, transforming, and validating data. This is done with the objective of discovering valuable information and facilitating sensible decision making through the use of recommended solutions. There are various features and methodologies which incorporate classified tactics under the mixture of names in diverse business, science and social science domains which are mostly examined and explained in data analysis section.

This section presents results from the empirical analysis of the data. The results are summarized in tables and graphs. An R programing 3.2.4 revised software Matlab and Oxmetrics 6 software's are used to execute the analysis. The aim of the study is to explore the possibility of estimating the MS-BVAR model and to use the estimated regimes in logistic regression to quantify the possibility of inflation crisis in South Africa. The results are meant to help address the objectives outlined in Chapter 1.

It is important to note that the current study is a follow-up of Makatjane (2015) study who used a univariate MS(2)-AR(1) and the logistic regression models to determine a warning sign for inflation rate in South Africa. The study only used a quarterly inflation data from quarter 1 of 2001 to the last quarter of the year 2014. Repo rate was not considered in this study. The current study used a Monte Carlo monthly simulated data and extends the Markov Switching and logistic regression models to do multivariate analysis. The results are compared in order to determine the effectiveness of these models in the analysis of inflation rates.

The remainder of this chapter is organized as follows: Section 4.2 discusses the results to explore the variables used in the study and further checks if the data is ready and fit for the proposed methods discussed in Chapter 3. Section 4.3 deliberates on MS-BVAR and the logistics regression models. The results for model diagnostics are given and discussed in Section 4.4. Section 4.5 presents the forecasting performance of the estimated $\mathrm{MS}-\mathrm{VAR}(\mathrm{p})$ and the logit EWS results are presented in Section 4.6. Concluding remarks for this chapter are given in Section 4.7.

4.2 Preliminary results

This section of the study presents the preliminary data analysis. Simulated inflation rate and repo rate are explored for time series properties and together with the nonlinearity properties. Results are presented in tables and figures.

4.2.1 Exploratory data analysis results

In this part of the analysis, the data is explored. According to Makatjane and Moroke (2016), it is of utmost importance to assess the behavioural pattern of the data so as to be able to identify the associated properties and to help decide on the type of time series model. Following their preliminary analyses, the study employs the descriptive statistics in order to provide a comprehensive understanding of the data. To complete the preliminary analyses, the study also uses nonlinear and nonlinear unit root tests to assess the nonlinearity and nonstationarity of the series. The results are discussed in preceding sections.

4.2.2 Graphical presentation of data

Figure 4.1 presents the graphical presentation of the Monte Carlo monthly simulated inflation rate and repo rate of South Africa for the period of January 1999 to June 2016. The year 1999 marks the period before the South African Reserve Bank (SARB) adopted the inflation targeting framework policy.

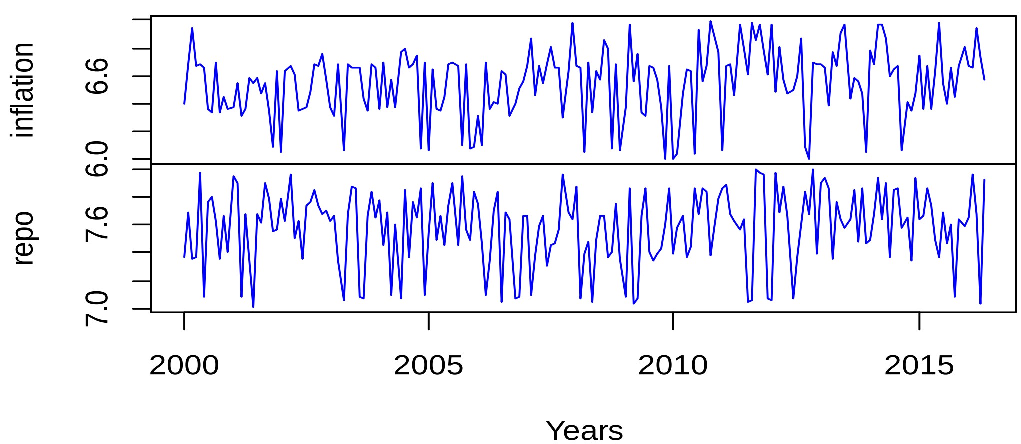

Figure 4.1 Simulated South Africa Inflation and Repo Rate

Using an eye inspection, both the series seem to possess the same characteristics as they are moving towards one direction in the same wave length. The movements of the series from the year 2000 suggest the possibility of cointegration prior to imposing the transformation to the data. The up and down spikes are the indication of volatility and this is expected for financial and macroeconomic time series. The co-movement and irregular patterns served as a strong motivation to use these variables in multivariate MS-BVAR and logistic regression models. These series not trending and are perfectly suitable to serve as experimental units for this study and they perfectly fit the proposed frameworks.

Exploratory data analyses methods are also used to calculate the descriptive statistics presented in Table 4.1. The descriptive measures are used to further explain the South African inflation rate and repo rate for the period January 1999 to June 2016.

Table 4.1 Exploratory Data Analysis

Statistic	Inflation Rate_1	Repo Rate_1
Mean	6.328507	7.328604
Median	6.326821	7.327956
Std. Dev.	0.190202	0.190116
Jarque-Bera (prob)	0.722954 (0.696647)	1.125371 (0.569677)

According to the results, the mean of the inflation rate is 6.328507 which implies that on average, the SA inflation rate revolves around 6.3% monthly; while the repo rate revolves around 7.32%. This high repo rate is in line with the discussion of Van der Merwe and Mollentze (2010) who advised from the monetary policy transmission mechanism that in order to cause a decline in inflation rate, it is however best to set a high percentage of the repo rate which will eventually causes a decline in domestic assets prices. As revealed by the results, inflation rates are a bit lower than repo rate supporting these authors' view. Currently, according to the global rates.com's current reports, the South African repo rate stands at around 7% and inflation rates are reported to be 6.48% in May 2016. This suggests that simulated repo rates are insignificantly higher than the actual and simulated inflation rates are a little bit lower. This is not surprising as, in fact, these small differences are expected from the simulated and actual time series data sets.

The study simulated 210 observations, large enough for the assumption of normality to hold. This is in accordance with the discussion of Mordkoff (2011) who hinted that by central limit theorem, the distribution of sample mean approaches normality as the size of sample size (n) increases regardless of the distribution shape. Chen et al. (2010) explicitly bargained for Mordkoff's view by suggesting a sample size as big as 30 or more observations in order to protect the assumption of normality. On the same breath, Ismail and Isa (2006) also showed that the distribution of the BDS does not depart from asymptotic normal distribution like in small samples. The observed probabilities associated with the Jarque-Bera test of normality are both insignificant at 5% and 1% significance levels further confirming that the distribution from which the sample was drawn conforms to normal standards.

4.2.3 Nonlinear and nonlinear unit root tests results

In this section, the results to confirm if the data used are nonlinear and nonstationary are discussed. Theory dictates that nonlinear models are suited to capture these characteristics in the data, as a result it important to ensure that these assumptions are not violated. The results are presented in Tables 4.2.

Table 4.2 KSS Nonlinear unit root test

Variable	lag length	Coefficient	Std. Error	t-Statistic	Prob.	KSS
Inflation	2	-0.50185	0.06035	-8.316	0.00	-2.1013
Repo	2	-0.52636	0.05889	-8.937	0.00	-1.1818

Critical values of the KSS-NLADF test with constant and trend at the 10%, 5% and 1% significant levels are -3.13, -3.40 and -3.93, respectively

Alluding to the outcomes in Table 4.2, the null hypothesis of nonlinear unit root is rejected for both inflation rate and repo rate at all levels of significance, supporting the findings in Figure 4.1. The calculated probability values of the KSS test are all (significant) less than the conventional significance levels (1%, 5% and 10%). The results suggested that the data is asymmetric and nonlinear stationarity which then permitted the utilization of the proposed $MS - BVAR(p)$ model. Since the study has found that the series have nonlinear unit roots, the BDS test as the confirmation of the presence of nonlinearity is engaged and Table 4.3 gives summary report of the results.

Table 4.3 Nonlinearity test

BDS test for inflation rate				
Dimension	**BDS Statistic**	**Std. Error**	**z-Statistic**	**Prob**
2	0.130277	0.01233	10.56606	0.01
3	0.205071	0.019904	10.30314	0.01
4	0.255318	0.024083	10.60156	0.01
5	0.275317	0.025511	10.79205	0.01
6	0.277537	0.025009	11.09762	0.01
BDS test for repo rate				
Dimension	**BDS Statistic**	**Std. Error**	**z-Statistic**	**Prob**
2	0.149919	0.009737	15.39606	0.001
3	0.245242	0.015677	15.64347	0.001
4	0.303061	0.018912	16.02504	0.001
5	0.335905	0.01997	16.82056	0.001
6	0.349058	0.019513	17.88867	0.001

The reported BDS test for both the inflation and repo rates indicate that the two series possess some properties associated with nonlinearity. Since the reported probability value is less than the level of significance, henceforth the null hypothesis of linearity is rejected in favour of the nonlinearity.

Preliminary analysis of data confirmed that the Monte Carlo simulated inflation and repo rates data are suitable for analysis with the MS-BVAR and the Logistic regression models. All the assumptions are save confirming the readiness and worth of the data for primary purposes. From Section 4.3 onwards, the study employs the proposed methods mentioned with a view of achieving the objectives as outlined in previous sections.

4.3 Empirical results

In the following sub-section, the estimation of the proposed models is done according to the discussions in Chapter 3. Prior to the estimation of the $\mathrm{MS}-\mathrm{BVAR}(\mathrm{p})$ model, the $\mathrm{BAR}(\mathrm{p})$ model is estimated and tested for the linear specification. The optimum lag length for Markov Switching model is selected by the use of the BIC, AIC and HQ information criteria. Furthermore, $\mathrm{MS}-\mathrm{BVAR}(\mathrm{p})$ is estimated after which the residuals of the selected models are diagnosed for normality, serial correlation and heteroscedasticity.

Moreover, the forecasting performance is established using RMSE, MAE and MAPE error metrics as discussed in Chapter 3. The final stage of this chapter is the estimation of the logistic regression and its assessment for the performance as an early warning signal model. Lastly the marginal effects of the logistic model are estimated and interpreted.

4.3.1 Maximum lag length selection and model estimation

This section presents and discusses the results on the proposed $\mathrm{MS}-\mathrm{BVAR(p)}$ model. Prior estimation, the optimal lag length for the model is identified as to select the parsimonious lag order of the $\mathrm{MS}-\mathrm{BVAR(p)}$ model. The selected lag length is the one that is used to estimate the model. The three information criterions discussed in the previous chapter are estimated and Table 4.4 represented the associated results.

