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PREDICTING REGIME SHIFTS IN JOHANNESBURG STOCK EXCHANGE ALL-SHARE INDEX (JSE-ALSI): A MARKOV-SWITCHING APPROACH

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Abstract

It has been proven several times that linear models are unable to encapsulate nonlinear dynamics of macroeconomic and financial data such as inflation rates, exchange rates and stock prices to mention fewer. As a result, to overcome this problem, this current study adopted the nonlinear models due to the fact that they have required qualities to apprehend nonlinearity in a dataset. In order to predict a regime shifts, a five-day Johannesburg stock exchange all-share index (JSE-ALSI) spanning period from 02 January 2003 to 28 June 2019 was used as an experimental unit. This current study firstly employed Teräsvirta neural network test to detect the presence of nonlinearity and proceeded to estimate a two regime Markov-Switching autoregressive (MS-AR). The results of Teräsvirta neural network test revealed a highly significant nonlinearity with permanent seasonality as demonstrated by Kruskal-Wallis test. The predicted regime shifts by a latent dynamic allowed the autoregressive and variance parameters to promptly react to vital systemic shocks. As a result, this current study allowed volatility to oscillate between high and low volatility regimes that produced an expected duration of high volatility of two year and two months. This was a clear indication that there is a regime shifts in JSE-ALI which are modeled using Markov-Chain (MC) stochastic process. These findings may be used to inform robust policy making with the aim of safeguarding both the JSE and other global stock markets from the episodes of stock market crash. Moreover, other researchers can utilize the results of this study to calculate the risk associated with structural breaks and high volatility periods.

Keywords: All Share Index, Johannesburg Stock Exchange, Markov-Switching, Nonlinear Modeling

JEL Classifications: E42, C24, C45

1. Introduction

The 1990 financial crisis was one of the most unbearable crises to hit most economies in both developing and developed countries. According to Radelet and Sachs (1998), the 1990 financial crisis was declared the most severe to affect the developing markets following the 1982 debt crisis. Furthermore, this 1990 financial crisis was followed by a series of economic ills such as 1998 Russian debt crisis, 2001 terrorist attack on the World, US airlines bankruptcy, 2003 invasion of Iraq, 2007 subprime mortgage and the 2009 European sovereign crisis. According to Buchs (1999), the Russian debt crisis transpired as a result of crashed financial markets due to inability to match the new portfolio investments and the outflow of capital from treasury bill market. The United States was affected by the revenue loss in the US-Airlines and struggled to maintain financial solvency. According to Lai and Lu (2005), this US-Airline insolvency was followed by the 2007 sub-prime mortgage which extensively affected United States and resulted in the world great recession. The other predicament which extensively affected the Eastern European countries was the 2009 European sovereign crisis. According to Hadjimichalis (2011), this crisis affected three highly connected sectors namely the banks, real estate and private and public debt. All these economic ills destructed the financial prosperity of numerous countries and resulted in increased volatility. Moreover, the financial systems of many countries were threatened by these risky periods and the banks were forced to take counter measures together with the governments of affected countries.

Therefore, modeling these histrionic movements using the linear model such as a seasonal autoregressive integrated moving average (S)ARIMA or (S)ARIMA intervention model may give misleading results. According to Rapoo and Xaba (2017), linear models have the tendencies of leaving certain aspects unexplained hence the introduction of nonlinear models. With an intervention model, the assumption is that at time T, a time series is divided into two segments known as pre-intervention and post-intervention. The failure of the seasonal autoregressive integrated moving average (S)ARIMA or (S)ARIMA intervention model to capture nonlinear dynamics in financial and macroeconomic data has given Markov-Switching model (MSM) considerable attention. Markov-Switching model (MSM) was and is still acknowledged by scholars as a special form of model that can be utilized to capture nonlinear patterns as regime-shifts in the mean μ, variance σ^2 and within the parameters of an autoregressive (AR) process. This MSM approach accounts for the likelihood of business mechanism that generates a short rate that may undergo a finite number of changes. This implies that the mean and variance can oscillate across different interventions that are driven by a stochastic Markov process. According to Ang and Timmermann (2012), the conditional variance depends upon the level of a time series thus accommodates clustering volatility and dependence, nesting each individual specification as a special case.

