Modeling Stock Returns in the South African Stock Exchange: a Nonlinear Approach

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Abstract

This paper investigates the relationship between stock returns and macroeconomic variables, taking into account asymmetric adjustment behaviour in the stock market. The study applies the Smooth Transition Regression (STR) model to account for smooth asymmetric response of stock returns from economic variables. The results show that changes in dividend yield is an important factor in determining the asymmetric behaviour of stock returns on the South African stock market. Furthermore, the forecast performance of the STR model is compared with Ordinary Least Square (OLS) and Random Walk models. The STR, as a nonlinear model, outperforms the OLS and Random Walk models in an out-of-sample forecast. The findings of the paper violate the weak and semi-strong form test of the efficient market hypothesis.

Keywords: stock returns, smooth transition regression, forecast

1. Introduction

The debate surrounding the validity of the Efficient Market Hypothesis (EMH) is raging on. Central to the debate is the issue of whether stock market returns are predictable or not. Advocates of the EMH theory contend that stock prices (returns) incorporate all publicly available information, so that an average investor cannot earn abnormal returns based on his trading strategy. Therefore, according to the theory, it is impossible to consistently outperform the market by using any information that the market already knows. For Fama (1970), the prediction of future stock returns based on movements in macroeconomic variables is a fruitless exercise, since profit-maximising agents will ensure that all relevant information pertaining to changes in macroeconomic variables are fully impounded into current returns. According to the author, the implication is that technical analysis (which is a study of past prices, charts, etc.) and fundamental analysis (analysis of macroeconomic variables) would yield no better performance than an investor who adopts a buy-and-hold strategy (i.e. passive investment).

The notion that stock returns are not predictable, as implied by EMH, has been greatly challenged by many academics and finance practitioners. A number of studies have documented a robust predictable relationship between stock returns and macroeconomic variables or the so-called market anomalies (*see* Malkiel, 2003 for a comprehensive literature review of such anomalies). Macroeconomic variables such as inflation rates, term and default spread on bonds, aggregate output, money supply, exchange rates and unemployment rates are found to have significant influence in explaining stock returns (Rapach, Wohar & Rangvid, 2005). Pesaran and Timmerman (1995) provide evidence of predictable components in stock returns using macroeconomic variables such as interest rates, dividend yields, economic growth (industrial production) and inflation. The authors find the existence of a relationship between stock returns and macroeconomic variables, even after accounting for transaction costs. They ascribe the existence of predictability in stock returns to incomplete learning and the presence of time-varying premia.

In an attempt to examine whether predictability of stock returns is attributed to time variation in expected returns, Schwert (1990) finds evidence of a strong relationship between stock returns and macroeconomic variables, after controlling for time-varying risk premium and shocks. Hsieh (1991) shows that stock returns are not independently and identically distributed as assumed by EMH, and thus there exists a possibility of characterising a nonlinear relationship between stock returns and macroeconomic fundamentals. According to Summers and Schleifer (1990), nonlinearities in stock returns could arise due to noise trading, long memory in stock returns due to time variation in expected returns, and international feedback effects. Recent empirical studies have found evidence of nonlinearities associated with state dependence (i.e. regime switches) in the relationship between stock returns and macroeconomic variables, and that such relationship resembles asymmetric behaviour (McQueen & Roley, 1993). This view was supported by Chang (2009), who found that predictability of stock returns changes over time, such that the relationship is stronger in bad times (recession) than in good times (economic boom).

