AN EARLY WARNING SYSTEM FOR INFLATION USING MARKOV-SWITCHING AND LOGISTIC MODELS APPROACH

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Abstract

With the adoption of the inflation targeting by the South African Reserve Bank (SARB) in 2000, the average inflation radically went down. Earlier 2000, the inflation rate was recorded at 8.8% that is January 1999; then a year later went down to 2.65%. What's more, this paper builds up an early warning system (EWS) model for predicting the event of high inflation in South Africa. Periods of high and low inflation were distinguished by utilizing Markov-switching model. Utilizing the results of regime classification, logistic regression models were then assessed with the goal of measuring the likelihood of the event of high inflation periods. Empirical results demonstrate that the proposed EWS model has some potential as a corresponding instrument in the SARB's monetary policy formulation based on the in-sample and out-of-sample forecasting performance.

Keywords: Markov-Switching, South African Reserve Bank Inflation Targeting

1. INTRODUCTION

Price stabilization and low inflation is a common target that is being used by monetary authorities globally. The empirical evidence shows that price stability is crucial because the judgement that consumers make about their living standards has been twisted by the unstable inflation rates. These distortions, in turn lead to market failure which then slows down the rate at which the economy grows. The money available to buy goods and services will gradually wear off due to high inflation, eventually harming the low income households. Therefore, the sustainable economic growth is supported by the monetarises through stabilisation of inflation and keeping it to the low rate.

The inflation targeting (IT) framework has been adopted by the South African Reserve Bank (SARB) since the year 2000 as part of monetary policy formulation. Monetary authorities take modern ideas and calibrate rates of their policy to manage variance of expected inflation in the future. The future path of assessment on pressures of inflation had been provided to the monetarists with reliable forecasts through the utilisation of statistical models (Cruz & Dacio, 2013). In addition, to control and contain the inflation rate within the chosen interval, the SARB had previously used the repo rate instrument. However, the defaults of this method of combating inflation have not been criticized neither in the SA context but also internationally.

However, Svensson (2010) contends that a fruitful approach may be portrayed by 1) a publication of numerical expansion target, 2) the usage for fiscal strategy that provides for a significant part on the expansion forecast, 3) a selection from claiming short-run enthusiasm rates similarly as the best fiscal strategy instrument, but more importantly; 4) a secondary level for transparency and also its responsibility. Proponents of the inflation targeting, include many studies such as of Mishkin and Schmidt-Hebbel (2007); and Corbo *et al.* (2002); de A. Nadal-De Simone (2001) and Hyvonen (2004) which showed those experimental outcomes about that expansion which, may be connected with a change of generally financial execution.

Predictive models that quantifies the likelihood of the future occurrence of inflation crisis like the warning system that are being developed in this paper, will be used to supplement the current toolkit of the SARB in the assessment of inflation environment and the risk of inflation outlook. This will also provide policy makers with a warning indicator shifts in inflation regime which in real time is possible and finally forecast for the occurrence of the high inflation or low inflation for the period of 5 years. This empirical analysis is arranged in to four sections. The remaining part of the following paper is as follows: section two presents data and material used. Section 3 presents the empirical results as well as the evaluation of the proposed model; while section 4 outlines discussion and recommendations.

2. DATA AND MATERIALS

The study is based deeply in describing the key variable of interest for the inflation targeting framework (IT) by the SARB. The period that was sampled is from 2000q1, which is a year SARB has adopted the IT until 2014q4. The time series dataset was accessed from Quantec database. To maintain the assumption of normality, Mordkoff (2011) implied the distribution of the sample mean approaches normality as the sample size (n) increases through central limit theorem regardless of the shape of the distribution. 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. Furthermore, in order to alleviate the variance factor of the series, Sadowski (2010) put forward the log transformation as an optimal procedure with the standard deviation that increases linearly with the mean of the series. This transformation as highlighted by Montgomery *et al.* (2015) follows the form:

$$Y_t = \left[\frac{(X_t - X_{t-1})}{X_{t-1}}\right] * 100 \quad (1)$$

Pre-differencing transformation as proposed by Bruce *et al.* (2005), should sometimes be engaged so as to stabilize the properties of the series. Oxmetrics 6 and Eviews 9 are used for data analysis.

2.2. Material Used

Normality Test

The study firstly examines the data by the use of exploratory data analysis through the implementation of the descriptive statistics. And for the normality test of the data the Jarque-Bera statistic is used.

Jarque-Bera (JB) test is used in this study to test the speculation about the fact that a given sample X_s is a specimen from a normal distribution and the error term form the estimated model is normally distributed with mean zero and variance 1. The JB test of normality performs better when used on samples in excess of 50 observations. From the power computations, 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 estimated using the following formula:

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

where S is the skewness, K is the number of regressors from the regression model, n is the sample size and $2df$ is the number of 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:

$$H_0 : E[X_s] = 0$$
$$H_0 : E[X_s] \neq 0$$

The null hypothesis is rejected if the calculated probability value of the JB static is less than the 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 for small samples.