Therefore, this study is undertaken with the aim of predicting regime shifts in Johannesburg Stock Exchange-All share index. By so doing, this study will be contributing to the academic paradigm by filling a void in practical literature. Firstly, this current study will contribute by instantaneously navigating regime switching model, focusing on an asymmetric viewpoint of multiple interventions. Secondly, it will demonstrate that the parameters of the MSM model are time variant due to unobserved latent states. Lastly, it will demonstrate that parameters modeled by stochastic time-varying process are nonstationary and the distribution of the residuals from the estimated MS-AR model are not independently and identically distributed with mean zero and unit variance. This nature of studies is very scarce in literature as far as South Africa is concerned. Other researchers such as Xaba *et al*. (2015) and Alvarez *et al.* (2018) employ the regime switching models but the focus was not on predicting the regime shifts in the JSE-ALSI. For more reading about nonlinear and regime-shifts, see Hamilton, (2010); Chkili and Nguyen (2014); Ardia *et al.* (2018); and Wolf *et al.* (2019).

The rest of the study is organized as follows: Section 2 will present the methodology that helps to achieve the objective of the study whilst section 3 discusses the empirical analysis. Finally, section 4 presents conclusion and policy recommendation for further studies followed by references.

2. Methodology

This current study adopts the behavior of stochastic parameters through the utilization of the Markov-Switching autoregressive (MS-AR) model. The Markov-Switching autoregressive (MS-AR) methods and procedures are discussed in this section of the study. The results obtained in this section will serve as the guide regarding the nature of data and type of the model to estimate.

2.1. Markov-Switching Autoregressive Model

Given a time series $\{Y_t: t = 1,2,3, \dots, n\}$, Cruz and Mapa (2013) as well as Hamilton and Raj (2013) articulate that an MS-AR process is categorized by the two conditional assumptions. The first assumption is that given the estimations of $\{S_t\}t\grave{} < t$ plus $\{Y_t\}\, t\grave{} < t$, the conditional distribution of the latent series relies upon the estimation of one lag of the latent series. The first order Markov-Chain (MC) developed by an autonomous condition of the past series is probable to be a series type of $\{S_t\}$. In the current study, the series condition is JSE-ALI. Second assumption is that when Y_t is conditionally spreading, the given estimations of $\{Y_t\}\, t\grave{} < t$and $\{S_t\}t\grave{} < t$ have relied upon the estimation of S_t and Y_{t-1}, Y_{t-p} respectively. For a specific application, this means that JSE-ALI in this study is an AR procedure of an order $\rho \geq 0$ with coefficients advancing in time. Hamilton and Raj (2013) therefore present a two regime MS-AR by

$$Y_t - \alpha(S_t) = \Phi_1[Y_{t-1} - \alpha(S_{t-1})] + \cdots + \Phi_p\left[Y_{t-p} - \alpha\left(S_p\right)\right] + \varepsilon_t \tag{2}$$

in which, when re-parameterized yields

$$Y_t = C + \varphi_1 Y_{t-1} + \varphi_2 + \cdots + \varphi_p Y_{t-p} + \varepsilon_t \tag{3}$$

which is simplified to

$$Y_t = \sum_{i=1}^{p} \varphi_i Y_{t-1} + \varepsilon_t. \tag{4}$$

Note that the $AR(\rho)$ process coefficients are $\varphi_1, \varphi_2, \dots, \varphi_p$and the ε_t is the error term of the model and α and (S_t) are the regime or states depended on constants S_t and represent α_1 if the process is in 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 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 matrix

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix} = \begin{bmatrix} P_{11} & 1 - P_{11} \\ 1 - P_{22} & P_{22} \end{bmatrix}. \tag{5}$$

