The Evolving Efficiency Of The South African Stock Exchange

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ABSTRACT

This paper tests the weak-form efficiency in the South African stock exchange - the Johannesburg Securities Exchange (JSE) - under the hypothesis that emerging markets efficiency evolves through time as these markets constantly enhance their regulatory environment. The paper makes use of the time varying GARCH model in testing this hypothesis. In addition, the paper compares the out-of-sample forecast performance of the time varying and fixed parameter GARCH models in predicting stock returns in the JSE making use of MSE-F statistics for nested models proposed (McCracken, 1999). The findings of the paper show that the two models provide the same conclusion in showing that the JSE has been efficient during the period of the analysis. In addition, the time varying model outperforms the fixed coefficient model in predicting the JSE stock returns. This finding indicates that the time-varying parameter model adds a benefit in testing the weak-form efficiency or modelling stock return in the JSE.

Keywords: Weak-form Efficiency; Time-varying GARCH; Forecasts

INTRODUCTION

A number of studies have been conducted to test the efficiency of the stock market in the context of developed and emerging stock markets. While the findings of these studies support the weak-form efficiency for developed and mature stock exchanges (Fama, 1965 and 1970; Osborne, 1962), the research findings for emerging markets are mixed and mostly reject the weak-form efficiency in these markets (Smith, 2007; Poshakwale, 1996). The weak-form efficient market hypothesis postulates that future returns should be independent of past returns, thus past return series cannot be used to predict future returns. The implication of the weak-form efficient hypothesis is that no profitable investment-trading strategy can be derived based on past information.

Different reasons are provided to explain why a number of developing and emerging stock exchanges are inefficient (weak-form inefficient). Reasons, such as thin trading, low liquidity, and possibly less well-informed investors with access to unreliable information, are often evoked to explain the inefficiency of developing and emerging stock exchanges (Al-Khazali, 2008; Gupta and Parikshit, 2007).

A number of studies that have tested the efficiency of emerging stock markets relied on the autoregressive methods or a class of generalised autoregressive conditional heteroscedasticity (GARCH) methods assuming constant coefficients (see Magnus, 2008; Omet et al., 2002). Such an averaging methodology can be misleading in concluding about the degree of efficiency in emerging markets if one considers the evolving nature of stock markets in a number of emerging economies. These emerging market economies are constantly enhancing their regulatory environment, the participation and influence of these markets are considerably increasing, and a number of asset managers are diversifying their portfolio by investing in emerging market economies. These changes should improve the efficiency of emerging market economies.

Averaging time series techniques used by a number of studies to test efficiency in emerging markets may provide wrong conclusions if they do not account for the evolving nature of emerging stock markets. It is in this context that studies by Abdmoulah (2010) and Hall and Urga (2002) have used time-varying techniques to test the evolving efficiency of 11 Arab and Russia stock markets, respectively. In addition, Jefferis and Smith (2005) used a

GARCH approach with time-varying parameters to test the changing efficiency of seven stock markets in Africa, including South Africa. Compared with the rest of African stock market, the author finds that the South African stock market - the Johannesburg Securities exchanges (JSE) - is weak-form efficient. More importantly, Jefferis and Smith find that the autoregressive slope coefficient in the mean equation of the GARCH model is constant for South Africa. This should indicate that the test of efficiency for JSE does not necessitate the use of a time-varying technique.

This paper differs from previous studies that assess the weak-form efficiency dynamics of a number of stock exchanges in that it goes beyond analysing and estimating the time-varying dependency of the daily returns on their lagged values. In addition, this paper compares the forecast performance of the time-varying parameter model with the fixed parameter model in predicting stock returns in the JSE.