Nonlinearity test

To test for nonlinear effects in the SA inflation rate, the study uses the nonparametric method which is known as BDS. The method was used by Wang *et al.* (2006), to test serially independent series and nonlinear plan in a time series. The test is based on the integral correlation of the series and is defined as follows:

$$BDS_{m.M}(r) = \sqrt{M}\,\frac{C_m(r) - C_1^r(r)}{\sigma_{m.M}(r)} \quad (3)$$

Where M is the embedded points of the space with m dimension; r is the radius of a sphere centred on X_i, C is the constant and $\sigma_{m.M}(r)$ is the standard deviation of $\sqrt{M}C_m(r) - C_1^r(r)$.

Markov-Switching Model

Markov Switching models (MSM) have turned out to be progressively the mainstream in economic studies of industrial production, interest rates, stock prices and unemployment rates. So far there is no study that has showed in any subtle element of the moments that these models produced (Timmermann, 2000). The model was developed by Hamilton (1989a). Hamilton outlined that his algorithm can also be seen as a time series statistical identification of turning points procedures.

Furthermore, Calvet and Fisher (2001, 2004) point out that the assets returns by the MSM are been joined by the stochastic instability segments of heterogeneous durations. According to Lux (2008), MSM is able to determine the outliers, volatility and power in financial returns. Standard instability of the models in currency and equity series are shown differently by an MSM. For example, an out-of-sample models such as GARCH (1,1) and fractionally integrated GARCH (FIGARCH) is unsteady for the task. Due to these shortcomings of these models and others, researchers utilise an MSM as a part of the financial industries with the aim to forecast volatility and also to compute the risk and price derivatives.

Two Conditional independence assumptions are the ones that characterises a Markov Switching autoregressive (MS-AR) process. This includes in them, (1) the conditional distribution of laten series given the estimations of $\{S_t\}$t` < t what's more, $\{Y_t\}$ t` < t just relies upon the estimation of the one lag of the laten series. In different terms, the first order Markov Chain (MC) which its development is autonomous of the past series conditions is expected to be a series type of $\{S_t\}$. In the current study, the series condition is the inflation rate (CPI). (2) The conditional spreading of Y_t given the estimations of $\{Y_t\}$ t` < t and $\{S_t\}$t` < t just relies upon the estimations of S_t *and* Y_{t-1}, Y_{t-p}. Respectively. For a specific application, this implies that the inflation rate is an AR procedure of an order $P \geq 0$ with the coefficients advancing in time with the sequence of the inflation type.

Calvet and Fisher (2004) moved to the other series such as of exchange rate volatility. The GARCH (1,1) that they had compared, clearly showed that there are significant gains in forecasts of exchange rate volatility on the horizon of 10 days to 50 days (See also the work of (Klaassen, 2002a). Nonetheless, similar results were also obtained by Lux (2008) when using linear predictions. An empirical study of four daily exchange rate series revealed that when comparing the MSM with student-GARCH (1,1) of Bollerslev (1987), the

Markov-Switching GARCH (MS-GARCH) of Klaassen (2002b) and the FIGARCH of Baillie *et al.* (1996), then MSM is said to give precise results over all the stated models.

MSM fit in mainly with a class of mixed distributions. Econometricians enthusiasm for this class of distributions takes into account their capacity functions and create a more extensive scope of qualities for the skewness and kurtosis than its realistic through utilization of a single distribution (Timmermann, 2000). Vargas III (2009) added to the existing literature by emphasizing that MSM is a creative instrument to go with currency traumas and in addition, deciding the variables that lead the economy starting with one state then onto the next, say, from conventional period to a turbulent period.

The uses of MSM however, were started by Engel and Hakkio (1996). Engel and Hakkio in their study of currency crises established these models which eventually gained popularity in the use of the studies of the EWS models. The MSM in Brunetti *et al.* (2008); Abiad (2003) and Mariano *et al.* (2002) deals with wrong classification of crises when future disturbing periods in the data are included.

On the other hand, it is however, showed by Ailliot and Monbet (2012) that the MS-AR is the generalization of the Hidden Markov Models (HMM) and autoregressive (AR). Different AR models are combined and this leads to the process at different time and the transition between these AR models are being controlled by a hidden MC such as that of HMM. Numerous regime with lower AR models have been proposed in the literature for modelling meteorological time series see (Parlange & Katz, 2000).

The MSM of Hamilton (1989, 1990) offered an ascent investigation of the dynamics of exchange rate movements and one territory is the study of currency crises. According to Vargas III (2009), modelling of EWS for currencies by the implementation of the Markov switching Regression (MSR), where two regimes are considered together with stable and volatility as a mixture distribution of two normal, was first modelled by Engel and Hakkio in 1996. Then, again, utilization of the time varying transition probability (TVTP) of the MSR model shows a proof of contagion in an Asian financial crises where an ISP of Thailand and Korean enhanced the estimation of the conditional likelihood of the crisis in Indonesia.