Ismail and Isa (2007), Hamilton (2010) as well as Cruz and Mapa (2013) suggest an underlying $MS(k) - AR(\rho)$ model where k is the number of regime shifts and ρ is the order of AR parameters is given by

$$Y_t = \begin{cases} \phi_1 + \sum_{i=1}^{\rho} \varphi_1 Y_{t-i} \varepsilon_{1,t}, & \text{if } S_t = 1 \\ \phi_2 + \sum_{i=1}^{\rho} \varphi_2 Y_{t-i} \varepsilon_{2,t}, & \text{if } S_t = 2 \end{cases}. \tag{6}$$

3. Empirical analysis

This section of the study presents empirical data analyses using a five-day JSE-ALI price index of South Africa. As already indicated above, this current study employs the Markov-Switching autoregressive (MS-AR) techniques. Based on Figure 1, the time series plot in the left panel show both upwards and downwards trends in conjunction with seasonality. This is a clear indication that the series is not stationary. This is further confirmed by the logarithm returns on the right panel that clearly illustrated volatile patterns in the series. Since the series are not stationary, this study estimates a nonstationary model.

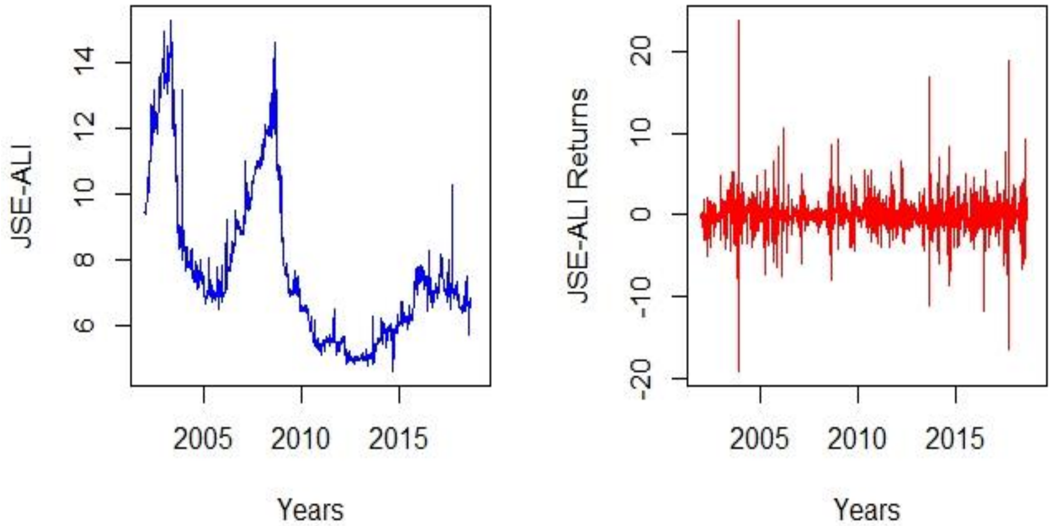

Figure 1. JSE-All Share Index

To study the nonlinearity in the JSE-ALI data, this study proceeded to perform the Teräsvirta and Kruskal-Wallis (K-W) tests. To reveal the nonlinear dynamics in the JSE-ASLI, the former was utilized, and the latter followed to reveal the presence of seasonal components. The Teräsvirta and Kruskal-Wallis (K-W) results are presented in Table 1.

Table 1. Teräsvirta and Kruskal-Wallis test

Teräsvirta	F-Statistic	sig
JSE-ALI	451.7496	***
K-W	Chi-Square Statistic	
JSE-ALI	46.187	***

Notes: *** 0.001 ** 0.01 * 0.05

The Teräsvirta results as presented in Table 1 revealed that a high significant of nonlinearity as the calculated probability value of this NN test is less than the observed significance level of 5%. Therefore, this current study concluded that JSE-ALI are nonlinear and cannot be modeled using linear models. This Teräsvirta results agree or conform to the ones presented in Figure 1.