METHODOLOGY AND EMPIRICAL RESULTS

Empirical tests for weak-form efficient market hypothesis have been developing over years. A number of empirical studies support the use of an AR(1)-GARCH(1,1)-M process for modelling stock returns and testing the weak-form efficient market hypothesis in emerging stock markets (Abdmoulah, 2010; Shin, 2005; Salman, 2002; Zalewska-Mitura and Hall, 1999). The advantage of this model over a simple AR model is that while it examines the relationship between the current and past returns, it also accounts for the changing variance of the error structure of the model. If this changing variance structure is omitted, a model may incorrectly suggest the rejection of market efficiency. The other benefit of this model is that it explains the trade-off between stock returns and risk, which is a common feature in emerging stock markets (Lin, 2008; Estrada and Serra, 2005). Moreover, Bonga-Bonga and Mwamba (2011) indicate that the AR(1)-GARCH(1,1)-M model underlines the importance of the autoregressive specification as well as the conditional volatility in forecasting the mean of stock returns. To underscore the importance of the use of one lag in a GARCH specification to model stock exchange in South Africa, Samouilhan and Shannon (2008) show that GARCH(1,1) specification provides the best forecast of volatility of the JSE among all the symmetric specifications.

The AR(1)-GARCH(1,1)-M with constant parameters is expressed as follows:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \gamma\sigma^2 + e_t \tag{1}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \tag{2}$$

$$e_t \sim N(0, \sigma_t^2) \tag{3}$$

where r_t is the stock market return, σ_t^2 is the time-varying conditional variance, β_0, β_1 and γ are intercept, AR(1) is the coefficient and risk premium parameter, respectively, in the mean equation. The coefficients α_0, α_1 and α_2 are the intercept, the coefficient of the lag of the residual, and the coefficient of the last period's forecast variance, respectively. ε_t is a Gaussian innovation with a zero mean and a time-varying conditional variance σ_t^2. These coefficients provide the long-run estimates of the mean and conditional variance equations. For example, if β_1 is significantly different from zero in a given sample period, this indicates that the stock market is *weak-form inefficient* during this sample period. Using such an average measure to test the efficiency of emerging stock markets can be misleading. These markets learn and mature over time, changing from being efficient to becoming efficient. For these markets, the test of efficiency requires the use of the AR(1)-GARCH(1,1)-M model with time-varying parameters expressed as follows:

$$r_t = \beta_0 + \beta_{1t} r_{t-1} + \gamma\sigma_t^2 + e_t, \quad e_t \sim N(0, \sigma_t^2) \tag{4}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \tag{5}$$

$$\beta_{1t} = \beta_{1t-1} + \upsilon_t \,,\ \upsilon_t \sim \left(0, \sigma^2\right) \tag{6}$$

This model is estimated using the standard Kalman filter where Expression (4) represents the signal or measurement equation and Expressions (5) and (6) represent the state equations. The maximum likelihood function is used to estimate the time-paths of β_{1t} as well as all coefficients in the measurement and state equations.

Weekly data from March 1995 to December 2007 are used to estimate the AR(1)-GARCH(1,1) with constant parameters, as well as the AR(1)-GARCH(1,1), with time-varying coefficients. This starting sample period corresponds with the liberalisation of the JSE. In fact, in an effort to stimulate economic growth, the South African government lifted all controls on non-resident investors in March 2005, allowing liberalisation of stock exchange in South Africa (Tswamuno et al, 2007). In addition to model estimations, the paper will assess the out-of-sample forecast performance of the two models. Weekly data from January 2008 to December 2009 are used to assess the out-of-sample performance of the two models.

Table 1 presents the results of the estimation of the AR(1)-GARCH(1,1) model with constant parameters as in Equations 1 and 2.