Also, Abiad (2003) and Mariano *et al.* (2003) utilized an MSR with TVTP to build up an EWS and they utilized the MS of the adjustment in nominal exchange rate with three classifications of early warning indicators. Brunetti *et al.* (2008) further improved the model of Marino and others by accounting for large variances over time in periods of crises by building a conditional variance GARCH model.

Therefore, Hamilton (1989b) presented the MS-AR which follows the form:

$$Y_t - \alpha(S_t) = \Phi_1[Y_{t-1} - \alpha(S_{t-1})] + \cdots + \Phi_p\big[Y_{t-p} - \alpha\big(S_p\big) + \varepsilon_t \tag{4}$$

In which, when re-parameterised yields: $Y_t = C + +\varphi_1 Y_{t-1} + \varphi_2 + \cdots + \varphi_p Y_{t-p} + \varepsilon_t$

Which it is further simplified to

$$Y_t = \sum_{i=1}^{p} \varphi_i Y_{t-1} + \varepsilon_t \tag{5}$$

where the $AR(p)$ process coefficients are $\varphi_1, \varphi_2, \dots, \varphi_p$ and the $\varepsilon_t \sim iid(0, \sigma_t^2)$ and $\alpha\ and\ (S_t)$ are the regime or states depended constants S_t and represent α_1 if the process is in state or regime 1 ($S_t = 1$), α_2 if the process in state or regime 2 ($S_t = 2$) and α_R if the process is in state or regime R ($S_t = R$) the last state or regime. The process of one regime changing to the other and vice versa, is been administered by the first order MC R state with the flowing transition probability:

$$\begin{aligned} p(S_t = 1 \mid S_{t-1} = 1) &= P_{11} \\ p(S_t = 1 \mid S_{t-1} = 2) &= P_{12} \\ P(S_t = 2 \mid S_{t-1} = 1) &= P_{21} \\ P(S_t = 2 \mid S_{t-1} = 2) &= P_{22} \end{aligned} \tag{6}$$

and $P_{11} + P_{12} = P_{21} + P_{22} = 1$ which are also known as the transition probabilities and are estimated from the two-regime MS-AR model. The underlying MS-AR (p) model is then given by:

$$\begin{gathered} Y_t = \alpha(S_t) + \left[\sum_{i=1}^{p} \beta_i (y_{t-1} - \alpha(S_{t-1})\right] + \varepsilon_t \\ \varepsilon_t \sim iid(0, \sigma^2(S_t)) \\ S_t = j, S_{t-i} = i \dots i, j = 1 \end{gathered} \tag{7}$$

Whereas $S_t$is the latent state component that takes the values of 1 for high regime period or 0 for low regime period.

The MS-AR permits one to make inference about the observed regime value S_t , through the behaviour of the exogenous Y_t.This inferences follows the filtered probabilities, which when estimated, the simple iterative algorithm is used to compute both the probability function repeatedly and the conditional filtered probability on the accompanying set of observations $\xi_t = \big(X_{t,} X_{t-1}, \dots, X_0\big)$ till to time t which are defined as $P(S_t = i|\xi_t)$. On the other hand, smoothed probabilities are obtained if the data set is used as a whole. These probabilities however, are conditionally estimated on the whole sample size n observation. i.e. $\xi_t = (X_t, X_{t-1}, \dots, X_0)$. The most important information which is extracted from the transition matrix is the expected duration of the i^{th} regime and additionally the normal duration of the i^{th} regime. Meanwhile, $\frac{1}{P_{ij}}$ is a reciprocal of the expected duration of the process to stay in i^{th} regime. The value of P_{ij} for $i \neq j$ when it is small it reveals that the process takes a longer time in regime i while the corresponding $\frac{1}{P_{ij}}$ reveals the duration in which the process stays in the regime i. The assumption that Hamilton made is that $MS - AR \sim N(0,1)$ and the state is assumed to be a discrete state of the Markov process.

Logistic Regression

In order to fit the logistic model, James *et al.* (2013) indicated that maximum likelihood estimates (MLE) is an optimal procedure to fit the best model; and the model always give out an S shaped curve regardless of the value of X. Furthermore, sensible results will always be obtainable. In many literature such as of Cimpoeru (2015), there are three methodologies for developing an EWS for banking crisis being the bottom-up methodology, the aggregate methodology and the macroeconomic methodology. In the first method, the likelihood of bankruptcy is addressed for every bank and the systemic volatility is activated and signed if the likelihood of bankruptcy becomes significant for a high extent of the resource in the banking sector of a certain economy. For the second method, the model is applied to data other than individual banking data. On the third method, the focal point is centred 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.