In an attempt to better describe nonlinearities due to regime changes in economic variables, most studies adopted the Markov regime-switching models assuming nonlinear stationary process (*see* Hamilton, 1989) and the Threshold Autoregressive Model (TAR) (*see* Tong, 1990). In support of evidence of nonlinearities associated with regime-switching process, Moolman (2004) made a significant contribution in this field of research from the emerging market perspective in general – and South Africa in particular – by investigating the relationship between stock returns and macroeconomic variables. Using the Markov regime-switching model, the author found evidence that stock returns on the Johannesburg Securities Exchange (JSE) depends on the state of the business cycle. Nonetheless, in challenging the application of the Markov switching and TAR models in modelling stock returns , Sarantis (2001) argues that these models may be successful in capturing nonlinearity between variables, but in the context of modelling stock returns these models are too restrictive in that they assume a sharp regime switch. For Sarantis (2001), the use of Smooth Transition Regression Models (STR) is appropriate, as the changes in regime are smooth, rather than abrupt, in the stock markets. In addition, Aslanidis *et al*. (2002) contends that the STR model is more appealing and in line with economic theory, in the sense that economic agents react differently to changes in economic variables. As a result, the degree to which such agents adjust to different regimes is gradual, rather than instantaneous or abrupt, such as claimed by the Markov switching and TAR models.

In the light of the abovementioned studies, it should be evident that stock returns can be predicted from macroeconomic variables, if a nonlinear model specification is used to account for asymmetric behaviour present in the stock exchange market. The predictability of stock returns should present a challenge to the EMH.

The main objective of this paper is to examine the relationship between stock returns and macroeconomic variables in South Africa, with emphasis on smooth transition to capture nonlinearity in the stock exchange market. The results of this paper will inform on the degree of the speed with which the South African stock market changes from one regime (bull market) to another (bear market). Furthermore, the out-of-sample forecasting performance of the STR model is compared with the simple linear (OLS) and random walk models. In doing so, the implications for market efficiency will then be assessed.

The paper is structured as follows: Section 2 briefly summarises some of the literature concerning the relationship between stock returns and macroeconomic variables. Section 3 outlines the methodology to be used in the paper. Section 4 presents the data and empirical results. Section 5 concludes the paper and provides areas for future research.

2. Literature review

A number of studies were conducted to assess the determinants of stock returns. Fama (1970) was the first to introduce the asset pricing model based on the EMH theory. The author examined the behaviour of daily changes over a selected 30 stocks of the Dow Jones Industrial Average for the period 1957 to 1962, and found consistent evidence of serial positive and negative dependence on the daily changes in stock returns.

An important implication of the EMH is that stock prices should follow a random walk in that future price changes are random, and thus unpredictable (Mishkin and Eakins, 1998). The random walk hypothesis is related to the weak form of the efficient market hypothesis, in that the current stock price already incorporates all the information of the past stock prices. The consequence of the EMH is that no structural model for stock return determination can outperform the random walk model. Nonetheless, a number of studies have rejected the principle of EMH, whereby current stock prices fully reflect all security market information, in favour of structural models (*Li & Lam, 1995)*. These studies argue that there exists a relationship between stock returns and macroeconomic variables, and that this relationship is time varying and cannot be captured by conventional or traditional linear frameworks. In other words, these studies assert that once a proper functional method is used to account for the relationship between stock returns and macroeconomic variables, structural models can outperform the random walk model, and thus well-informed investors can realise excess returns.

The literature analysing the relationship between stock returns and macroeconomic variables using a nonlinear framework, has been in existence for some time. For example, Bredin, Hyde and O'Reilly (2008) tested the forecasting ability of the STR model, using stock market indices of six developed economies, i.e. United States, United Kingdom, Germany, Canada, France and Japan. For each country, the authors used the world index, changes in interest rates, dividend yield, inflation, exchange rate, industrial production and changes in oil prices to explain stock returns. The results of their study show that the STR model outperforms the linear model in explaining stock returns.

In addition to the multivariate (STR) studies, a number of studies have used the univariate smooth transition autoregressive (STAR) model to prove a nonlinear adjustment of stock returns. For example, Bradley and Jansen (2004) found that the univariate linear model outperforms the nonlinear model (STAR) in modelling stock returns.