Table 1: Estimation of the AR(1)-GARCH(1,1)-M Model with Fixed Parameters

	Coefficient	Standard Error	Z-Stat	Probability
Mean Equation				
r_{t-1}	0.0457	0.043	1.044	0.296
σ_t^2	4.418	1.39	3.173	0.0015
Variance Equation				
α_0	0.000026	0.0000089	2.942	0.0033
ε_{t-1}^2	0.1002	0.0185	5.399	0.0000
σ_{t-1}^2	0.867	0.027	32.061	0.0000

Source: Author's Estimation

The results in Table 1 show that the coefficient β_1 is not statistically different from zero. This indicates that JSE has been efficient in the long run during the period March 1995 to December 2007. In addition, some specification tests - the Q-statistics for the residual test of the AR(1)-GARCH(1,1)-M model reported in Table 2 - show that the null hypothesis of no serial correlation is not rejected up to lag 4 at 5% significance.

Table 2: Residual Correlation Test of the AR(1)-GARCH(1,1)-M Model: Q-statistics

Lag	Q-statistics	Probability
1	0.0101	0.920
2	0.0886	0.957
3	1.4872	0.685
4	1.7453	0.782

The null hypothesis of no serial correlation is not rejected at 5% level of significance.

In order to assess whether the weak-form efficient characteristics of the JSE have changed over time, we estimate the AR(1)-GARCH(1,1)-M with time-varying parameters. Fig. 1 shows the evolution of β_{1t} as estimated from Equation 4 by making use of the Kalman filter method of estimation.

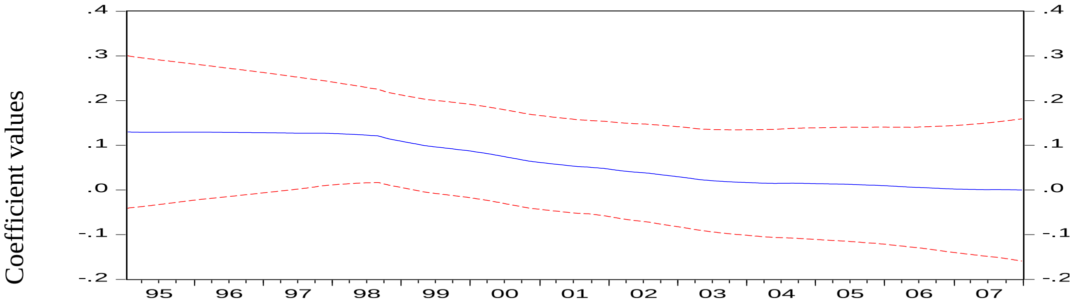

Figure 1: Evolution of the Coefficient β_{1t}

Note: The continuous line is the mean of β_{1t} and the dotted lines are the 95% confidence interval.

Given the upper and lower bound of the 95% confidence interval, as well as the mean values of β_{1t}, the results in Figure 1 show that the estimate of the time-path of β_{1t} ,while time varying, is not statistically different from zero during the period March 1995 to December 2007. The results show that the JSE has been weak-efficient during that period. This indicates that the JSE presents the characteristics of a mature stock market in the like of a number of stock markets in developed economies. The liberalisation of the JSE in March 1995 and the subsequent relaxation of exchange control in South Africa should have played a very important role in making JSE efficient.

Next, the paper compares the performance of the two models in predicting stock returns in the short term. It is important to note that the short-term predictability of stock returns does not mean that there is a possibility of a profitable trading rule. Transaction costs and risk can preclude such a possibility. The paper intends to assess which of the two models between the time varying and fixed coefficient GARCH predict better stock returns in the JSE.

FORECASTING PERFORMANCE OF THE TIME VARYING AND FIXED PARAMETERS GARCH

Weekly data from January 2008 to December 2009 are used to assess the out-of-sample forecast performance of the time varying and fixed parameter AR(1)-GARCH(1,1)-M models. The paper uses the root mean square error (RMSE) as the loss function to evaluate the accuracy of the forecast generated by the two models in predicting stock returns. The RMSE is obtained as follows:

$$\sqrt{\frac{1}{N}\sum_{t=1}^{n}\left(y_t - \hat{y}_t\right)^2}$$

where y_t and $\hat{y}_t$ are the actual and predicted values, respectively, and N is the total number of observations.