In the binary models study of Moysiadis and Fokianos (2014), more emphasis was made to a time series that follows a categorical setting by showing that it is pushed by an inactive procedure or system input and kinds of models are very close in resembling GARCH models. But for them they to replace conditional variances, they are been described in terms of conditional log-odds.

The application of logistic regression analysis in the prediction of bankruptcy has been pioneered by Ohlson (1980). He described the logit model as a non-linear change of the linear regression and a system that weighs the covariates and then assigns a score. The logit methodology joins together the nonlinear changes and make use of the cumulative distribution function from the logistic to maximise 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).

To reduce randomness in assigning the observed time category in a time series, Fokianos and Kedem (2003) proposed that t^{th} observation of categorical time series nevertheless the measurement scale should be defined as a vector. For example, variables that are nominal. In this case, the multinomial logit model that is defined by Agresti (2013) is mostly used in analysing a nominal scale time series.

Because of the small samples and the need to keep the degrees of freedom, Kolari *et al.* (2002) added to the work of EWS for bank crises 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. Even though, Demyanyk and Hasan (2010) conducted the similar study to that of Demirgüç-Kunt and Detragiache (2005) where they both reviewed signal approach and multivariate probability model. However, with the Kunt and Detragiache's multiple logit method, the likelihood of occurrence of a crisis is thought to be a vector of explanatory variables. To estimate the probability of the crisis, Demirgüç-Kunt and Detragiache (1998) developed an econometric logit model which is fitted to the data and maximised the likelihood function.

More formally, neither the country is encountering a crisis nor is it not in every period. As needs be, the response variable is set to zero if there is no crisis and set to one if there is a crisis. The likelihood that in a certain country at a specified time a crisis will occur is said to be a vector component of n explanatory variables $X(i,t)$.

While building the EWS model for inflation, the study uses a logistic regression model to model the probability of high inflation regime. Being guided by the discussion of Tong (2012), the study then design a binary series outcome with values 0 or 1 respectively denoting a low inflation and high inflation regimes. Then again the corresponding P-dimensional vector of the past covariates $t = 1,2,3\ldots,T$ comes from the set series of say $W_{t-1} = \left(W_{(t-1)1},\ldots,W_{(t-l)p}\right)$ and represents the process as W_t .The main focus of the study is a successful likelihood conditional estimation which is represented by

$$P_\beta(Y_t = 1|S_{t-1}) \tag{8}$$

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

In guaranteeing that $P_\beta(Y_t = 1|S_{t-1})$ produce proper probability estimates, a suitable inverse link $h \equiv F$ is chosen and employed in such a way that it maps both real line and the interval [0,1]. Finally, denoting the probability of success given F_{t-1}asΠ_t, then it is obvious that the model is demonstrated as:

$$\Pi_t(\beta) = \mu_t(\beta) = P_\beta(Y_t = 1|S_{t-1}) = F(\beta^{`} Z_{t-1}) \tag{9}$$

F is continuous and strictly an increasing function, and returns values ranging between 0 and 1, the column vector of the parameters from the same p-dimension is denoted by β this comes from the covariate process W_{t-1}. Thereafter, the logit model is determined by the choice of F which has the standard cumulative logistic function that leads to the generalisation of the logistic regression model presented by:

$$\Pi_t(\beta) = P_\beta(Y_t = 1|S_{t-1}) = \frac{1}{1+e^{\left(-\beta^{`} Z_{t-1}\right)}} \tag{10}$$

where the column vector of parameters of the same p-dimension from the covariate process W_{t-1} is given by β. Furthermore, the inverse link is been defined by $F \equiv \Phi$, with Φ being a cumulative function from a standard normal distribution. In the study of Nyberg (2010), the same results were obtained while using the logit and probit models.

Hosmer Jr *et al.* (2013) provided a large discussion using maximum partial likelihood estimation (MPLE) for estimating β. They however indicated that when $N \to \infty$, then $\hat{\beta} \to \beta$ in probability because the MPLE of $\hat{\beta}$ is surely unique for sufficiently large N.

Model Selection

For model selection, the study employs the of Akaike Information Criterion (AIC), and likelihood ratio. According to Pan (2001), Akaike Information

Criterion (AIC) is most powerful and recently widely used by most researchers and it was proposed by Akaike (1973) as:

$$AIC = -2L(\beta; D) + 2p \tag{11}$$

Likelihood ratio test is one of the methods that are recently employed to select the model. The test is thought to test the goodness of fit between models of which null model is unique from the other which is the alternative. This test has been popularized by Bevington and Robinson (2003).

$$T_{LTR}(x) = -2logR(x) \tag{12}$$

where $R(x) = \frac{SUP_{\theta e \Theta_0} L(\theta|x)}{SUP_{\theta e \Theta} L(\theta|x)}$ with $L(\theta|x)$ denoting the likelihood function.