As far as the South African literature is concerned, the econometric analysis of the relationship between stock returns and macroeconomic variables is very limited, and confined to linear models. For example, Van Rensburg (2000) examines the impact of macroeconomic variables on the JSE stock returns using the Arbitrage Pricing Theory (APT) over the period January 1980 to December 1994. With the aid of the vector autoregressive (VAR) technique, the author found that stock returns on the Johannesburg Stock Exchange (JSE) are driven mainly by resource and industrial sectors in South Africa.

Jefferis and Okeahalam (2000) used the co-integration technique to examine the relationship between stock returns and macroeconomic variables in South Africa, Botswana and Zimbabwe for the period 1985 to 1995. The authors found that stock returns in these countries were driven by real exchange rate, long-term interest rates and GDP.

Moolman (2004) 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.

3. Econometric methodology

Smooth transition models are receiving much attention in the finance literature. According to Teräsvirta (2003), the smooth transition model is essentially an extension of switching regression model and can either be univariate or multivariate. The univariate version is referred to as Smooth Transition Autoregressive Model (STAR) whereas the Smooth Transition Regression (STR) involves a multivariate analysis.

Teräsvirta (1994:209) defines an STR model as a combination of the threshold autoregressive model and the exponential autoregressive model and can be expressed by the following equation:

$$y_t = \phi' z_t + \theta' z_t G(\gamma, c, s_t) + u_t, \qquad (1)$$

Where $G(\gamma, c, s_t)$ is the transition function, $\theta = (\theta_0, \theta_1, \ldots \theta_p)$ and $\phi = (\phi_0, \phi_1 \ldots \phi_p)$ are parameter vectors, z_t is the vector of explanatory variables, c denote the threshold variable, and γ is the slope of the transition function.

Anderson and Teräsvirta (1992) distinguish between two forms of STR that allow for time varying in autoregressive decay. One form of STR model is known as Logistic STR (LSTR), which can be expressed as follows:

$$G(\gamma, c, s_t) = \left(1 + \exp\{-\gamma \prod_{k=1}^{K} (s_t - c_k)\}\right)^{-1}, \gamma > 0 \qquad (2)$$

In terms of the above equation, the transition variable increases in tandem with the logistic function. Teräsvirta, Van Dijk, and Franses (2002:4) demonstrate that as $\gamma \rightarrow$ zero or ∞, the transition function becomes abrupt, such that the model becomes an AR; in other words, the STR model becomes indistinguishable from the linear (AR) model.

Another form of STR model is known as the Exponential Smooth Transition Model (ESTR), and can be defined as follows:

$$G_E(\gamma, c, s_t) = \left(1 - \exp\{-\gamma (s_t - c_1)^2\}\right), \gamma > 0 \qquad (3)$$

ESTR is a non-monotonous transition function and is ideal in cases where the dynamic behaviour of a process is similar in both upswing and downswing (Teräsvirta, 2003:224). According to Sarantis (2001:461), the ESTR model suggests that while the behaviour of economic variables in the transition period can differ, the regimes will still have similar characteristics, and, as a result, both ESTR and LSTR models have the capabilities of explaining asymmetry in stock prices.

Unlike the TAR and Markov switching models, The STR model does not require a prior assumption of abrupt switching between regimes, but rather allows the data to dictate whether the regime change is abrupt or smooth (Tong, 1990). It is this characteristic that makes the STR models more appealing in their application in stock markets, simply because such markets are characterised by a large number of participants, i.e. traders, speculators, analysts etc., and such participants react differently to economic news or public information (Sarantis, 2001:460).