Table 4.4 Lag-length selection

	Information criterions		
Number of lags	**AIC**	**BIC**	**HQ**
1	0.692876	0.791141**	0.732634**
2	0.689489	0.853264	0.755752
3	0.713370	0.942656	0.806140
4	0.730615	1.025411	0.849890
5	0.766823	1.127129	0.912603
6	0.793876	1.219693	0.966162
7	0.811747	1.303074	1.010539
8	0.842562	1.399399	1.067859

*****signifies a significant lag***

As reported in Table 4.4, the BIC and HQ selects the optimal lag length as 1. The AIC has the smallest value at lag length of 2 contradicting the suggestions by the SBC and the HQ criteria. However, theory suggests the optimal lag selected by the SBC should be considered and this should be a final decision (Tsay, 2005). Moreover, following the discussion of Scott and Hatemi (2008) for each simulated models with large samples, SBC and HQ are found to be the best performers to select the optimal lag length. The current study adopted the suggestion by the mentioned authors, hence the optimal lag length for the study is 1.

4.3.2 Estimation of BAR(1) model and RAMSEY reset test results

The main focus of the study is to explore the possibility of estimating the MS-BVAR model and use the estimated regimes in logistic regression to quantify the possibility of inflation crisis in South Africa. The first step in the empirical investigation is verifying whether the inflation rate and repo rate exhibits the regime switching behaviour. For this purpose, the study proceeds to test the null hypothesis of no regime shifts against the alternative of there is regime shifts between the inflation rate and the repo rate. Formally, the Ramsey reset test which was developed by Ramsey (1969) is used to make the final choice of the suitable modelling approaches by estimating individual BAR(1) models.

The study follows the methodology of Chkili and Nguyen (2014) where they used the likelihood ratio to test if there is regimes shifts within the AR models for the BRICS countries using the exchange rate and stock market returns data. Their study has rejected the individual linear specifications of the AR models and accepted the alternative that there are regime shifts. With that note, hence the current study uses a Ramsey RESET test to test the individual BAR (1) models for both inflation and repo rate.

Table 4.5 reports on the estimated BAR(1) model parameters using the EM algorithm as discussed in Chapter 3 together with the RAMSEY RESET test results to confirm there is indeed regime shifts across the simulated inflation rate and repo rate.

Table 4.5 Estimated BAR(1) models with nonlinear test

		repo rate		
Parameter	**Coefficient**	**Std. Error**	**Test Statistic**	**Prob**
Φ_1	65.676	0.527118	14.532	0.000000
Φ_2	3.229	0.080387	0.109	0.000000
Reset Test	208.53			0.00000
		inflation rate		
Φ_1	6.602590	0.454971	14.512	0.0000
Φ_2	-0.006515	0.059803	-0.109	0.0002
Reset Test	25.509			0.00001

Two important information can be derived from the results which is:

(1) All the estimated parameters of the specified BAR(1) models for inflation rate and repo rate are all significant as shown in Table 4.5. All the probability values are less than 1%, 5% and 10% level of significance respectively. (2) The estimated Ramsey RESET test rejects the null hypothesis of Φ_{ij} =0 because the calculated probability value is also found to be less than the observed probabilities of 1%, 5% and 10% respectively. This implies that the estimated model follows some nonlinear estimations within the specified time horizon of January 1999 to June 2016.

4.3.3 Parameter stability test results of BAR(1)

Following the previous results reported in Table 4.5, the CUSUM measure is used to test the stability of the estimated BAR(1) models parameters and the results are presented as Figure 4.2.

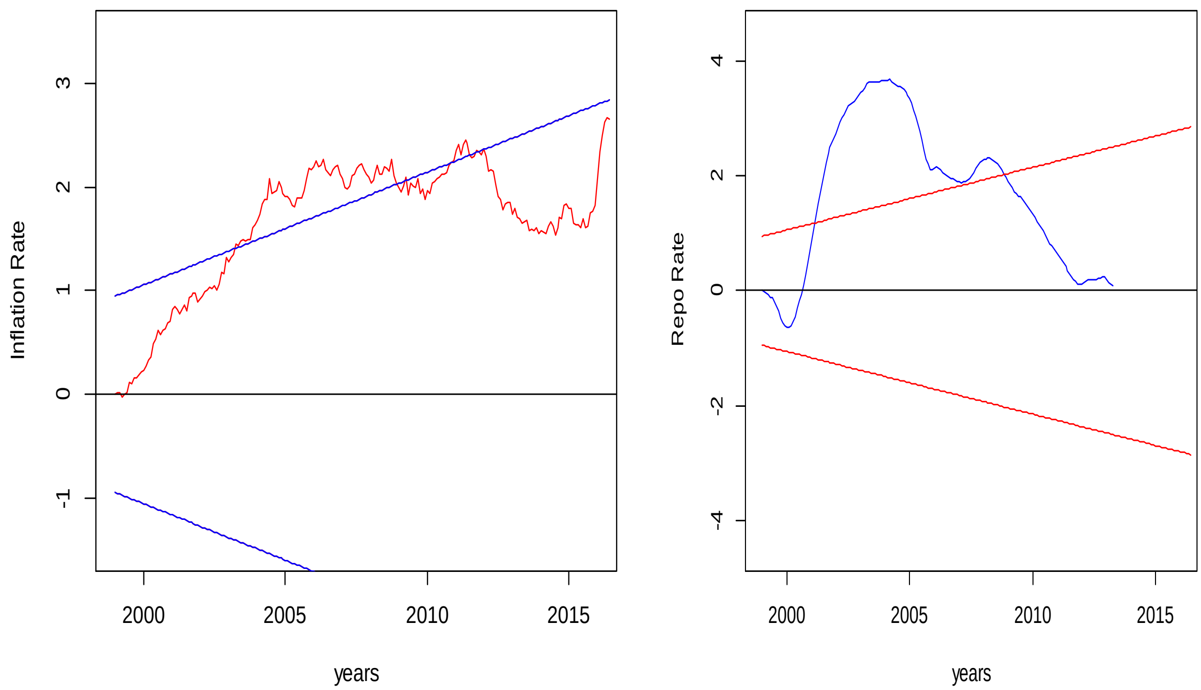

Figure 4.2 CUSUM of BAR(1) for inflation rate and repo rate

For both the models, the residuals are plotted as Figure 4.2. The visualization of the plots shows that both the series are moving outside the bounds suggesting that both repo rate and inflation rates of South Africa are not stable. This further implies some structural change within the series as the residuals of the model are outside the 95% bounds indicated by the blue lines in the graph. These findings are in support of Figure 4.1 and one could infer that both series tend to hike outside the specified target of 3%-6% of inflation and the fixed value of 7% for repo rate.

4.3.4 Structural breakpoints test results

Ramsey RESET test and the CUSUM of squares revealed that there is no linear independence in the estimated BAR(1) models, which therefore implied the high chance of the structural breaks within inflation rate and repo rate. To test presence of structural breakpoints, a Bai-Peron multiple breakpoints test is established. This procedure tests for more than one structural breakpoint within the entire time frame of the series. The structural breakpoint results are summarized in Table 4.6.

Table 4.6 multiple breakpoint test

		inflation rate		
Breaks	**# of Coefs**	**Sum of Sq. Resids**	**Log-Likelihood**	**SBC**
0	1	1376.66	-467.25	1.981455
1	3	1285.70	-460.58	1.967180
2	5	907.95	-426.67	1.673398
3	7	643.24	-393.06	1.382799**
4	9	634.10	-391.67	1.422582
5	11	712.77	-403.07	1.593609
		repo rate		
0	1	1959.92	-501.69	2.33
1	3	1689.52	-487.21	2.24
2	5	1479.09	-474.25	2.16
3	7	1105.66	-445.88	1.92**
4	9	1094.34	-444.87	1.97
5	11	1153.78	-450.03	2.08

*****signifies significant break points***

In relation to the results reported in table 4.6, both the sum of squared residuals (SSR), log likelihood, indicates that the BAR(1) for both inflation rate and repo rate has four structural change points while the SBC reports three structural change points within the inflation rate and repo rate model. Bai and Perron (2003) suggest the SBC as the best information criterion for selecting the number of breaks within the series. The finding of the current study are in agreement with those of Bai and Perron (2003) and Hall et al. (2013) who in their studies of inference on structural breaks have found that the SBC performed well for both the data with and without breaks. The reader is also referred to similar studies by Bai and Perron (2003b), Paye and Timmermann (2006) and Timmermann (2001). Therefore, this study uses the SBC as the best information criterion in this regard and table 4.6 reports the periods of the structural breaks.

The three structural breaks are summarized in Table 4.7.

Table 4.7. Periods of structural breaks

	inflation rate		
Number of breaks	**Breaks**		
1	2004(03)		
2	2004(03)	2006(06)	
3	2006(06)	2007(11)	2011(07)
	repo rate		
Number of breaks	**Breaks**		
1	2004(03)		
2	2004(03)	2006(06)	
3	2006(06)	2007(11)	2011(07)

NB: numbers in (.) represents the month of the structural break

The periods of the structural change towards inflation rate and repo rate are reported in Table 4.7. The first break point occurred in June 2006. According to Bonga-Bonga and Kabundi (2015), these structural change is caused by the reason that the SARB started to follow the contractionary policy by increasing the repo rate from 7% to 11%Furthermore, the 2007 break is due to the global financial crisis that started in the US. Acharya et al. (2009) pointed out the six events which they believe might be causes of this crisis. This includes in them also as commented by Global Economist: (1) Repeal of Glass-Steagall act in 1999 by the Clinton administration. Glass-Steagall act is one of the biggest post-depression piece of legislations, separating commercial banks and investment banks.

Although this “deregulation” did not repeal the most important section distinguishing the role of commercial banks and investment banks (Wallison, 2011). (2) The surge in the number of subprime mortgages as a response to high level of housing speculations and building up of the bubble. (3) The Depository Institutions Deregulation and Monetary Control Act of 1980. (4) The creation of new financial instruments which was risky, hard to assess and shifted the accountability between agents. (5) Fall of the real interest rate, combined with the Federal Reserve’s expansionary monetary policy. (6) Global Financial Imbalances. According to Moroke et al. (2014), 2007-2009 financial crisis is the period in which the resources were relegated, companies retrenched people causing unemployment rates to rise rapidly with the overall weakening of the economic growth.

4.3.5 $\mathbf{MS(2)-BVAR(1)}$ model estimation results

In this section of the study, $\mathrm{MS}(2)-\mathrm{BVAR}(1)$ is estimated and the results are reported in table 4.8.

Table 4.8 MS-BVAR (1) Parameter estimates for inflation

	Regime 1		
Parameter	**Coefficient**	**Standard error**	**Significance**
C_1	2.474009	0.69	0.01079
ϕ_{11}	0.432757	0.020611	0.04815
ϕ_{21}	0.724848	0.259446	0.01088
σ_1	11.3598204	0.099216	0.01
	Regime 2		
C_2	0.668062	0.47962	0.0001
ϕ_{12}	0.127502	0.032863	0.0103
ϕ_{22}	0.651025	0.111504	0.01075
σ_2	0.4947452	0.010203	0.00233
	Transition Probabilities		
Regime1 [Low Inflation]		**Regime2 [High Inflation]**	
0.995337316		0.001406	
0.001127		0.981245	

The results in table 4.8 indicate that the estimated coefficients for capturing the impact of repo rate movement (Φ_{21} and Φ_{22}) on the inflation rate are significant in all the cases. These findings suggest that the fluctuations in the SA repo rate do have strong effects on the dynamics of inflation rate. Furthermore, the effects of inflation rate on repo rate movement are captured by the coefficients(Φ_{11} and Φ_{12}) and they are all significant. The transition probability matrix presented as $\begin{matrix} p(S_t = 0|S_{t-1} = 0) = 0.995337 \\ p(S_t = 1|S_{t-1} = 1) = 0.981245 \end{matrix}$ suggests that the probability of inflation rate in low regime is higher than that of high inflation regime.