The model with the least AIC is the favoured model. Granger and Jeon (2004) made a comparison study between the AIC and SBC. They discovered that on average, AIC reformed models though SBC fitted parsimonious AR models and out-performed AIC. SBC performed better than the AIC regarding minimizing the mean squared estimates. But with the likelihood ratio, the favoured model is the one with the highest likelihood ratio. The current study uses both AIC and likelihood ratio.

3. EMPIRICAL ANALYSIS

This section provides and discusses the preliminary and primary analyses results.

3.1. Exploratory Data Analysis

The study begins by exploring the data through the use of descriptive statistics to assess the behaviour the inflation rate. For the assumption of normality, the JB test is established and the results are presented in table 1.

Table 1. Descriptive Statistics

Statistic	*Inflation*
Mean	6.112942
Median	6.056707
Std Deviation	0.985579
Skewness	0.066392
Kurtosis	2.95683
JB	0.045488
P-Value	0.977513

The mean value of inflation reveals that, on average the SA economy has inflation rate of 6.11% per quarter. On the other hand the median value also indicates that, SA inflation takes 6.1 quarters to increase or decrease. One other important result is the Skewness, and kurtosis. Both the values of kurtosis and skewness implies that the data is normally distributed hence the JB statistic confirms that the data is normally distributed with a probability value of 0.977513.

3.2. Nonlinearity test

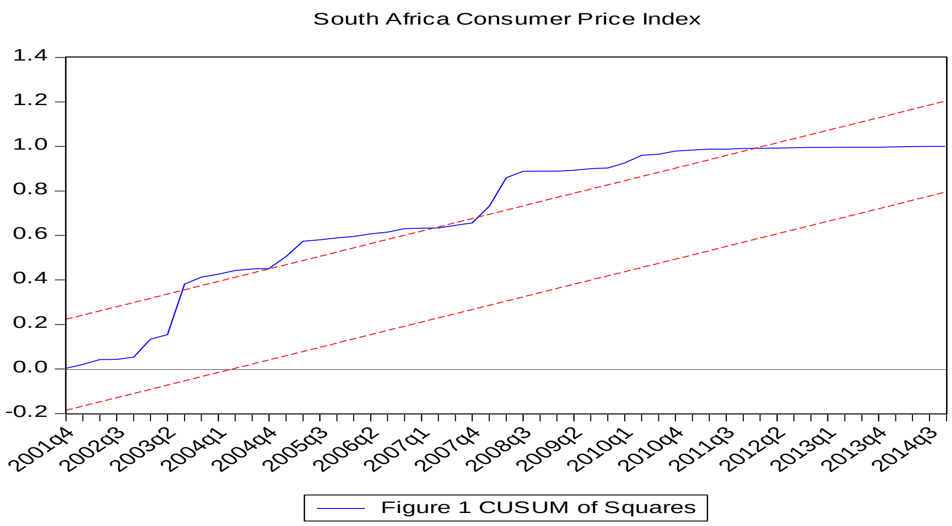
In this part of the paper, the linearity test by the use of the BDS test is conducted and reported results are in table 2.

Table 2. BDS Test for Nonlinearity

Dimension	*BDS Statistic*	*Std. Error*	*Z-Statistic*	*Prob*
2	0.13492	0.009686	13.92983	0.0000
3	0.161693	0.009016	17.93356	0.0000
4	0.149425	0.006304	23.70191	0.0000
5	0.126663	0.003864	32.7822	0.0000
6	0.103706	0.002194	47.27753	0.0000

The BDS results in table 2 indicates that there is some nonlinear effects in the inflation rates series hence the data can be model using a nonlinear model. Confirming the BDS results, an $AR(2)$ model was estimated and examined for the stability of the model coefficients by employing the CUSUM of squares which was proposed by Brown *et al.* (1975) and the results are presented in figure 1 which indicates that the SA CPI is unstable because the series is out of the control bends of the graph.

Figure 1. CUSUM of Squares



Still in-line with the nonlinear testing, the study continues by employing a Bai-Perron structural breakpoint test. From the results in table 3, there are only three structural breaks identified with the period of 2001q1 to 2014q4. The procedure used to select the number of breaks is the Bayesian information criterion (BIC). According to Bai and Perron (2003), the best information criterion to select the number of breakpoints is the BIC criterion (Also see (Bai and Perron 2003b, Paye and Timmermann 2006 and Timmermann 2001).

Table 3. Multiple Breakpoint Test

Breaks	*Number of Coefficients*	*Sum of sqrd Residual*	*Log-likelihood*	*BIC*	*LWZ*
0	2	107814.3	-286.5145	7.726553	7.818475
1	5	89446.25	-281.3783	7.758363	7.990875
2	8	67598.33	-273.6768	7.69689	8.073598
3	11	43669.54	-261.6611	7.478539	8.003527
4	14	39409.34	-258.8383	7.594473	8.272399
5	17	39284.42	-258.751	7.80988	8.646113

Table 4 presents the periods of the structural break points that have been detected. The first break point occurred in 2003q2 and followed 2005q3 then 2008q1 and 2010q1. Periods on 2008q1 and 2010q2 are associated with the financial crisis that hit the global markets.