Teräsvirta (1994:210) proposes procedures in building an STR model. These include linearity test, estimation and evaluation of the model. A linearity test is performed for the purpose of selecting an appropriate transition variable. In choosing the transition variable, the modeller should be guided by economic theory. Terasvirta (2003:227) suggests a linearity test for each candidate transition variable. In terms of this approach, the variable with the lowest p-value (strongest rejection of linearity) is chosen as the transition variable[1]. Luukkonen, Saikkonen and Teräsvirta (1988:493) argue that testing for linearity is not a straightforward exercise, due to the fact that the model is only identified under the alternative hypothesis. As a result of identification problem, the normal test procedures such as the Likelihood ratio, the Lagrange Multiple and the Wald Test will produce undesirable estimations of parameters. Instead, Luukonen et al. (1988: 493) suggest that one should approximate the alternative model by adopting a Taylor series expansion of the transition function as a means to circumvent the identification problem.

The Taylor expansion function is mathematically expressed as follows:

$$y_t = \beta_0 z_t + \sum_{j=1}^{3} \beta_j \tilde{z}_t s_t^j + u_t, t = 1,.....T \tag{4}$$

β_0 and β_j are the dimension column vectors of parameters. The null hypothesis of linearity is H_0: $\beta_1 = \beta_2 = \beta_3 = 0$, i.e. both parameters are jointly tested for zero against the alternative hypothesis. The hypothesis is carried out using the LM test, and the F-test is used instead of χ^2 – distribution.

The transition function is derived from the auxiliary regression as shown in (4). The following tests must be performed to discriminate between LSTR and ESTR, i.e. to choose an appropriate STR model.

(i) Test of the null hypothesis H04: $\beta_3 = 0$
(ii) Test of the null hypothesis H03: $\beta_2 = 0/ \beta_3 = 0$
(iii) Test of the null hypothesis H02: $\beta_1 = 0/ \beta_2 = \beta_3 = 0$

The above hypotheses are tested using the F-test. The decision rule is that the LSTR is chosen if the p-value of H04 or H02 is highly significant. Conversely, the ESTR is selected if the p-value of H03 is highly significant. Should it happen that the test fails to provide a clear-cut choice between the two options, it is recommended to fit both models and decide on the appropriate one at an evaluation stage (Teräsvirta, 2003:227). The chosen model can then be estimated and evaluated as outlined in Eitrheim and Teräsvirta (1996:60), i.e. test of no remaining nonlinearity, no autocorrelation and parameter constancy.

[1] JMulti software (www.jmulti.de) automatically select the transition variable; however one still has to examine whether the variable chosen is sensible or in line with economic theory.

4. Data and empirical results

4.1. Data

In order to assess the relationship between stock returns and macroeconomic variables, this study makes use of the following variables extracted from I-Net Bridge Database, and Bloomberg: the JSE ALL Share Index return (ALSI), the ALSI dividend yield (DY), Rand/Dollar R/$ exchange rate (RAND), the FTSE Index (FTSE) and S&P 500 Index (SP500). The use of the FTSE and S&P 500 indices aims at capturing the positive relationship that exists between the domestic stock exchange and the foreign exchange market, especially the London and New York stock exchanges (Samouilham, 2006). The data consist of weekly observations from May 1988 to December 2006. High frequency data, such as weekly data, are essential to capture the nonlinear relationship that exists in the data (McCulloch & Tsay, 2001).

The paper estimates the relationship between the JSE stock returns and macroeconomic variables, with the use of the STR method to assess the degree of regime changes in the South African exchange market. Furthermore, the forecasting performance of the STR method is compared with the random walk and linear methods.

4.2 Empirical Results

Table 1 in the Appendix presents the results of the unit root tests for the variables used in the paper. The results show that the null hypothesis of unit root is rejected. This implies that all variables are nonstationary. Furthermore, the results in Table 1 suggest that all the variables are stationary at first difference, I (1), as the null hypothesis of unit root is rejected at 1% level for all the variables at first difference.