The expectation maximum (E-M) algorithm for parameter estimate was used to estimate twelve AR (1) models subjected to two regimes, i.e. MS (2)-AR (1) to MS (2)-AR (12). To select a parsimonious lag-length, the Bayesian information criterion (BIC), Hanan Quin (HQ) and Akaike information criterion (AIC) were employed. Bozdogan (2000), Pan (2001), Posada (2003) and Posada and Buckley (2004) suggested that the AIC was the most powerful in the best model compared to likelihood ratio test. However, according to Scott and Hatemi (2008), for each simulated model with large samples, BIC and HQ are found to be the best performers to select the optimal lag length, hence this study employs both. Based on the results of these three criterions, a parsimonious lag-length of one is selected. The study then proceeds with a non-stationary MS (2)-AR (1) and the results are presented in Table 2.

Table 2. Two-Regime MS (2)-AR (1)

	Regime 1		
Parameter	**Coefficient**	**Std.Error**	**t-value**
μ_0	4.47072	0.07061	63.3***
Φ_0	0.878079	0.05813	15.1***
σ_0	0.0374713	0.005936	6.31***
	Regime 2		
μ_1	4.5404	0.06781	67.0***
Φ_1	1.02245	0.02148	47.6***
σ_1	0.0228429	0.001628	14.0***
	Transition Probabilities		
P11	0.92235	**P12**	0.036427
P21	0.077654	**P22**	0.96357

Note: *** 0.001 ** 0.01 * 0.05

Each of the two regimes identified has a clear economic interpretation. The variance in regime one is higher than the variance in regime two by 1.4%. Similar results are obtained in Ismail and Isa (2007). This is a clear indication that the conditional distribution is less volatile, and it is subject to regime-shifts with a weekly value of 6.31%. Nevertheless, when the JSE-ALI follows the first regime, on daily average, it falls to 4.47%. This means that when the series is in regime one, its probability to switch to regime two is $P\,(S_t = 2|S_t = 1) = 0.078$. The average duration of each regime also supports this behavior. Based on the expected duration, regime one has approximately 8 months and two days while regime two has only 24 months and two days. We, therefore, conclude that there is a significant regime shifts in JSE-ALI and it can be shown using the filtered and smoothed probabilities in Figure 2.