Table 4. Periods of Structural Breaks

Number of breaks	*Break dates*		
1	2003Q2		
2	2003Q2	2005Q3	
3	2003Q2	2008Q1	2010Q1

All over again, table 5 presents the estimated AR (2) model. From this model, at 5% level of significance, all the estimated AR parameters are found significant. Then misspecification of the model is examined by the RESET test. The main purpose of the Ramsey RESET test is to test the instability of model variance or misspecification of the model. In this case, the F statistic of the RESET test is significant with a probability value of 0.0463, hence the results conform to the CUSUM test and BDS test that there is a nonlinear cases in the data set.

Table 5. Estimated AR Model with Nonlinearity test

Variable	*Coefficient*	*Std. Error*	*Test Statistic*	*Prob.*
Φ_0	6.068751	0.533497	11.37543	0.0000
Φ_1	0.879985	0.055843	15.75815	0.0000
σ^2	0.192842	0.024323	7.928264	0.0000
RESET TEST	2.857062			0.0463

3.3. Model Estimation and Selection

Six two regime MSM, which are $MS(2)-AR(1)$ *to* $MS(2)-AR(6)$ are been estimated The best model is selected based on the AIC of each model because AIC is said to be more powerful in detecting the best model compared to likelihood ratio test as Posada and Buckley (2004) and Bozdogan (2000);Pan (2001) and Posada (2003) have highlighted in their work. In reference to table 6, the best model is selected to be $MS(2)-AR(2)$ because the AIC associated with the model is found to be 9.942339 which is the smallest of all other estimated $MS(2)-AR(P)$ models. Nevertheless, based on the parsimony principle, and also looking at the statistical significance of the lags, the study then chooses $MS(2)-AR(1)$ as the final model.

All the estimated coefficients of $MS(2)-AR(1)$ are found to be significant at 5%. The other interesting part of the analysis is the transition probability metrics which is presented as $p(S_t=1|S_{t-1}=1)=0.95053$, $p(S_t=2|S_{t-1}=2)=0.90268$ this suggests that the probability of low inflation is higher than that of high inflation. When the process is in regime 0, there is a low probability that it switches to regime 1 (high inflation) and the probability of switching to high inflation $P(S_t=2|S_{t-1}=1)=0.04947$. The average duration of each regime also support this. Based on the expected duration, the low inflation regime has 11.67 approximately 12 quarters while the high inflation has only 10 quarters respectively. This denotes that SA economy will be in state one (low inflation for an average of 12 quarters and high inflation to an average of 10 quarters).

The probabilities of the smoothed, filtered and forecast for each regime are reported in Figure 2. It can be observed that the low inflation regime dominates the counter part of the high inflation regime. This coincides with results reported earlier in table 7 that there is high expectation of a low inflation regime in SA. In addition to that, from 2001q2 to 2001q4, 2005q1 to 2007q4 and lastly 2010q1 to 2014q4, the fluctuations for inflation rate is extremely high which forces the process to be in regime 0 with $0.5 \le P \le 1$ and on the remaining quarters of the frequency which is 2002q1-2004q4 and 2008q1 to 2009q 4 are the episodes of high inflation.

Table 6. Model Estimation and Selection

Models(MS-AR)	*Number of states*	*Number of lags*	*log likelihood*	*AIC*
1	2	1	-266.84216	9.9942603
2	2	2	-258.44315	9.942339
3	2	3	-267.18838	10.535411
4	2	4	-245.36920	9.9757386
5	2	5	-251.14978	10.437246
6	2	6	-236.46173	10.178469