To test the number of cointegration relations, an initial vector autoregressive model (VAR) was set up, with a lag length of the VAR process, $p=4$, selected according to the Hannan-Quinn (HQ) information criteria. The LM-test, not reported here, indicated that there is no serial correlation in the VAR residual when the lag length of 4 is selected. The results of the trace and Max-eigenvalue tests of cointegration, reported in Table 2, indicate the presence of one cointegrating relation or rank $(r=1)$. Table 3 presents the results of the OLS estimation when ALSI is endogenised. Though the results indicate that all coefficients are statistically significant, the linear model fails a number of specification tests, such as the presence of serial correlation, represented by the Durbin-Watson statistics, as well as the CUSUM test which denotes that the coefficients are not stable, as shown in Figure 1.

As a linear model fails to model stock returns adequately from macroeconomic variables, the next step in the paper consists in testing whether a nonlinear model will be appropriate for this model. Table 4 displays the results of the linearity test. All the variables were selected as candidate transition variables. As reported in Table 4, the results of the F-test show that the null hypothesis of linearity is rejected for all the variables at 1% level of significance. The rejection of the null hypothesis is highly significant for DY. Moreover, An LSTR(1) model is implied by the linearity test, given that the null hypothesis H02 is highly significant.

The fact that dividend yield is selected as a transition variable, is theoretically appealing. Extensive research exists which demonstrates the nonlinear relationship between stock returns and dividend yields. For example, McMillan (2004) adopted the Exponential Smooth Transition Regression models (ESTR) to demonstrate the ability of dividend yields in explaining the asymmetric behaviour of UK stock returns. Gombola and Liu (1993) found the existence of a negative relationship between stock returns and dividend yields during a bull market. Conversely, the relationship between stock returns and dividend yields was found to be positive in a bear market. The authors attribute such behaviour to the so-called differential yield effect.

The results reported in Table 5 show that the coefficients of the explanatory variables are statistically significant in the linear and nonlinear part of the LSTR(1) estimation. The results reported in Table 5 are reported in equation form as follows:

$$Alsi_t = -0.0146 - 1.029DY_t - 0.382FTSE_t + 0.145Rand_t + 0.29SP500_t +$$
$$\left(0.017 + 0.24DY_t + 0.428FTSE_t - 0.139Rand_t - 0.267SP500_t\right)\left[1 + \exp(-33.66\left(DY_t + 0.038\right))\right]^{-1} \quad (5)$$

The results reported in Expression 5 show a high value of the slope parameter, $\gamma = 33.66$. This result is confirmed in Figure 2, that shows a rapid transition between the two extreme regimes. The results suggest that returns in the South African stock market are characterised by asymmetric cycles with a relatively high degree of transition between regimes determined by the dividend ratio, DY_t. In as far as regime change is concerned, the results indicate that if the transition function, $G(\gamma, c, DY)$, moves toward one, that is $\lim_{DY \to \infty}$, the magnitude of the positive effect of the devaluation of the rand on stock return is lower, compared to the case where $\lim_{DY \to 0}$. It is important to note that $\lim_{DY \to \infty}$ signals a bear market with decreasing price of stocks, and $\lim_{DY \to 0}$ should indicate a regime related to a bull market, characterised by increasing stock prices. Figure 2 shows that most observations of the dividend yields are situated in the bear market, during the period of the analysis.

On assessing the importance of a nonlinear method in modelling stock returns, forecasting performance of linear, nonlinear and Random Walk models are compared. Table 6 presents the results of the out-of-sample root mean square error (RMSE) as a criterion for forecasting performance of the three models. It is evident from these results that the LSTR (1) outperforms all the others models in an out-of-sample forecast, in terms of the RMSE criterion. This suggests the importance of a nonlinear methodology in modelling stock returns in South Africa.

5. Conclusion

This paper aimed at assessing the importance of a nonlinear model in assessing the relationship between stock returns and macroeconomic variables in South Africa. The paper shows the importance of the nonlinear model that focuses on smooth transition between regimes in explaining stock returns. The smooth transition regression model is used toward this end. The results of this paper show that the STR model is appropriate for modelling stock returns in South Africa. Furthermore, the results of the STR model show that the magnitudes of some macroeconomic variables, in explaining stock returns, varies according to regimes. These regimes are determined by the size of dividend yield. The superiority of the STR model, as a nonlinear model, over the competing models, i.e. OLS and random walk in an out-of-sample forecast, is confirmed when criteria such as the RMSE is used for assessing forecast performance.