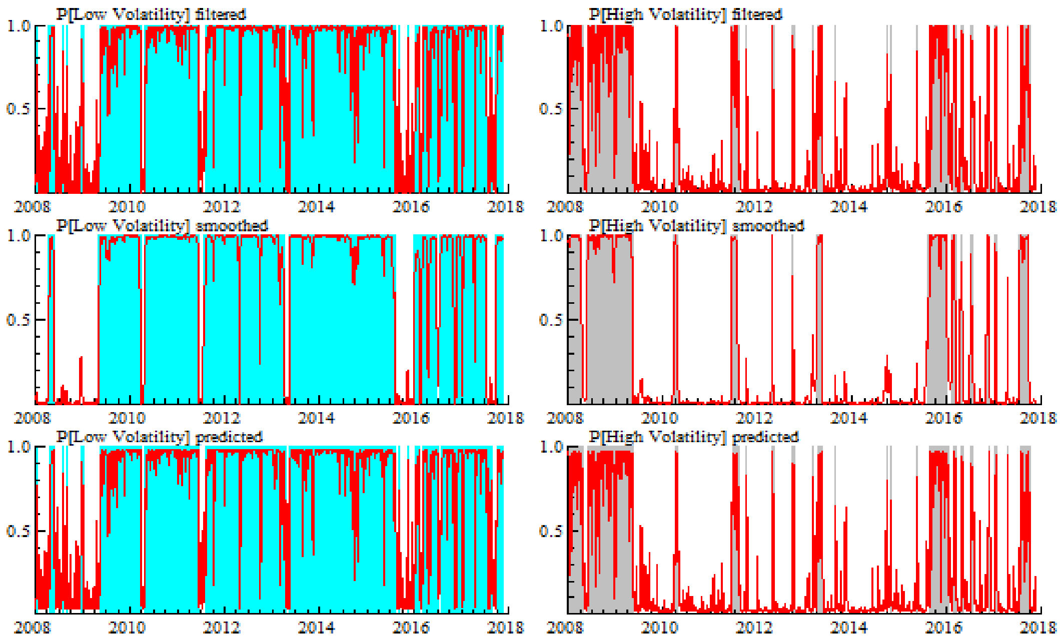

Figure 2. Filtered, smoothed and predicted probabilities

Assessing the goodness of fit (GoF), the results of the chi-square GoF, Kolmogorov-Smirnov, and Anderson Darling reveal that the residuals of the fitted MS(2)-AR(1) are non-normal, however, they follow some of the advanced distribution due to observed extreme values in the tails of the model. The study, therefore, fits six advanced namely the generalized extreme value distribution, the generalized Pareto distribution, the generalized Logistic distribution, Log-Pearson 3, Phased Bi-Exponential and finally Wakeby and compared their goodness of fit and rank accordingly from 1 to 6 and their results are presented in Table 3.

Table 3. Goodness of fit of advanced distributions

Distribution	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
	Statistic	Rank	Statistic	Rank		Rank
Gen.ExtremeValue	0,17353	3	0,58347	3	2,146	4
Gen.Logistic	0,19478	5	0,75423	5	0,99486	1*
Gen.Pareto	0,13179	1*	0,42514	1*	1,876	2
Log-Pearson3	0,18666	4	0,66749	4	2,4004	5
Phased Bi-Exponential	0,99995	6	155,06	6	2,2510	6
Wakeby	0,13179	2	0,42514	2	1,876	3

According to the three GoF tests, the Kolmogorov Smirnov and the Anderson Darling select the generalized Pareto distribution according to the rank 1 while the chi-squared selects the generalized Logistics distribution. Therefore, this current study concludes that the distribution of the residuals of the MS (2)-AR (1) follows a generalized Pareto distribution. The survival period of time-varying parameters in each regime as reported in Figure A1 in Appendix are in accordance with the predicted volatility in Figure 2 and the expected duration of each regime. This is the reason the fitted hazard function for each regime is exponentially related to non-stationary regimes as seen in Figure A2 in Appendix.

4. Conclusion and policy recommendations

This study explored MS (2)-AR (1) to predict regime shifts in JSE-ALI. Periods of high and low volatility were identified by the regime clusters, giving JSE-ALI a high probability of staying in low regime with expected duration of 8 months and two days. Within volatility dynamics of JSE-ALI, the study found that there is a persistence conditional volatility which nests the popular generalized autoregressive conditional heteroscedasticity (GARCH) in each regime. We further showed that the residuals of the estimated model follow a generalized Pareto distribution and they are non-normal with the survival function and hazard being exponentially related to time-varying parameters. Therefore, this study provides practical information to monetary policy committee (MPC) of South Africa Reserve Bank (SARB) that will assist in decision making regarding the unexpected movements in the Johannesburg stock exchange.

For further research, this study revealed that financial time series interrupted by policies, political instabilities and other movements the stock markets cannot be modeled using SARIMA intervention as suggested by Wongsathan (2018). This current study recommends usage of autoregressive model subjected to a regime switching process. The SARIMA intervention models were criticized for not being able to capture structural changes of a very volatile series such as all-share index. This is due to the fact that this time series possess unknown multiple break points, but an intervention model only assumes known break points some of which may be left behind.