This implicitly says that when the inflation series is in Regime 0 (Low inflation regime), the probability that it switches to the high inflation regime denoted as regime 1, is $P(S_t = 1|S_{t-1} = 0) = 0.001127$ which is lower than that of regime 1. This finding of the study predict that the inflation rate of SA could be lower specifically within the given interval of 3% to

6%. The average duration of each regime also supports these findings and it is expected to be 136.7 months which is approximately 11 years starting from January 1999 to June 2016 with inflation expected to be high for 101.7 months which is approximately 8 and half years. The filtered probabilities for inflation rate are plotted and reported in Figure 4.3.

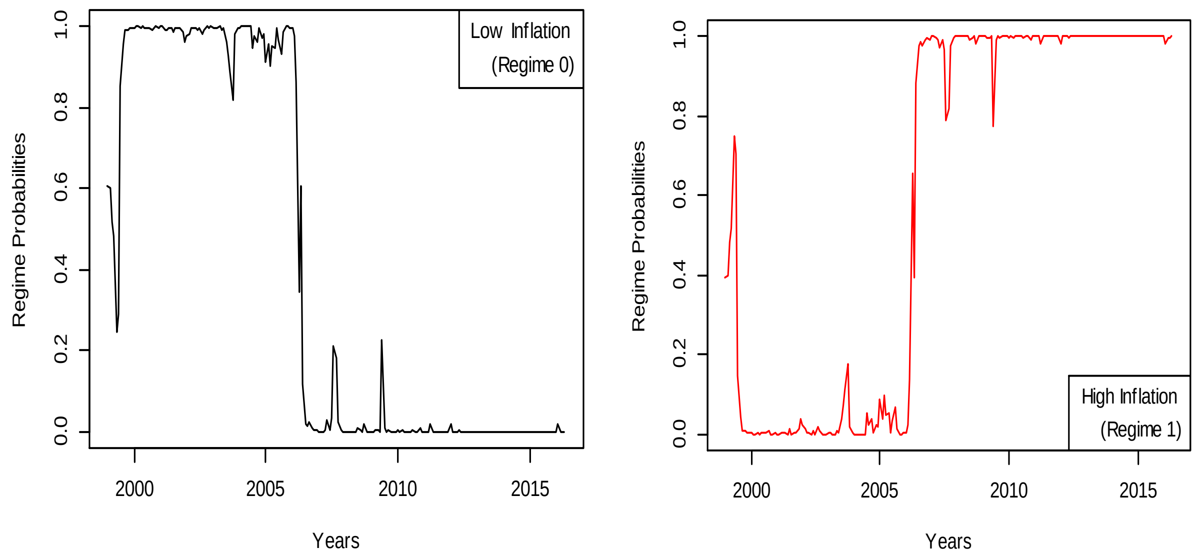

Figure 4.3 Filtered Probabilities for low Inflation and high inflation

The results approve that the inflation rate stayed stay longer in regime 0 than in regime 1. It can be observed that the low inflation regime dominates the high inflation regime. Since the year 2000, the low inflation has been dominating the high inflation regime until early 2015 when the inflation rate started to fluctuate between the high and low inflation rates. Furthermore, the inflation rate had become volatile but still in the low inflation regime as depicted in Figure 4.4.

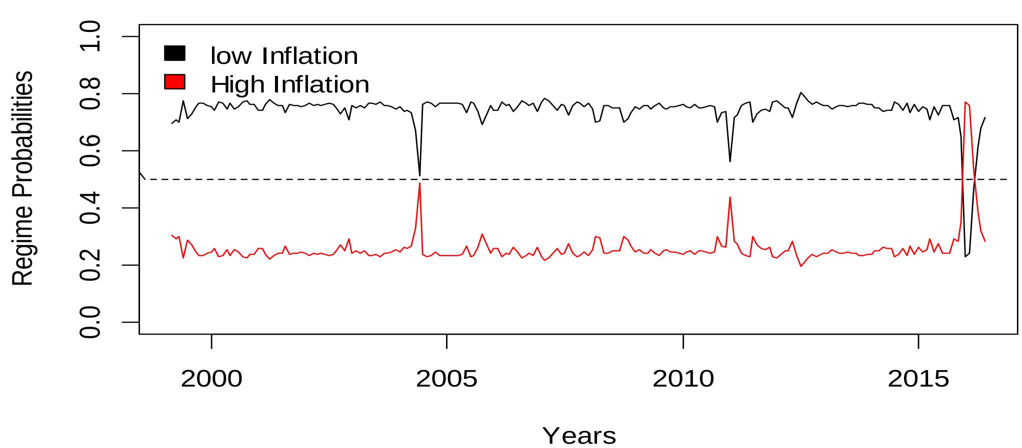

Figure 4.4 Smoothed Probabilities for Inflation

4.3.6 Logistic regression results

In building SA's early warning system for inflation rates, the Logistic Regression Model (LRM) framework is followed. The reported probabilities from the logistic model give a sensible appraisal about the achievability of SA inflation crisis. Through the grouping of the regimes from the $\mathrm{MS}-\mathrm{BVAR}(1)$, the response variable to the LRM become binary with a scene of high inflation coded 1 while that of low inflation is named 0 and covariate to the LRM is the repo rate. The results of an estimated EWS Logit model are summarized in Table 4.9.

Table 4.9 Estimated logit model

Variable	Coefficient	Std. Error	z-Statistic	Prob
cons	-27.6876	5.692925	-4.86	0.00
repo	3.733378	0.7706061	4.84	0.00
Probabilities for each Regime				
	Regime 1		**Regime 2**	
Probability	0.43		0.57	

The coefficient signs of the repo rate as an indicator to the inflation crisis are found not to be consistent with the expectations from the monetary theory. The positive repo rate is directly proportional to the inflation rate; hence inference of surge in the value of the repo rate increases the likelihood that the country enters in high inflation period. These results are in conjunction with the ones reported by the $\mathrm{MS}-\mathrm{BVAR}(1)$ in table 4.8. Leshoro (2014) also reported that a shock in the repo rate increases the inflation.

Van der Merwe and Mollentze (2010) suggested that an increase in the repo rate causes a decrease in the inflation rate. This is a monetary transmission mechanism of the SARB through the repo rate channel. On the same breadth, the current study found that the inflation rate remains in low inflation regime (regime 0) as revealed by the logistic model in Table 4.6. These results are in agreement with those in Table 4.8. The results also signposted that a percent of crisis correctly called (PCCC) is 57% while the wrong issued signal of the high inflation rate by the model is only at 43%.

4.3.7 Marginal effects

In order to quantify the possibility of the occurrence of an incidence of high inflation, the marginal effects coefficient of the repo rate is reported as 0.8164759 which is directly proportional to the inflation rate as long-established by the logistic model in Table 4.9.

The inference that one can make here is that a 1% increase in repo rate in the past months say a 3 months ago, increase the probability of the country to enter into the inflation crisis by approximately 81% per month. The same results of increment of repo rate that causes the inflation rate to rise also are confirmed by Bonga-Bonga and Kabundi (2015) in their study of monetary policy instrument and inflation in South Africa showed that a positive shock in the repo rate increases prices for more than 18 months which gives no evidence of the likelihood of prices to decrease after a positive monetary shock. In addition Mboweni et al. (2008) and Gupta and Komen (2009) found the similar results.

4.4 Model diagnostic checking

After model estimation, the estimated residuals of the $\mathrm{MS-BVAR}(1)$ and logistic regression models are subjected to a battery of diagnostics as discussed in Chapter 3 and the summary of these tests is given in Table 4.10.

Table 4.10 Model diagnostic checking

MS-BVAR		
Test	**Test Statistic**	**prob**
Jarque-Bera	2.64778	0.4898
ARCH	14.905	0.79
Godfrey test	65.637	0.3774
Logistic regression		
Jarque-Bera	1.496	0.158
ARCH	10.568	0.1478
Godfrey test	10.98	0.11101

For the greater part of the statistical diagnostic tests, the assumptions of the error term are not violated. The residuals are observed to be normally distributed as shown by the insignificant observed probability values associated with the normality tests of each model. Again, the serial correlation of the error term of each model, Godfrey serial correlation test infers that the error term is not serially correlated. Moreover, the ARCH test is used to test the homogeneity of the variance of the error term.

The outcome of this test reported that there is no issue with the homogeneity of the variances of the error term which means the confidence intervals for the out-of-sample of the estimated MS-BVAR model could be realistic. The observed probabilities of the three tests are in excess of the 1%, 5% and 10% significance levels. The findings suggest that the estimated models and its parameters are efficient in determining the inflation rate regimes as discussed in the next pages.

4.5 Forecasting performance of $\mathbf{MS(2) - BVAR(1)}$

In order to come up with EWS for the next coming years, the out-of-sample forecasts are extracted then used to re-estimate the $\mathrm{MS}(2) - \mathrm{BVAR}(1)$ model to correctly classify the inflation regimes accordingly. An out-of-sample test has the ability to control either the possibility of over-fitting or over-parametrization problems, and gives a more powerful framework to evaluate the performance of the estimated model. Nonetheless, Appendix A presents the results of the out-of-sample forecasts. The results indicate that over the next 5 years, keeping the repo rate at an average of 7% per month, will help to keep the inflation rate at an average of 6% per month.

To check the in-sample and out-of-sample forecast performance of the $\mathrm{MS} - \mathrm{BVAR}(1)$, the RMSE, MAE and MAPE are estimated respectively and the results are reported in Table 4.11.

Table 4.11 Forecasting performance of $\mathbf{MS - BVAR(1)}$

sample	RMSE	MAPE	MAE
in-sample	0.007966	0.02526	0.006828453
out-of-sample	0.13281	0.5687	0.070

As indicated in table 4.11, the in-sample forecasts are much better than the out-of-sample forecasts. By individually looking at the metrics, the Root mean squared error (RMSE) has increased by 12.84% from the in-sample forecasts to the out-of-sample forecasts. Then mean absolute percentage error (MAPE) has increased by 54.3% while mean absolute error increased by 6.31%. Because both the RMSE and MAE increment is less than 50%, then the study concludes that for both in sample and out-of-sample forecasts, the estimated $\mathrm{MS} - \mathrm{BVAR}(1)$ mimics the actual simulated data.