A number of studies make use of the Diebold-Mariano (DM)(1995) test to assess whether the forecast of two competing models are equally accurate in terms of a given loss function. Nonetheless, McCracken (1999) and Clark and McCracken (2001) show that the DM test is not appropriate in the case of nested models. The authors propose the mean square error – F statistic (MSE-F) test to test the null hypothesis of equal forecast accuracy between two nested models. McCracken (1999) derives the test statistics, as well as the asymptotic critical values of the MSE-F test, as the test has non-standard distribution. In deriving the asymptotic critical values for the nested models, Clark and McCracken (2001) focus on 1-step ahead forecast and show that for multi-step forecasts, the asymptotic distribution of the tests seem to depend on the parameters of the data-generating process.

This paper applies the MSE-F test to compare the forecast accuracy of the fixed-coefficient AR-GARCH-M model with the time-varying coefficient model as the latter is unrestricted and nests the fixed-coefficient model - the restricted model. The F-type test of equal MSE developed by McCracken is expressed as follows:

$$MSE - F = P \times \frac{P^{-1} \sum_{t=R}^{T} \left(\hat{u}_{1,t+1}^{2} - \hat{u}_{2,t+1}^{2} \right)}{P^{-1} \sum_{t=R}^{T} \hat{u}_{2,t+1}^{2}} = P \times \frac{MSE_1 - MSE_2}{MSE_2}$$

where $\hat{u}_{1,t+1}$ and $\hat{u}_{2,t+1}$ are 1-step ahead forecast errors from models 1 and 2. R represents the number of observations used for the estimation of the model and P represents the number of 1-step ahead predictions. The MSE-F is a one-sided test under the null hypothesis of equal forecast accuracy between models 1 and 2. The alternative hypothesis is that model 2 is correct and outperforms model 1.

Table 3 presents the MSE-F statistic, as well as the RMSE, for the out-of-sample 1-step ahead forecasts of the fixed-coefficient AR(1)-GARCH(1,1)-M model ($RMSE_1$) and time-varying parameter AR(1)-GARCH(1,1)-M model ($RMSE_2$). The critical values of the MSE-F test are provided by McCracken (1999) and relate to the case when $\pi = \frac{P}{R} \approx 0.2$.

Table 3: MSE-F test Statistic and the RMSE of the Two GARCH Models

MSE-F Statistic	**Asymptotic Critical Value for $\pi = 0.2$**			**$RMSE_1$**	**$RMSE_2$**
	99%	95%	90%		
1.111	2.129	1.038	0.659	0.043500	0.043265

Source: Author's estimation.

The results reported in Table 3 show that the null hypothesis of equal predictability by the two models is rejected at 95% confidence level. This indicates that the alternative hypothesis that model 2 - the time-varying AR(1)-GARCH(1,1)-M model - outperforms the fixed-coefficient model (model 1) in predicting stock returns in South Africa. This finding indicates that the time varying parameter model adds some benefits, compared to a fixed parameter model, in testing the weak-form efficiency and modelling stock returns in South Africa.

CONCLUSION

This paper endeavoured to test the weak-form efficiency in the South African stock exchange - the JSE. Given the premises that emerging markets' efficiency evolves through time as these markets constantly enhance their regulatory environment, this paper made use of a time varying model, in addition to the fixed parameter model, to test the weak-form efficiency in the JSE. The findings of the paper show that the two models provide the same conclusion in showing that the JSE has been efficient in the periods March 1995 to December 2007.

In addition, the periods January 2008 to December 2009 are used to assess the performance of the two models in testing the weak-form efficiency and modelling stock returns in South Africa. The results of the out-of-sample 1-step ahead forecasts show that the time-varying parameter model outperforms the fixed coefficient model and thus, the time varying parameter model adds some benefits, compared to a fixed parameter model, in testing the weak-form efficiency and modelling stock returns in South Africa.

AUTHOR INFORMATION

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