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Appendix

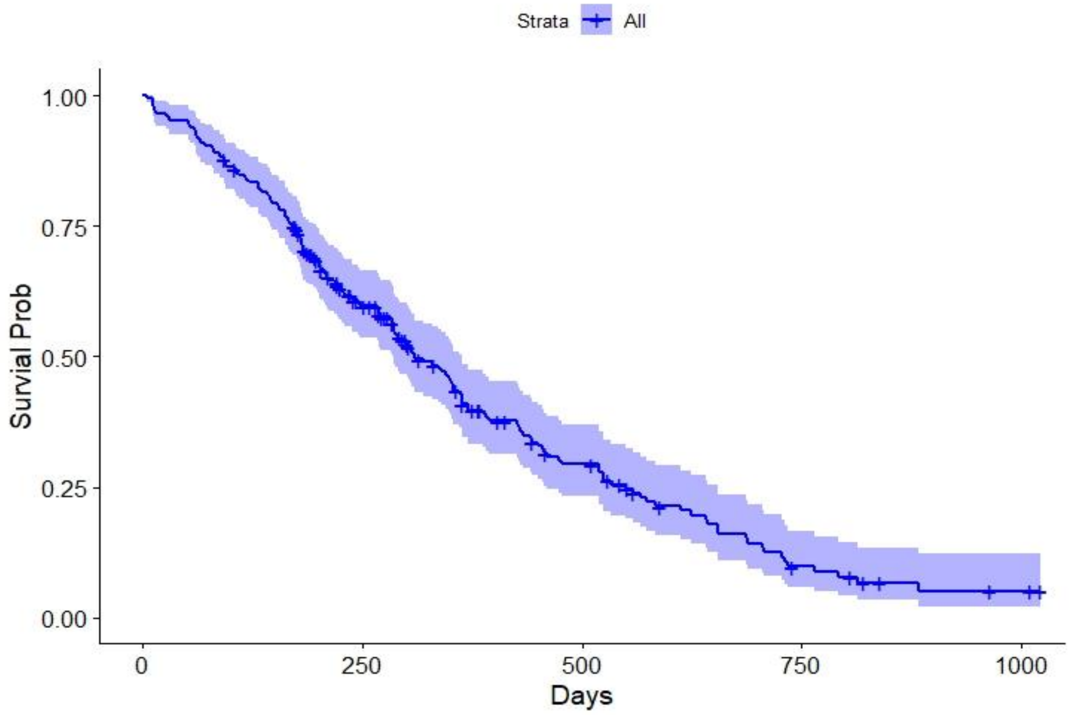

Figure A1. Survival of JSE-ALI Returns in each regime

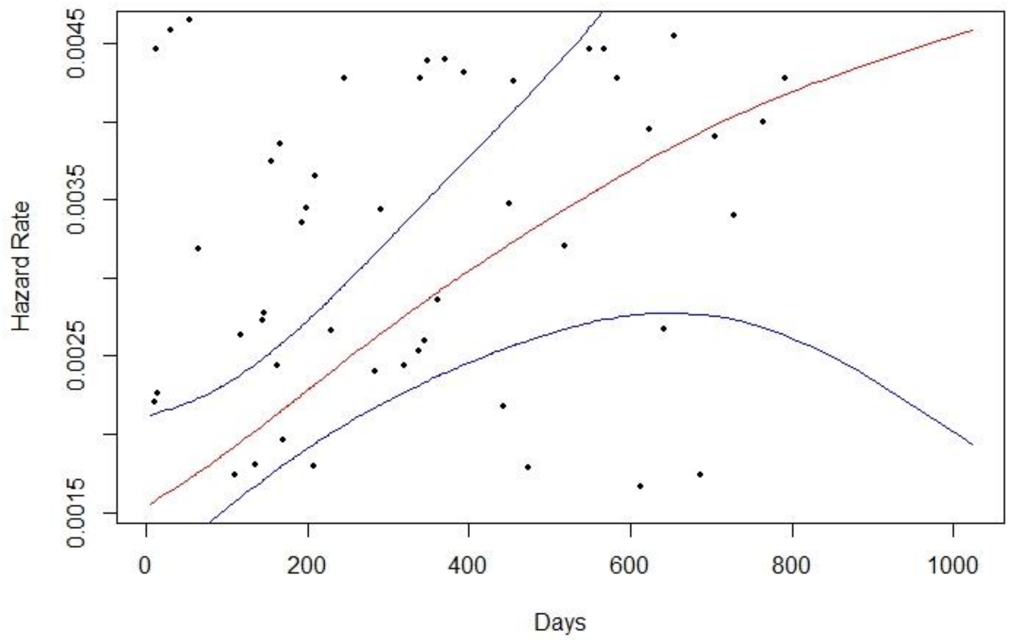

Figure A2. Hazard of JSE-ALI Returns in each regime