4.6 Assessment performance of the EWS

The performance assessment results of the Logit based EWS model are given as summary in Table 4.12 and Table 4.14.

Table 4.12 Forecasts of the EWS Model

In-sample		**High Inflation**		**Low-inflation**		**Total**
Predicted	**High Inflation**	53.58	57%	17.40		**59.38**
	Low inflation	40.42		98.60	85%	**150.62**
	Total	**94**		**116**		**210**
Out-of-sample		**High Inflation**		**Low-inflation**		**Total**
Predicted	**High Inflation**	10.8	45%	7		**17.8**
	Low inflation	13.2		29	81%	**42.2**
	Total	**24**		**36**		**60**

The results in Table 4.12 infer that the model has some EWS potential. In view of the in-sample estimates, the model has the capacity to accurately predict 57% of high inflation and 85% of low inflation occasions. As it is, the proportion of a high inflation event given a signal is relatively high at 90% as reported in table 4.14. The proportion of false alarms to total alarms shown in Table 4.14 is relatively at 29%. One could in other words report that this is a perfect warning to the monetary committee in South Africa.

Given the future projection of 8 and half years of high inflation rates in South Africa could have bad implications in the overall economic growth and this could also tarnish the image of this country even further. This problem could be avoided if attended to urgently and sufficiently. Overall, 72% of observations are correctly predicted by the model, implying that the model is best to be used as a EWS. There is more-or-less similarity between the in-sample and out-of-sample predictions provided by the logit model.

4.6.1 Predictive power logistic regression models

The performance of a predictive model is overestimated when it is simply determined on the sample of subjects that are used to hypothesis the model. Several internal validation methods are available that aim to provide a more accurate estimate of model performance in new subjects. In the current study, model power analysis for the in-sample and out-of-sampling of the logistic regression models are employed by following the methodology of Makatjane and Moroke (2016) and set the predictive threshold power at 0.8 and the results are reported in 4.13.

Table 4.13 Model power test

Model estimation	Mean difference	Actual power
In-sample-estimation	0.7872	0.999998
Out-of-sample estimation	0.9591	0.938837

Reported in table 4.13 is the power test of each logit model for both in-sample and out-of-sample prediction. For the in-sample prediction model, the reported actual power is 0.9999 and that of the out-of-sample forecast is 0.9388. These implies that the in-sample predictive model has more predictive power than the out-of-sample with the predictive power of 0.061161 approximately 6.1151% more powerful than the out-of-sample. This is also in line with the forecasting performance of the $\mathrm{MS}-\mathrm{BVAR}(1)$, which is reported in table 4.9 which indicates that the in-sample forecasting of the $\mathrm{MS}-\mathrm{BVAR}(1)$ has less forecasting error that the out-of-sample.

In assessment of the performance of the EWS model, various performance criteria as suggested in Bussiere and Fratzscher (2006) are calculated and the results are presented in Table 4.14. The re-estimated EWS logit model is used to make projections from July 2016 to June 2021, i.e. a five-year forecasts period.

Table 4.14 Assessment performance of the EWS

	In-Sample	Out-of-sample
PCCC	57	45
PNCCC	85	80
POCC	72	66
ANSR	26	43
PRGS	90	61
PRGNS	27	31
PFA	29	39

Results in Tables 4.14 indicate that there is 45% chance of high inflation rates in the future and this probability is about 12% less than the current situation, confirming that the country should still expect hikes in this sector in the near future. However, this probability is not as high as compared to the current probability of 57%. In addition, the proportion of the expected false alarm

(PFA) to the total alarm is calculated as 39% which is higher than that of the in-sample by 10%. The out -of-sample percent of the non-crisis correctly called is 80%, 5% less than that of the in-sample. In five years to come, the predicted out-of-sample percentage of crisis correctly called (PCCC) is 45%, and this is 12% lower than that of the in-sample. One could conclude that after all inflation rates could be lower in future.

4.7 Concluding remarks

This chapter presented empirical results using the proposed methods discussed in Chapter 3. The purpose of the chapter was to model simulated inflation rate with the MS-BVAR framework as well as a logistic regression model to bring about the warning signals of inflation which are driven by the classification of the low and high inflation from the MS-BVAR and then logistic regression to quantify the process. Prior estimation of MS-BVAR model and nonlinear tests were established to reveal whether there exist nonlinear patterns between the inflation rate and the repo rate. A summary of findings and recommendations for future research are presented in the next chapter.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

In this study, the main focus is to explore the likelihood of estimating the MS-BVAR model and to implement the estimated regimes in a logistic regression model. This is done with the expectation that the logistic regression model might give the results that quantifies the probability of inflation crisis in South Africa. Monte Carlo simulation is used to generate the series on inflation and repo rates for January 1999 to June 2016 on monthly basis. The two-time series are selected on the assumption that they are cointegrated.

This study is innovative in a sense that no similar study in the context of South Africa has used a Bayesian vector autoregressive (BVAR) enhanced Markov Switching (MS) model together with the Logistic regression models in predicting the possibility of inflation crisis. The estimation of the two models has delivered an enhanced understanding of the prediction and classification of inflation crises together with the relationship between the selected variables. In particular, the study is unique in terms of uniting econometric multivariate methods in predicting inflation crisis in South Africa. Jointly, the results can be useful in guiding policy makers in identifying episodes of high inflation rates in South Africa and safe guard the inflation crisis well on time.

The remainder of this chapter is organized in this manner: Section 5.2 gives a discussion around the study objectives and provides the conclusions drawn, Section 5.3 provides the recommendations based on the findings and the last two sections briefly highlight on study limitations and chapter summary.

5.2 Research objectives and conclusions

This section replies the research objectives and gives a summary of findings obtained in Chapter 4. Also highlighted is how the study enhanced knowledge in this area of research.

Research objective 1

To simulate the inflation and repo rates data using Monte Carlo method.

Conclusion 1

In choosing the variables, the study followed the monetary transmission mechanism of South Africa through the repo rate channel which is recommended by Rossouw et al. (2014). This theory has given direction in selecting the variable that influences the inflation rate. Explaining the past is much easier than predicting the future. This uncertainty raises a significant number of issues when generating a financial plan for a client. The study considered the data generating process of Gamerman and Lopes (2006). Monte Carlo simulations illuminate the nature of that uncertainty, but only if advisors understand how it should be applied. Preacher and Selig (2012) have shown that the performance of this simulation method is comparable to other widely accepted methods. This method can be used when only summary data are available, as it is a case for this study. Monte Carlo simulation method is recommended in situations where rival methods (e.g. bootstrapping and distribution of the product methods) are difficult or impossible. It is not as computer-intensive as other methods.

The sample size of the study was chosen in such a way that the three selection criterion as discussed in experimental design and simulation section in Chapter 3 are achieved by setting power to be 80% as Dell et al. (2002) recommended. This method was used effectively to generate 210 observations for the period of January 1999 to June 2016. This data was later used in the current study to achieve other objectives. The sample size is significant enough to protect assumptions of normality and autocorrelation. It also allows the researcher to make sense of the performance of inflation during post-apartheid era in South Africa and 2008-2009 global financial crisis.

Research objective 2

To estimate the Markov-Switching Bayesian vector autoregressive model using the inflation rate and repo rate of South Africa.

Conclusion 2

To achieve this objective, the Markov-Switching Bayesian vector autoregressive (MS-BVAR) method was implemented to simulated data. This Regime Switching model was designed to capture discrete changes in the series that generate the data. Further than that, it allowed the transition between the regimes to be abrupt and the movement between regimes to be unrelated to the past process. Table 4.3.5 summarised the results for these analyses.

The study has extended the univariate analysis to the multivariate analysis which in this case the estimated model was the $\mathrm{MS}(2)-\mathrm{BVAR}(1)$. Prior to the estimation of the $\mathrm{MS}(2)-\mathrm{BVAR}(1)$, the simulated data was tested for nonlinearity unit root and the results confirmed that this assumption was not violated according to Kapetanios et al. (2003). Other assumptions such as structural break points were also confirmed to be valid for this model.

The findings of this study reported that the $\mathrm{MS}(2)-\mathrm{BVAR}(1)$ model generated two probabilities of regime switching of inflation series. It is evident according to the findings that the probability of high inflation in South Africa is lower than that of low inflation. This also implies that the country might stay in low inflation regime for the maximum of 11 years. Nevertheless, the present study is the first study to estimate MS-BVAR model for inflation crises. However, the study findings are in accordance with those reported by Chkili and Nguyen (2014) who used MS-VAR model to examine the dynamic linkages between stock markets and foreign exchange markets in BRICS countries using the original data not simulation methods. They found that the low volatility regime has more average duration than that of high volatility regime. However, the context of the current study, the low volatility of exchange rate is represented by the low inflation regime respectively.

Research objective 3

To estimate the logistic regression model as a classifier of inflation crises on the basis of repo rate.

Conclusion 3

In order to classify inflation crises optimally on the basis of the repo rate, the logistic regression model was estimated. The two regime probabilities from the $\mathrm{MS}(2)-\mathrm{BVAR}(1)$ model were incorporated in the logistic model as binary dependent variable. The low inflation regime was denoted as zero and high inflation denoted as one. Logistic regression is the most important model for categorical response data and it is commonly used for a wide variety of applications. The main idea for this study objective was to develop an early warning system (EWS) for inflation rate of South Africa. The intention was to add to few studies available since empirical literature on EWSs with an explicit forecasting objective is relatively new.

Fuertes and Kalotychou (2007) reported that scant attention has been paid to forecasting issues and to the design and validation of an EWS tailored to the decision maker's preference. The authors used a pooled logit model for testing the predictive power of macro data. In the current study, the logistic forecasts are combined by means of a parametric regression to assess the potential improvement in the predictive power of inflation crisis. The predictive power of the models was established through model power test following the method of Makatjane and Moroke (2016). The findings revealed that the in-sample forecasts of the logit model have more predictive power than the out-of-sample forecasts. These results are reported in Table 4.11.

The study here addresses the events of high and low inflation accordingly and found that for the in-sampling, the model has indicated that the probability of high inflation is 57%. This infers that South Africa has 57% chance that it will be in inflation crises. The out-of-sample reported only 45% of high inflation in the next five coming years.

In reckoning the likelihood of the inflation rate crises, the study established the marginal effects test and the conclusion made was that, as long as the repo rate increases, the inflation rate is likely to increase by 81%. This confirmed the reported results in Table 4.6. The estimation of the marginal effects was done by following the recommendations of the (Bartus, 2005). The current study reported a positive sign. One could conclude that fragmented results on the marginal interaction effects in terms of the sign have been reported. In addition, the same results were reported by (Cruz and Mapa, 2013).

5.3 Recommendations

This section proposes the recommendations for forthcoming studies on the basis of the outcomes of this study.

Recommendation 1

The monetary transmission mechanism of South Africa does not revolve around the repo rate only. Variables such as wealth, balance sheet, lending and investment rate, general consumption and output together with employment were also accredited (Cheng, 2006). Based on the study findings, these other variables could be factored in a multivariate model to check their credibility in detecting the inflation crisis in South Africa. Other than focusing on the repo rate alone as a determinant of inflation rate in South Africa, the other variables such as lending and investment rate might play a vital role towards detecting inflation crises.