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APPENDICES

Table 1 – Unit Root Test (Augmented Dickey-Fuller Test)

Variable	ADF Test Statistic (Level)	ADF Test Statistic (First Differences)
ALSI	3.313	-29.745
S&P 500	-3.311	-32.314
FTSE	-1.156	-27.396
RAND	-1.185	-27.387
DY	-0.683	-28.129

*The critical values for the augmented Dickey-Fuller test statistic are -3.436, -2.864 and -2.568 for 1%, 5% and 10% respectively.

Table 2 – Johansen Co-integration Test

A. Trace Test

Null Hypothesis (Trace Test)	Statistic	Critical Value (5%)	Prob
None *	93.07	69.81	0.0002
At most 1	40.66	47.85	0.1996
At most 2	24.16	29.79	0.1933
At most 3	12.43	15.49	0.1375
At most 4	0.99	3.84	0.3184

B. Maximum Eigenvalue Test

Null hypothesis	Statistic	Critical Value (5%)	Prob
None *	52.41	33.87	0.0001
At most 1	16.49	27.58	0.6236
At most 2	11.74	21.12	0.57331
At most 3	11.43	14.26	0.1338
At most 4	0.99	3.84	0.3184

*denotes rejection of the hypothesis at the 5% level

Table 3 – Linear Model Estimation of stock return (ALSI)

Variable	Coefficient
C	-2886.82*
DY	-4.70*
FTSE	316.77*
RAND	21.57*
SP500	15965*
Durbin-Watson	0.014

*Denotes statistically significant at 1% level of significance. Standard errors are corrected using the Newest-West Heteroscedasticity and Autocorrelation Consistent Variance (HAC)

Figure 1 Test for stability of Coefficient: CUSUM test

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Table 4 P-Value of the linearity test

Hypothesis	P-Value			
	DY	FTSE	Rand	S&P 500
F-statistic	0.00000	0.00012	0.00005	0.0079
H04	0.00221	0.12158	0.06363	0.52868
H03	0.01144	0.00075	0.00002	0.00062
H02	0.00039	0.01518	0.27085	0.37624

The p-value of the test of H03 is much larger than the corresponding H02 and H04 for DY; therefore the null hypothesis of linearity is rejected and LSTR (1) model is chosen.

Table 5: Estimated STR model

variable	*estimate*	*SD*	*t-stat*	*p-value*
	Linear Part			
CONST	-0.01462	0.0055	-2.6348	0.0086
DY	-1.0298	0.1103	-9.3386	0.0000
FTSE	-0.38252	0.1207	-3.1698	0.0016
Rand	0.14503	0.0643	2.257	0.0242
SP500	0.29457	0.1104	2.6691	0.0077
	Nonlinear Part			
CONST	0.01719	0.0056	3.0868	0.0021
DY	0.24017	0.1114	2.1568	0.0313
FTSE	0.42887	0.1258	3.4094	0.0007
Rand	-0.13924	0.0698	-1.9957	0.0463
SP500	-0.26751	0.1158	-2.3098	0.0211
Gamma	33.66855	28.7218	1.1722	0.2414
C1	-0.03869	0.0009	-43.7685	0.000
R^2:	0.784			
adjusted R^2:	0.784			
variance of transition variable	0.0009			
SD of transition variable	0.0297			
variance of residuals:	0.0001			
SD of residuals:	0.0121			

Table 6: Out-of-sample forecasting results

Model	**RMSE**
STR	0.008888
Linear	0.009305
Random Walk	0.022390

Figure 2 – Transition Function