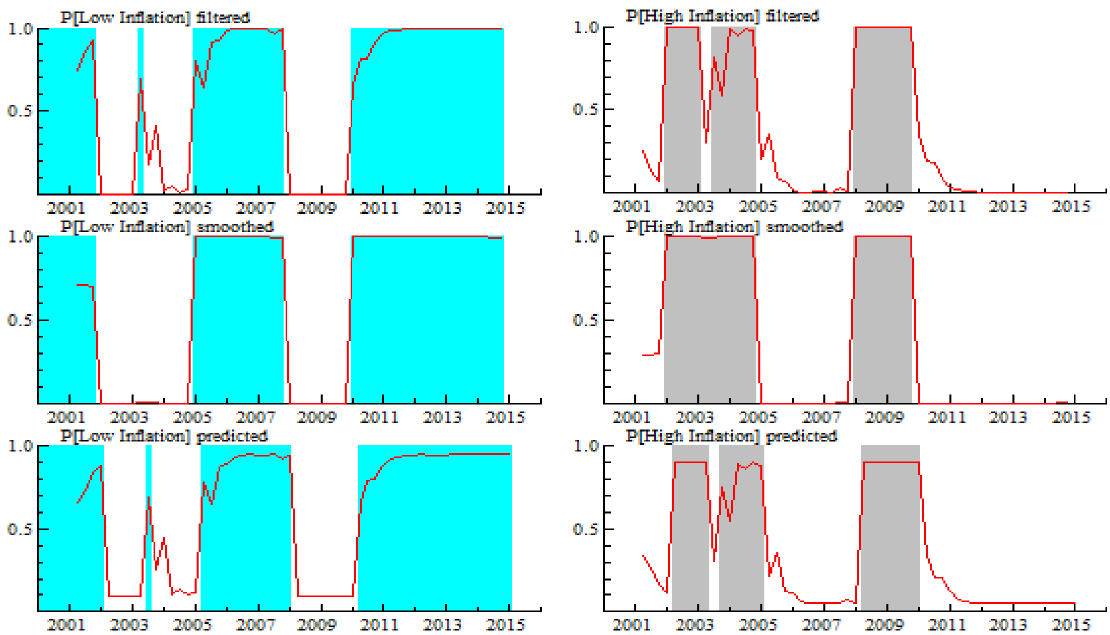
Estimated $MS(2) - AR(1)$ *Coefficients*

Table 7. Markov-Switching parameters

Parameter	*Coefficients*	*Stand Error*
C_1	575.174	20.34
Φ_1	0.871363	0.03501
σ_1	14.8421	1.845
C_2	688.274	20.4
Φ_2	1.11463	0.08675
σ_2	54.5374	8.86
Regime 0 [Low inflation]	**Regime 1[High Inflation]**	
0.95053	0.097318	
0.04947	0.90268	

The causes of high inflation episodes in 2002 to 2004 are the results of the adjustment made to sudden reversals of capital and its difficulties in attracting foreign direct investment and also the reflection of the macroeconomic policy for the maintenance of stability and improvement of growth rates by trying to avoid the overheating and appreciation of real exchange rate by the SARB. In the period 2008 to 2009, the high inflation was caused by the financial crisis that started in the United States (U.S). According to Moroke *et al.* (2014), most of the developing countries such as SA also suffered the effects of this crisis because there is much evidence that this crisis is still lingering and in many cases the crisis is still on-going.

Figure 2. Filtered, smoothed and forecast probabilities for each regime



The results of MSM can be useful to cluster the quarters into low inflation or high inflation as per table 8. To identify the periods of low and high inflation, the smoothed probabilities are used and the results indicate that from 2001q2-2001q4, 2005q1-2007q4 and from 2010q1-2014q4 are periods of low inflation, while the other remaining quarters within the same frequency are periods of high inflation.

Table 8. Episodes of High and Low Inflation

Low Inflation	*High Inflation*
2001(2)-2001(4)	2002(1)-2004(4)
2005(1)-2007(4)	2008(1)-2009(4)
2010(1)-2014(4)	

3.4. Model Diagnostic Test

After model estimation, the best model was then checked for diagnostics. For all of the statistical diagnostic tests, the assumptions of the error term were found not have been violated. For Normality test, the residuals were found to be normally distributed. Moreover, the study tested for correlation of the error term. Godfrey serial correlation test of the error term concludes that the error term is not serially correlated. On the other hand, the ARCH test is used to test the homogeneity of the variance of the error term. The results reported that there is no problem of the homogeneity in the variance of the error term. Table 9 presents the diagnostics test results.

The Performance Assessment of the Logit based EWS Model

The following scenarios are provided by the logit model after the probability estimates:

1) Incident A presents the time the model indicates a crisis when a high inflation event indeed occurs.

2) Incident B is an event of a wrong signal from the model.

3) Incident C reports the probability of missing signal from the model

4) Incident D indicates a situation in which the model does not predict a crisis and no crisis occurs.

In addition to that, the study uses the standard value of 0.5 to discriminate the probabilities of crisis signals.

Table 9. Model Diagnostic Checking

Test	*Test Statistic*	*Prob*
Normality	2.0316	0.3621
ARCH 1-5	1.1113	0.3712
Serial Correlation	15.781	0.2015

3.5. Logistic Regression Model

In building the SA's EWS for high inflation, the LRM is considered. The likelihood from the logit model provides a reasonable assessment about the feasibility of SA inflation crisis. Through the classification of the MSM, 1 is given to the scene of high inflation while that of low inflation is named 0.

Table 10 reports the logit model results. The coefficient signs of the indicators to the crisis are found consistent with the expectations from the theory. The negative constant is related to the inflation, hence inference of surge in the value of the constant degreases the likelihood that the country will enter in high inflation period.