Recommendation 2

The study has followed the recommendation of Makatjane (2015) with simulated data and an extended MS framework. The results of the current study also confirmed those obtained by the author. As such, the EWS developed in the current study have been tested for robustness and maybe used by SARB as the inflation targeting framework tool. Taking other roots of transmission mechanism, such as interest rate, the relevant committee in the country could take into account the consumption behaviour of residents. Moroke (2014) warned that a reduction of the interest rate could have high likelihood of causing the country to fall into the inflationary time, and that might cause further financial crises also.

Recommendation 3

For future Studies, scholars may also use the same developed EWS model in the cointegration approach where they would focus on the co-movement of the variables in the long run and short run. In this, the case vector error corrected or vector autoregressive moving average enhanced Markov Switching model may be used. The results of the two models may be compared with the current one. Other data generating processes other than Monte Carlo simulation may be used.

5.4 Limitations

The study is limited to the literature of early warning system while utilising both the $\mathrm{MS}-\mathrm{BVAR}(1)$ and Logit models. Few studies on the subject are published, as a result very few sources are available. On the other hand, Monte Carlo simulations suffer from the negative sign problem which makes it difficult to simulate some data using a random number generator hence therefore the need to employ more complex methods of data generating process under the Monte Carlo methods to avoid negative values of simulation.

The other issue is that, the outcomes at the tails of some distributions that are specified by the researcher. For example, in the current study a multivariate distribution that is used to simulate both inflation rate and repo rate may not be precise because there is uncertainty about both the accuracy of the inputs and the underlying distribution in the Monte Carlo experiments. Multivariate tests such as those for the misspecification of the model in the Bayesian vector setting could not be undertaken due to the complex procedure involved. Most software lack algorithms for these tests. Hence the study resorted to the univariate testing.

MS(2)-BVAR(1) is estimated using the EM algorithm in which nonlinear modelling approach with higher dimensions such as MS-BVAR becomes more complicated because it has positive semi-definiteness constraints for covariance matrices. Moreover, the robustness of the EM is far from the optimal value because it became weaker near the optimal value as it converged very slowly. Lastly, there are very few and old studies that uses logistic regression analyses for the purpose of prediction of inflation rates crises. Other dedicated methods such as Taylor's curve is also available but could not be considered for this study. Only statistical methods were explored to explain inflation dynamics.

5.5 Summary

In the current study, the EWS model has shown the potential to detect and forecast the inflation crises in South Africa. First and foremost, the Markov-Switching vector autoregressive model with Bayesian priors was estimated to predict the transition of high and low inflation rate together with the expected duration of inflation in each regime. For the $\mathrm{MS}(2)-\mathrm{BVAR}(1)$ model, the forecasting performance was extracted showing the in-sample model having less forecasting error than the out-of-sample model. These results were also confirmed by the model power analysis of the prediction of the logit model for both in-sample and out-of-sample models. All the objectives set by the study were achieved using the proposed methods and data.

REFERENCES

Abiad, A. 2007. Early Warning Systems for Currency Crises: A Regime-Switching Approach. (*In* Mamon, R.S. andElliott R.J., *eds*. Hidden Markov Models in Finance. Boston, MA: Springer US. p. 155-184).

Abiad, M.A. 2003. Early Warning Systems: A Survey and a Regime-Switching Approach (EPub). International Monetary Fund.

Acharya, V., Philippon, T., Richardson, M. and Roubini, N. 2009. The financial crisis of 2007-2009: Causes and remedies. *Financial markets, institutions & instruments,* 18 (2):89-137.

Ailliot, P. and Monbet, V. 2012. Markov-switching autoregressive models for wind time series. *Environmental Modelling & Software,* 30:92-101.

Ailliot, P., Monbet, V. and Prevosto, M. 2006. An autoregressive model with time-varying coefficients for wind fields. *Environmetrics,* 17 (2):107-117.

Akaike, H. 1974. A new look at the statistical model identification. *Automatic Control, IEEE Transactions on,* 19 (6):716-723.

Ang, A. and Bekaert, G. 2002. International asset allocation with regime shifts. *Review of Financial studies,* 15 (4):1137-1187.

Arias, G. and Erlandsson, U. 2004. Regime switching as an alternative early warning system of currency crises-an application to South-East Asia. *Working Papers, Department of Economics, Lund University,* (11).

Asteriou, D. and Hall, S.G. 2015. Applied econometrics. Palgrave Macmillan.

Bai, J. and Perron, P. 2003. Critical values for multiple structural change tests. *Econometrics Journal,* 6 (1):72-78.

Barber, D., Cemgil, A.T. and Chiappa, S. 2011. Bayesian time series models. Cambridge University Press.

Barnett, G., Kohn, R. and Sheather, S. 1996. Bayesian estimation of an autoregressive model using Markov chain Monte Carlo. *Journal of econometrics,* 74 (2):237-254, 10//.

Bartus, T. 2005. Estimation of marginal effects using margeff. *Stata Journal,* 5 (3):309-329.

Baum, L.E., Petrie, T., Soules, G. and Weiss, N. 1970. A maximization technique occurring in the statistical analysis of probabilistic functions of Markov chains. *The annals of mathematical statistics,* 41 (1):164-171.

Baur, D.G. 2012. Financial contagion and the real economy. *Journal of banking & finance,* 36 (10):2680-2692.

Bekaert, G., Ehrmann, M., Fratzscher, M. and Mehl, A.J. 2011. *Global crises and equity market contagion*: National Bureau of Economic Research.

Bernanke, B.S. and Woodford, M. 1997. *Inflation forecasts and monetary policy*: National Bureau of Economic Research.

Bonga-Bonga, L. and Kabundi, A. 2015. Monetary policy instrument and inflation in South Africa: Structural vector error correction model approach.

Borio, C.E. and Drehmann, M. 2009. Assessing the risk of banking crises–revisited. *BIS Quarterly Review, March*.

Box, G.E., Jenkins, G.M. and Reinsel, G.C. 2013. Model Diagnostic Checking. *Time Series Analysis, Fourth Edition*:333-352.

Box, G.E., Jenkins, G.M., Reinsel, G.C. and Ljung, G.M. 2015. Time series analysis: forecasting and control. John Wiley & Sons.

Boyer, B.H., Kumagai, T. and Yuan, K. 2006. How do crises spread? Evidence from accessible and inaccessible stock indices. *The Journal of Finance*, 61 (2):957-1003.

Bozdogan, H. 2000. Akaike's information criterion and recent developments in information complexity. *Journal of mathematical psychology,* 44 (1):62-91.

Brandt, P. and Davis, W. 2014. MSBVAR: Markov-Switching, Bayesian, vector autoregression models. *R package version 0.9-1*.

Brandt, P.T., Freeman, J.R., Lin, T.-M. and Schrodt, P.A. 2012. A Bayesian time series approach to the comparison of conflict dynamics. (*In* APSA 2012 Annual Meeting Paper organised by

Brock, W., Dechert, W., Scheinkman, J. and LeBaron, B. 2001. A test for independence based on the correlation dimension'. *Growth theory, non-linear dynamics, and economic modelling: scientific essays of William Allen Brock*, 15 (3):324.

Brooks, C. 2001. A double-threshold GARCH model for the French Franc/Deutschmark exchange rate. *Journal of Forecasting*, 20 (2):135-143.

Brown, R.L., Durbin, J. and Evans, J.M. 1975. Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society. Series B (Methodological)*:149-192.

Brunetti, C., Scotti, C., Mariano, R.S. and Tan, A.H. 2008. Markov switching GARCH models of currency turmoil in Southeast Asia. *Emerging Markets Review*, 9 (2):104-128.

Bussiere, M. and Fratzscher, M. 2006. Towards a new early warning system of financial crises. *journal of International Money and Finance*, 25 (6):953-973.

Calvet, L.E. and Fisher, A.J. 2004. How to forecast long-run volatility: regime switching and the estimation of multifractal processes. *Journal of Financial Econometrics*, 2 (1):49-83.

Carriero, A., Clark, T.E. and Marcellino, M. 2015. Bayesian VARs: specification choices and forecast accuracy. *Journal of Applied Econometrics*, 30 (1):46-73.

Chan, K.S. and Tong, H. 1986. On estimating thresholds in autoregressive models. *Journal of Time Series Analysis*, 7 (3):179-190.

Chen, C.W.S., So, M.K.P. and Lin, E.M.H. 2009. Volatility forecasting with double Markov switching GARCH models. *Journal of Forecasting*, 28 (8):681-697.

Chen, L.H., Goldstein, L. and Shao, Q.M. 2010. Normal approximation by Stein's method. Springer Science & Business Media.

Chen, W.W. 2009. Analysis of Integrated and Cointegrated Time Series with R. *Journal of Time Series Analysis*, 30 (5):575-575.

Cheng, M.K.C. 2006. A VAR Analysis of Kenya's Monetary Policy Transmission Mechanism: How Does the Central Bank's REPO Rate Affect the Economy?: International Monetary Fund.

Chkili, W. and Nguyen, D.K. 2014. Exchange rate movements and stock market returns in a regime-switching environment: Evidence for BRICS countries. *Research in International Business and Finance*, 31:46-56.

Cosslett, S.R. and Lee, L.F. 1985. Serial correlation in latent discrete variable models. *Journal of econometrics*, 27 (1):79-97.

Cruz, A. and Mapa, D. 2013. An Early Warning System for Inflation in the Philippines Using Markov-Switching and Logistic Regression Models. *Munich Personal RePEc Archive*.

Dai, Q., Singleton, K.J. and Yang, W. 2007. Regime shifts in a dynamic term structure model of US treasury bond yields. *Review of Financial studies*, 20 (5):1669-1706.

Davis, E.P. and Karim, D. 2008. Comparing early warning systems for banking crises. *Journal of Financial Stability*, 4 (2):89-120, 6//.

Dell, R.B., Holleran, S. and Ramakrishnan, R. 2002. Sample Size Determination. *ILAR Journal,* 43 (4):207-213, January 1, 2002.

Dendukuri, N., Rahme, E., Bélisle, P. and Joseph, L. 2004. Bayesian sample size determination for prevalence and diagnostic test studies in the absence of a gold standard test. *Biometrics,* 60 (2):388-397.

Diebold, F.X. and Inoue, A. 2001. Long memory and regime switching. *Journal of econometrics,* 105 (1):131-159.

Doucet, A., De Freitas, N. and Gordon, N. 2001. An introduction to sequential Monte Carlo methods. (*In* Sequential Monte Carlo methods in practice. Springer. p. 3-14).

Droumaguet, M. 2012. Markov-Switching Vector Autoregressive Models: Monte Carlo experiment, impulse response analysis, and Granger-Causal analysis. p.

Drukker, D.M. 2003. Testing for serial correlation in linear panel-data models. *Stata Journal,* 3 (2):168-177.

Edison, H.J. 2000. Do indicators of financial crises work? An evaluation of an early warning system. *An Evaluation of an Early Warning System (July 2000). FRB International Finance Discussion Paper,* (675).

Enders, W. 2008. Applied econometric time series. John Wiley & Sons.

Engel, C. and Hakkio, C.S. 1996. The distribution of exchange rates in the EMS. *International Journal of Finance & Economics,* 1 (1):55-67.

Engle, R.F. 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*:987-1007.

Forbes, K.J. and Rigobon, R. 2002. No contagion, only interdependence: measuring stock market comovements. *The Journal of Finance,* 57 (5):2223-2261.

Francq, C. and Zakoıan, J.-M. 2001. Stationarity of multivariate Markov–switching ARMA models. *Journal of econometrics,* 102 (2):339-364.

Franses, P.H. and Van Dijk, D. 2000. Non-linear time series models in empirical finance. Cambridge University Press.

Freedman, D.A. 2009. Statistical models: theory and practice. cambridge university press.

Frühwirth-Schnatter, S. 2006. Finite mixture and Markov switching models. Springer Science & Business Media.

Fuertes, A.M. and Kalotychou, E. 2007. Optimal design of early warning systems for sovereign debt crises. *International Journal of Forecasting,* 23 (1):85-100.

Gamerman, D. and Lopes, H.F. 2006. Markov chain Monte Carlo: stochastic simulation for Bayesian inference. CRC Press.

Gentle, J.E. 2013. Random number generation and Monte Carlo methods. Springer Science & Business Media.

Goldfeld, S.M. and Quandt, R.E. 1973. A Markov model for switching regressions. *Journal of econometrics*, 1 (1):3-15.

Greenberg, E. 2012. Introduction to Bayesian econometrics. Cambridge University Press.

Grigg, O.A., Farewell, V. and Spiegelhalter, D. 2003. Use of risk-adjusted CUSUM and RSPRTcharts for monitoring in medical contexts. *Statistical Methods in Medical Research,* 12 (2):147-170.

Gunsel, N. 2005. Financial ratios and the probabilistic prediction of bank failure in North Cyprus. *Editorial Advisory Board e,* 18 (2):191-200.

Gupta, R. and Komen, K. 2009. Time aggregation and the contradictions with causal relationships: can economic theory come to the rescue? *University of Pretoria, Pretoria,* 0002.

Hall, A.R., Osborn, D.R. and Sakkas, N. 2013. Inference on Structural Breaks using Information Criteria. *The Manchester School,* 81:54-81.

Hamilton, J.D. 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the Econometric Society*:357-384.

Hamilton, J.D. 2005. *What's real about the business cycle?* : National Bureau of Economic Research.

Hamilton, J.D. 2008a. Regime-switching models. *The new palgrave dictionary of economics,* 2.

Hamilton, J.D. 2008b. Regime Switching Models. The New Palgrave Dictionary of Economics. SN Durlauf and LE Blume: Basingstoke, Palgrave Macmillan.

Hamilton, J.D. 2010. Regime switching models. (*In* Macroeconometrics and Time Series Analysis. Springer. p. 202-209).

Hamilton, J.D. and Raj, B. 2013. Advances in Markov-Switching Models: Applications in Business Cycle Research and Finance. Springer Science & Business Media.

Hammersley, J. 2013. Monte carlo methods. Springer Science & Business Media.

Hannan, E.J. and Quinn, B.G. 1979. The determination of the order of an autoregression. *Journal of the Royal Statistical Society. Series B (Methodological)*:190-195.

Hjort, N.L. 2008. Model selection and model averaging. Cambridge Series in Statistical and Probabilistic Mathematics. Cambridge University Press.

Hyvonen, M. 2004. Inflation convergence across countries. Reserve Bank of Australia.

Ismail, M.T. and Isa, Z. 2006. Modelling exchange rates using regime switching models. *Sains Malaysiana,* 35 (2):55-62.

James, G., Witten, D., Hastie, T. and Tibshirani, R. 2013. An introduction to statistical learning. Springer.

Jeanne, O. and Masson, P. 2000. Currency crises, sunspots and Markov-switching regimes. *Journal of International Economics,* 50 (2):327-350.

Jonathan, D. and Kung-Sik, C. 2008. Time Series Analysis With Applications in R. New York: Springer Science and Business Media , LLC.

Kantz, H. and Schreiber, T. 2004. Nonlinear time series analysis. Vol. 7: Cambridge university press.

Kapetanios, G., Shin, Y. and Snell, A. 2003. Testing for a unit root in the nonlinear STAR framework. *Journal of econometrics,* 112 (2):359-379.

Kaufmann, S. 2000. Measuring business cycles with a dynamic Markov switching factor model: An assessment using Bayesian simulation methods. *The Econometrics Journal,* 3 (1):39-65.

Kaufmann, S. 2002. Is there an asymmetric effect of monetary policy over time? A Bayesian analysis using Austrian data. *Empirical Economics,* 27 (2):277-297.

Kedem, B. and Fokianos, K. 2005. Regression models for time series analysis. Vol. 488: John Wiley & Sons.

Kenourgios, D., Samitas, A. and Paltalidis, N. 2011. Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *Journal of International Financial Markets, Institutions and Money,* 21 (1):92-106, 2//.

Kilian, L. 2006. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market.

Kim, C.J., Morley, J. and Piger, J. 2005. Nonlinearity and the permanent effects of recessions. *Journal of Applied Econometrics,* 20 (2):291-309.

Kim, C.J. and Nelson, C.R. 2001. A Bayesian approach to testing for Markov-switching in univariate and dynamic factor models. *International Economic Review,* 42 (4):989-1013.

Kinderman, A.J. and Ramage, J.G. 1976. Computer Generation of Normal Random Variables. *Journal of the American Statistical Association*, 71 (356):893-896.

Kleiber, C. and Zeileis, A. 2008. Applied econometrics with R. Springer Science & Business Media.

Kolari, J., Glennon, D., Shin, H. and Caputo, M. 2002. Predicting large US commercial bank failures. *Journal of Economics and Business,* 54 (4):361-387.

Krolzig, H.-M. 1998. Econometric modelling of Markov-switching vector autoregressions using MSVAR for Ox.

Krolzig, H.-M. 2000. Predicting Markov-switching vector autoregressive processes. Nuffield College.

Krolzig, H.-M. 2013. Markov-switching vector autoregressions: Modelling, statistical inference, and application to business cycle analysis. Vol. 454: Springer Science & Business Media.

Kumar, M., Moorthy, U. and Perraudin, W. 2003. Predicting emerging market currency crashes. *Journal of Empirical Finance,* 10 (4):427-454.

Kyrtsou, C. and Serletis, A. 2006. Univariate tests for nonlinear structure. *Journal of Macroeconomics,* 28 (1):154-168, 3//.

Lee, Y.-J., Zhu, Y.S., Xu, Y.H., Shen, M.-F., Zhang, H.X. and Thakor, N. 2001. Detection of non-linearity in the EEG of schizophrenic patients. *Clinical Neurophysiology*, 112 (7):1288-1294.

Leroux, B.G. 1992. Maximum-likelihood estimation for hidden Markov models. *Stochastic processes and their applications,* 40 (1):127-143.

Leshoro, T.L. 2014. Does the Repurchase Rate Affect Inflation in South Africa? An Empirical Analysis Using an Impulse Response Function. *Journal of Economics and Behavioral Studies,* 6 (7):524-531.

Liu, C.-C. and He, L.Y. 2010. KSS unit root test of nonlinearity and nonstationarity in China's agricultural futures markets. *Physics Procedia*, 3 (5):1753-1756.

Lux, T. 2008. The Markov-Switching Multifractal Model of Asset Returns. *Journal of Business & Economic Statistics*, 26 (2):194-210, 2008/04/01.

Maas, C.J. and Hox, J.J. 2004. Robustness issues in multilevel regression analysis. *Statistica Neerlandica*, 58 (2):127-137.

Makatjane, K. 2015. An Early Warning System for Inflation in South Africa Using Markov-Switching and Logistic Models. North West University Honours Mini Dissertation.

Makatjane, K.D. and Moroke, N.D. 2016. Comparative Study of Holt-Winters Triple Exponential Smoothing and Seasonal Arima: Forecasting Short Term Seasonal Car Sales in South Africa. *Risk governance & control: financial markets & institutions,* 6 (1).

Makridakis, S. and Hibon, M. 2000. The M3-Competition: results, conclusions and implications. *International Journal of Forecasting,* 16 (4):451-476.

Marcucci, J. 2005. Forecasting stock market volatility with regime-switching GARCH models. *Studies in Nonlinear Dynamics & Econometrics,* 9 (4).

Mariano, R.S., Abiad, A.G., Gultekin, B., Shabbir, T. and Tan, A.H. 2002. Markov Chains in Predictive Models of Currency Crises-With Applications to Southeast Asia.

Mboweni, T., Cross, M.J., Thahane, M.T., Marcus, M.G., van der Merwe, E., Wiese, M.C., et al. 2008. Statement of the Monetary Policy Committee. *South African Reserve Bank, December,* 6.

McLachlan, G. and Krishnan, T. 2007. The EM algorithm and extensions. Vol. 382: John Wiley & Sons.

Mishkin, F.S. and Schmidt-Hebbel, K. 2007. *Does inflation targeting make a difference?* : National Bureau of Economic Research.

Montgomery, D.C. 2007. Introduction to statistical quality control. John Wiley & Sons.

Montgomery, D.C., Jennings, C.L. and Kulahci, M. 2015. Introduction to time series analysis and forecasting. John Wiley & Sons.

Moolman, H.C. 2005. An asymmetric econometric model of the South African stock market. p.

Mordkoff, J. 2011. The assumption (s) of normality. *Unpublished manuscript*.

Moroke, N.D. 2014. Household debts-and macroeconomic factors nexus in the United States: A cointegration and vector error correction approach. *Journal of Economics and Behavioral Studies,* 6 (6):452.

Moroke, N.D., Mukuddem-Petersen, J. and Petersen, M. 2014. A Multivariate Time Series Analysis of Household Debts during 2007-2009 Financial Crisis in South Africa: A Vector Error Correction Approach. *Mediterranean Journal of Social Sciences*, 5 (7):107.

Moysiadis, T. and Fokianos, K. 2014. On binary and categorical time series models with feedback. *Journal of Multivariate Analysis*, 131:209-228.

Mustafa, Y. 2006. Determining the optimal sample size in the Monte Carlo experiments. *Selçuk J Appl Math*, 7:103-108.

Muthén, L.K. and Muthén, B.O. 2002. How to use a Monte Carlo study to decide on sample size and determine power. *Structural Equation Modeling*, 9 (4):599-620.

Ng, S.K., Krishnan, T. and McLachlan, G.J. 2012. The EM algorithm. (*In* Handbook of computational statistics. Springer. p. 139-172).