Table 10. Estimated Logit Model

Variable	*Coefficient*	*Std. Error*	*t-statistic*	*prob*
Constant	-0.510826	0.276	-1.85	0.07
AIC	1.35884076			
LR statistic	29.959			
Prob(LR statistic)	0.0000			

To evaluate the EWS model performance, the study utilizes the following performance criteria which were proposed by Kaminsky *et al.* (1998)

a) Percent of crisis correctly called (PCCC) : $\frac{A}{B+C}$

b) Percent of non-crisis correctly called (PNCCC) : $\frac{D}{B+D}$

c) Percent of observations correctly called (POCC): $\frac{A+D}{A+B+C+D}$

d) Adjusted noise-to-signal ratio (ANSR): $\frac{B}{B+D} / \frac{A}{A+C}$

e) Probability of an event of high inflation given a signal (PRGS): $\frac{A}{A+B}$

f) Probability of an event of high inflation given no signal (PRGNS): $\frac{C}{C+D}$

g) Percent of false alarms to total alarms (PFA): $\frac{B}{A+B}$

Table 11. Forecasts of the EWS model

In-ample		*High Inflation*		*Low-inflation*		*Total*
	High	21.88	(63%)	7.87		30
	Inflation					
Predicted	Low					
	inflation	13.12		13.13	(63%)	26
	Total	35		21		56
Out-sample		High Inflation		Low-inflation		Total
	High					
	Inflation	5.04	(46%)	7.04		12
Predicted	Low					
	inflation	5.96		5.96	(46%)	12
	Total	11		13		24

The results demonstrated in table 11 suggest that the model has some EWS potential. In view of the in-sample estimates, the model has the capacity to accurately predict 63% of high inflation and 63% of low inflation occasions. Overall, 63% of observations are correctly identified by the model. Moreover, the proportion of a high inflation event given a signal is relatively high at 63% while the proportion of false alarms is relatively low at 37%.

A satisfactory performance of the in-sample of the model does not link a great performance of the out-of-sample. In assessing the out-of-sample inferences, the EWS model is re-estimated by utilising the sample period of 2015 to 2020.

Results in Tables 12 indicate that there is 46% chance of high inflation incidence which is lower than the 63% from the in-sample. In addition, the proportion of false alarm is 46% which rose slightly from the 37% of the in-sample.

Table 12. Forecasting Performance of the EWS model

	In-Sample	*Out-of-sample*
PCCC	63	46
PNCCC	63	53
POCC	63	46
ANSR	59	1.17
PRGS	63	46
PRGNS	37	54
PFA	37	46

4. DISCUSSION AND CONCLUSION

The following paper has developed a EWS model for predicting the occasion of inflation crisis in SA to supplement the SARB's present suite of inflation policy framework models. Scenes of high and low inflation have been recognized by a Markov-Switching model. At that point, by the utilization of results from the regime classification, a logistic regression model was then considered with the objective of measuring the probability of the occasion of episodes of inflation crisis.

The paper had publicised that SA inflation can be modelled as a two state $MS(2) - AR(1)$, with episodes of high inflation being lower than that of low inflation. In addition, the duration of low inflation is more twice than that of high inflation. Overall, the results of the MSM lend support the effectiveness of the SARB's monetary policy instruments in monitoring inflation in SA. The plots of the smoothed probabilities of the two regimes clearly demonstrated the fluctuations of the SA inflation rate and also indicated that episodes of low inflation took more time (11 quarters) than their counter part which took only (10 quarters).

The warning signals from logistic regression model indicated that from 2015-2020 there is only 54% chance that SA will face an inflation crisis therefore the monetary policy committee will have to safeguard the crisis by preparing for the problem in revaluating the current monetary policy.

4.1. Recommendations

Even though the EWS model has been revealed as a potential reciprocal of the SARB current monetary tool, the new policies regarding the inflation crisis can be formulated based on the in-sample and out of sample forecasting performance. There is a high likelihood that the preliminary analysis covered by the univariate modes will behave poorly in macroeconomic variable forecasting, but introducing models like Markov-Switching vector autoregressive (MS-VAR) models for macroeconomic variables might enhance the short-term performance forecasting of these models. MS-VAR can also provide a promising framework for analysing the contagion effects of an inflation crisis and other financial crisis. Other than using a single equation models for modelling the inflation rate and its determinants in SA, the SARB can use this warning system to identify the danger zone of the high inflation rates where the monetary policy committee can be able to see when the inflation rate will be below or high above the targeted interval of 3%-6%, since the warning signals indicated that there is only 54% chance that the SA will phase the inflation crisis. Even though this likelihood seems to be uncertain, the MPC must not take chances, but only safeguard the problem in time by revaluating the current monetary policy by increasing the prime rates which will eventually decreases the money circulation in the economy in the short-run level. Therefore the SARB will be in the position to monitor the inflation and its determinants in the long run through the use of several monetary transmission mechanisms which include the interest channel, other assets channel and credit channel.

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