Norton, E.C., Wang, H. and Ai, C. 2004. Computing interaction effects and standard errors in logit and probit models. *Stata Journal*, 4:154-167.

Nyberg, H. 2010. Studies on binary time series models with applications to empirical macroeconomics and finance. *Unpublished manuscript*.

Ohlson, J.A. 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research*:109-131.

Pan, W. 2001. Akaike's information criterion in generalized estimating equations. *Biometrics*, 57 (1):120-125.

Paye, B.S. and Timmermann, A. 2006. Instability of return prediction models. *Journal of Empirical Finance*, 13 (3):274-315, 6//.

Piger, J. 2009. Econometrics: models of regime changes. (*In* Complex Systems in Finance and Econometrics. Springer. p. 190-202).

Preacher, K.J. and Selig, J.P. 2012. Advantages of Monte Carlo confidence intervals for indirect effects. *Communication Methods and Measures*, 6 (2):77-98.

Psaradakis, Z. and Sola, M. 1998. *Generated Regressors and Markov-Switching Models*: Mimeo.

Ramsey, J.B. 1969. Tests for specification errors in classical linear least-squares regression analysis. *Journal of the Royal Statistical Society. Series B (Methodological)*:350-371.

Rodriguez, J.C. 2007. Measuring financial contagion: A Copula approach. *Journal of Empirical Finance*, 14 (3):401-423, 6//.

Rossouw, J., Vermeulen, J. and Leshoro, L. 2014. Monetary Economics in South Africa. *OUP Catalogue*.

Sawilowsky, S.S. 2003. You think you've got trivials? *Journal of Modern Applied Statistical Methods*, 2 (1):21.

Sawilowsky, S.S. and Fahoome, G.C. 2003. Statistics via monte carlo simulation with fortran. *Rochester Hills, MI, JMASM*.

Schimmelpfennig, M.A., Roubini, N. and Manasse, P. 2003. Predicting sovereign debt crises. International Monetary Fund.

Schwarz, G. 1978. Estimating the dimension of a model. *The annals of statistics,* 6 (2):461-464.

Scott, R. and Hatemi, A. 2008. Optimal lag-length choice in stable and unstable VAR models under situations of homoscedasticity and ARCH. *Journal of Applied Statistics,* 35 (6):601-615, 2008/06/01.

Shumway, R.H. and Stoffer, D.S. 2010. Time series analysis and its applications: with R examples. Springer Science & Business Media.

Sims, C.A., Waggoner, D.F. and Zha, T. 2008. Methods for inference in large multiple-equation Markov-switching models. *Journal of econometrics,* 146 (2):255-274.

Sims, C.A. and Zha, T. 2006. Were there regime switches in US monetary policy? *The American Economic Review,* 96 (1):54-81.

Smith, A., Doucet, A., de Freitas, N. and Gordon, N. 2013. Sequential Monte Carlo methods in practice. Springer Science & Business Media.

Stollenwerk, N., Drepper, F.R. and Siegel, H. 2001. Testing nonlinear stochastic models on phytoplankton biomass time series. *Ecological Modelling,* 144 (2):261-277.

Svensson, L.E. 2005. *Monetary policy with judgment: Forecast targeting*: National Bureau of Economic Research.

Svensson, L.E. 2010. *Inflation targeting*: National Bureau of Economic Research.

Terui, N. and Van Dijk, H.K. 2002. Combined forecasts from linear and nonlinear time series models. *International Journal of Forecasting,* 18 (3):421-438.

Timmermann, A. 2000. Moments of Markov switching models. *Journal of econometrics,* 96 (1):75-111.

Timmermann, A. 2001. Structural breaks, incomplete information, and stock prices. *Journal of Business & Economic Statistics,* 19 (3).

Tong, H. 1978. On a threshold model in pattern recognition and signal processing,(Ed) C. *Chen. Sijhoff and Noonhoff, Amsterdam*.

Tong, H. 2012. Threshold models in non-linear time series analysis. Vol. 21: Springer Science & Business Media.

Troug, H.A. and Murray, M. 2015. Crisis Determination and Financial Contagion: An Analysis of the Hong Kong and Tokyo Stock Markets using an MSBVAR Approach.

Van der Merwe, E. and Mollentze, S.L. 2010. Monetary economics in South Africa. South Africa: Oxford University Press.

Wallison, P.J. 2011. Did the "Repeal" of Glass-Steagall Have Any Role in the Financial Crisis? Not Guilty. Not Even Close. (*In* Financial Market Regulation. Springer. p. 19-29).

Wang, W., Vrijling, J., Van Gelder, P.H. and Ma, J. 2006. Testing for nonlinearity of streamflow processes at different timescales. *Journal of Hydrology,* 322 (1):247-268.

Xaba, D., Moroke, N.D., Arkaah, J. and Pooe, C. 2016. Modeling South African Banks closing stock prices: a Markov-Switching Approach. *Journal of Economics and Behavioral Studies,* 8 (1):36-40.

Xaba, L., Moroke, N., Arkaah, J. and Pooe, C. 2015. A Comparative Study of Stock Price Forecasting using nonlinear models. (*In* Proceedings of International Academic Conferences organised by International Institute of Social and Economic Sciences.

Yang, M. 2000. Some properties of vector autoregressive processes with Markov-switching coefficients. *Econometric theory,* 16 (01):23-43.

Zhang, G.P. 2003. Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing,* 50:159-175.

Zhou, D., Lu, X., Lei, L. and Fu, B. 2014. The Study of Nonlinear Correlation between Shanghai, Hongkong and American Stock Returns—An Empirical Analysis Based on MS-VAR Model and MS-DCC-MVGARCH Model. *Hongkong and American Stock Returns—An Empirical Analysis Based on MS-VAR Model and MS-DCC-MVGARCH Model (January 4, 2014).*

Zio, E. 2013. The Monte Carlo simulation method for system reliability and risk analysis. Springer.

Appendix A Forecasts of $\mathbf{MS(2) - BVAR(1)}$ model

Out-of-sample forecasts from $\mathbf{MS(2) - BVAR(1)}$

Years	Repo	Inflation	Years	Repo	Inflation	Years	Repo	Inflation
2016/July	7.0035412	6.0027295	2018/Mar	6.9430569	5.9465176	2019/Nov.	7.0075013	6.0063541
2016/Aug	6.9716615	5.9772494	2018/Apr	6.9939983	5.9950545	2019/Dec.	6.987336	5.9892728
2016/Sep	6.9917713	5.9934269	2018/May	7.0072729	6.006371	2020/Jan.	6.9685333	5.9733457
2016/Oct	7.0002909	6.0002473	2018/June	7.0453038	6.0413763	2020/Feb	6.9673245	5.9723218
2016/Nov	7.0118018	6.0098913	2018/July	6.9771531	5.979039	2020/Mar	7.0098198	6.008318
2016/Dec	7.0356482	6.0278564	2018/Aug	6.9887224	5.9901198	2020/Apr	6.9766345	5.9802079
2017/Jan	7.0064686	6.0055007	2018/Sep	7.029075	6.0256181	2020/May	7.0435763	6.0369119
2017/Feb	6.9771157	5.9795946	2018/Oct	7.0011842	6.001039	2020/June	6.9998584	5.99988
2017/Mar	6.9829812	5.9860009	2018/Nov	7.0052091	6.004551	2020/July	6.9593352	5.9655543
2017/Apr	6.9968949	5.9973143	2018/Dec	7.007902	6.0070472	2020/Aug	6.9769836	5.9805036
2017/May	7.0338687	6.0265789	2019/Jan	7.0118833	6.0106443	2020/Sep	6.9682397	5.973097
2017/June	6.9872027	5.989243	2019/Feb	6.9659694	5.9700785	2020/Oct	6.960115	5.9662148
2017/July	6.93522	5.9445632	2019/Mar	7.0077346	6.0073109	2020/Nov	7.0096814	6.0082008
2017/Aug	7.0189291	6.0165967	2019/Apr	7.0319614	6.0292599	2020/Dec	6.9914892	5.9927908
2017/Sep	7.024106	6.0220726	2019/May	7.0098641	6.0090464	2021/Jan	6.9892729	5.9909135
2017/Oct	7.0232235	6.020311	2019/June	7.0026816	6.0022523	2021/Feb	7.0487553	6.0412989
2017/Nov	7.0041576	6.0033965	2019/July	6.9669842	5.9710123	2021/Mar	7.0383598	6.0324932
2017/Dec	7.0774434	6.0662112	2019/Aug	6.9898886	5.9909185	2021/Apr	6.976815	5.9803608
2018/Jan	6.9978509	5.9981045	2019/Sep	6.9570493	5.9640143	2021/May	6.995496	5.9961848
2018/Feb	6.9874262	5.9892637	2019/Oct	6.9923596	5.9932353	2021/June	7.0221668	6.0187767

Appendix B Simulated data

Simulated Inflation and repo rate

inflation	repo	inflation	repo	inflation	repo
6.003751942	7.025876	6.338083	7.355008	6.670896	7.686515
6.009815967	7.037005	6.346009	7.360377	6.669824	7.702281
6.012136074	7.041836	6.34491	7.366194	6.675782	7.698394
6.013371921	7.041467	6.349592	7.363375	6.68385	7.698298
6.020942023	7.05559	6.349882	7.36132	6.68004	7.694539
6.022719752	7.047862	6.354274	7.371541	6.68736	7.707721
6.027450858	7.036857	6.354499	7.377494	6.701145	7.711026
6.026581039	7.0439	6.359036	7.380175	6.701425	7.705223
6.032615802	7.046666	6.363536	7.386842	6.701425	7.711916
6.035665443	7.058877	6.364238	7.385617	6.701425	7.709375
6.039391534	7.060096	6.37408	7.397708	6.701425	7.715228
6.043267541	7.064114	6.378349	7.398953	6.701425	7.716269
6.045666985	7.064949	6.383401	7.403014		
6.048279317	7.05955	6.377723	7.403043		
6.054510583	7.071795	6.385135	7.406365		
6.057725763	7.081844	6.389897	7.404299		
6.065044331	7.077397	6.389174	7.407591		
6.065332165	7.089013	6.393713	7.415828		
6.071372232	7.090728	6.401889	7.413911		
6.066969733	7.087112	6.392777	7.418501		
6.075673198	7.099592	6.399679	7.41978		
6.075585603	7.09116	6.406422	7.430961		
6.081376162	7.094697	6.41145	7.43978		
6.084892359	7.108706	6.416468	7.432442		
6.091429433	7.104725	6.42164	7.4371		
6.090226652	7.104912	6.414291	7.447235		
6.092364878	7.117517	6.42655	7.4309		
6.094374618	7.115492	6.42634	7.44935		
6.101996301	7.122404	6.431425	7.455905		
6.105112186	7.121805	6.437979	7.451922		
6.105280051	7.13192	6.432742	7.465508		
6.116274402	7.130791	6.443328	7.462716		
6.113829351	7.13474	6.44148	7.471043		
6.119543686	7.140289	6.45035	7.464257		
6.120830373	7.145509	6.449164	7.468787		
6.120635709	7.147808	6.458571	7.472385		
6.128749966	7.149567	6.458233	7.47839		

6.131836307	7.152307	6.462657	7.480444		
6.134005482	7.149586	6.464484	7.482591		
6.137954221	7.1586	6.468135	7.486804		
6.140894462	7.157388	6.468644	7.481648		
6.14395877	7.167002	6.474975	7.494874		
6.146566146	7.161761	6.481742	7.499611		
6.149549496	7.176739	6.480079	7.491946		
6.156430627	7.174117	6.485306	7.507124		
6.160652861	7.170471	6.494267	7.512319		
6.159285601	7.178174	6.493184	7.510848		
6.170129282	7.180515	6.490385	7.516962		
6.164585874	7.185637	6.500404	7.509536		
6.173083193	7.19179	6.50443	7.525063		
6.173842794	7.189863	6.50287	7.523618		
6.180485877	7.192672	6.501158	7.526276		
6.181312611	7.204982	6.509817	7.531417		
6.185432813	7.20094	6.516562	7.538048		
6.190323824	7.217964	6.519001	7.534587		
6.191443896	7.215228	6.518709	7.533799		
6.195459916	7.218517	6.525269	7.553841		
6.198939859	7.2223	6.527361	7.535741		
6.204254193	7.215798	6.527158	7.550653		
6.204285247	7.218937	6.527959	7.55609		
6.20893651	7.224823	6.537585	7.554765		
6.210928217	7.221616	6.536902	7.547499		
6.218176675	7.230988	6.539898	7.572454		
6.216900521	7.228119	6.540139	7.561285		
6.219384531	7.234171	6.549965	7.573344		
6.233333333	7.244347	6.548522	7.570083		
6.221893522	7.250964	6.561126	7.580641		
6.231268994	7.248235	6.559972	7.576892		
6.235599352	7.256745	6.56452	7.583156		
6.240009925	7.25129	6.562897	7.591109		
6.238119409	7.262077	6.572905	7.588803		
6.240573096	7.259133	6.568585	7.589578		
6.246780125	7.271299	6.575054	7.590866		
6.250202444	7.266965	6.578089	7.599125		
6.252631301	7.275078	6.584436	7.602846		
6.253129121	7.270157	6.587961	7.608304		
6.259582264	7.279122	6.585501	7.609769		
6.266125654	7.27565	6.595111	7.615295		

6.26857556	7.292603	6.597759	7.620189		
6.270866495	7.291939	6.60135	7.617365		
6.276667155	7.290406	6.602523	7.62873		
6.282336088	7.292769	6.608399	7.627894		
6.28448531	7.297903	6.609837	7.629501		
6.282740471	7.299725	6.613905	7.636195		
6.287552022	7.30379	6.621185	7.63808		
6.295816609	7.316925	6.624543	7.648779		
6.292619016	7.31655	6.625177	7.655547		
6.300758424	7.326811	6.62434	7.650908		
6.302465551	7.317408	6.633392	7.648896		
6.300062049	7.326128	6.640208	7.657907		
6.307214608	7.33111	6.637365	7.659286		
6.309497846	7.328964	6.648046	7.664724		
6.317093863	7.334244	6.643619	7.659621		
6.320125748	7.341224	6.644583	7.666574		
6.321614363	7.342455	6.650137	7.668364		
6.318533105	7.337079	6.650257	7.684922		
6.327770327	7.356361	6.658751	7.686386		
6.3258647	7.346856	6.661119	7.681864		
6.333904555	7.354578	6.661063	7.676492		

Appendix C R Commands

C1: Gibbs Sampling from a bivariate normal distribution

~~~~
```{r}s
library(gibbs.met); library(mcmc)
```
#### Gibbs Sampling   ####
```{r}
gibbs<-function (210, 0.01)
{
    mat <- matrix(ncol = 2, nrow = n)
    inflation <- 6
    repo <- 7
    mat[1, ] <- c(inflation, repo)
    for (i in 2:n) {
        inflation <- rnorm(1, 0.01 * repo, sqrt(1 - rho^2))+6
        repo <- rnorm(1, 0.01 * inflation, sqrt(1 - rho^2))+7
        mat[i, ] <- c(inflation, repo)
    }
    mat
}
```
~~~~

C2: Testing for the Convergence of the Sample

~~~~
```{r}
set.seed(100)
object = Gibbs.bnorm()
pnorm(abs(geweke.diag(mcmc(object$inflation))$z)
,lower.tail=FALSE)*2
pnorm(abs(geweke.diag(mcmc(object$repo))$z)
~~~~

~~~~
,lower.tail=FALSE)*2

gamma=(object$inflationmean(

object$inflation))*(object$repomean(

object$repo))

pnorm(abs(geweke.diag(mcmc(gamma))$z),lo

wer.tail=FALSE)*2

```

C3:     Preliminary data analysis

```{r}

matiisetso <- read.csv("~/Data Sets/R data/matiisetso.csv")

library(MSBVAR);library(DescTools);library(tseries);library(strucchange);library(vars);
library(DMwR)

```

#### Generating monthly time series ###

```{r}

kats<-ts(na.omit(matiisetso), start=c(1999,1), frequency=12)

##### Ploting of the Simulated Time series ###

```{r}

win.graph(pointsize=12, height=4.875, width=6)

plot(kats, type="l", lwd=1, col="blue", xlab="Years",main="", ylim=c(5,8))

```

#######    Test for multivariate normality of the data   #######

```{r}

JarqueBeraTest(coms[,1])

JarqueBeraTest(coms[,2])

#### KSS-NADF Test  ###

```{r}

lc<-ts(coms,start=c(1999,1), frequency=12)

lcc.uc0<-ur.df(coms[,1], lags=1, type="none")
~~~~

~~~
summary(lcc.uc0)

lc<-ts(coms,start=c(1999,1), frequency=12)

lcc.uc1<-ur.df(coms[,2], lags=1, type="none")

summary(lcc.uc1)
~~~

C3: Continued

~~~
##### The BDS Test   ###

```{r}

bds.test(coms[,1],  m = 6, eps = seq(0.5 * sd(coms), 2 * sd(coms), length = 2),

        trace = FALSE)

bds.test(coms[,2],  m = 6, eps = seq(0.2 * sd(coms), 2 * sd(coms), length = 2), trace = FALSE)

```

```{r}

##### Fitting the Bayesian Autoregressive model ####

```{r}

x <- c(Markov[,1])

x1<-c(Markov[,2])

y1 <- 2+x1+x^2

y2 <- 1 + x1

xx<-ts(na.omit(x), start=c(1999,1),  frequency=12)

xx1<-ts(na.omit(x1), start=c(1999,1),  frequency=12)

lmmfit<-lm(y1~x1)

summary(lmmfit)

lmmfit2<-lm(y2~x)

summary(lmmfit2)

resettest(lmmfit , power=2, type="regressor")

resettest(lmmfit2 , power=2, type="regressor")

```
~~~

~~~~
#### CUMSUM of inflation rate and repo rate  #####
```{r}
ocuss <- efp(y1~1+x1+x^2, type="Rec-CUSUM")
ocuss1<- efp(y2~x, type="Rec-CUSUM")
```
```{r}
bound.ocuss <- boundary(ocus, alpha=0.05)
bound.ocuss1<-boundary(ocus1, alpha=0.05)
```
```{r}
win.graph(width=4, height=4, pointsize=15)
plot(ocuss, boundary = TRUE, ylim=c(-3.5,2), ylab="Repo Rate", main="", xlab="", col="blue")
win.graph(width=4, height=4, pointsize=15)
plot(ocuss1, boundary = TRUE, ylim=c(-3.5,2), ylab="Inflation Rate", main="", xlab="", col="blue")
```
###### Bai Perrron structural break test  ######
```{r}
bp.model<-breakpoints(Inflation~-1+Repo, data=coms)
summary(bp.model)
bp.model1<-breakpoints(Repo~-1+Inflation, data=coms)
summary(bp.model1)
```
###### Using information criterion  #######
```{r}
bp.seat<-breakpoints(bp.model, breaks=5)
summary(bp.seat)
plot(bp.model)
breakpoints(bp.model)
```
~~~~

C4: Optimal lag length selection and model estimation

````
###### Optimal lag length selection and model estimation #####
```{r}
var.lag.specification(coms, lagmax=8)
VARselect(coms, lag.max = 8, type = "both")
```
#### Fitting Markov-switching Bayesian vector autoregressive model  ####
```{r}
set.seed(123456)
xmm <- msbvar(coms, p=1, h=2,
        lambda0=0.8, lambda1=0.40,
        lambda3=1, lambda4=1, lambda5=0, mu5=0,
        mu6=0, qm=12,
        alpha.prior=matrix(c(1,5,5,9), 2, 2))
summary(xmm$init.model)
```
#### Plotting filtered probabilities   #####
```{r}
win.graph(width=4, height=3.5, pointsize=12)
hopz<- ts(xmm$fp[,1], start=c(2000,1), frequency=4)
plot.ts(hopz,main="", ylab="Regime Probabilities", col=1, ylim=c(0,1), xlab="Years")
```
```{r}
win.graph(width=4, height=3.5, pointsize=12)
hopz1<- ts(xmm$fp[,2], start=c(1999,1), frequency=12)
plot.ts(hopz1,main="", ylab="Regime Probabilities", col=2, ylim=c(0,1), xlab="Years")
```
````

C5: Model diagnostic checking

Model diagnostic checking

```{r}
arch.test(xx2, lags.single = 16, lags.multi = 5, multivariate.only = TRUE)
normality.test(xx2, multivariate.only = TRUE)
serial.test(xx2, lags.pt = 16, lags.bg = 5,
type = c("PT.asymptotic", "PT.adjusted", "BG", "ES"))
```

C6: Forecasting with MS-BVAR

Forecasting with the MSBVAR model

```{r}
N1 <-210
N2 <-210
```

```{r}
xx2 <- gibbs.msbvar(xmm, N1=N1, N2=N2, permute=FALSE, Beta.idx=c(1,2), method=EM)
```{r}
jj<-forecast(xx2, nsteps=120, A0=t(chol(xx2$mean.S)),
shocks=matrix(0, nrow=nsteps, ncol=dim(xx2$ar.coefs)[1]),
exog.fut=matrix(0, nrow=nsteps, ncol=nrow(xx2$exog.coefs)),
N1, N2)
print(jj)
```

Forecasting Performance of the MSBVAR model

```{r}
forecasts<-forecast(fit.msbvar, nsteps=nrow(Y.sample2))
rmse(forecasts[(nrow(Y.sample1)+1):nrow(forecasts),], Y.sample2)
mae(forecasts[(nrow(Y.sample1)+1):nrow(forecasts),], Y.sample2)

```
mape(forecasts[(nrow(Y.sample1)+1):nrow(forecasts),], Y.sample2)
cf.forecasts(forecasts[(nrow(Y.sample1)+1):nrow(forecasts),], Y.sample2)
```