

VOLATILITY FORECASTING AND VALUE-AT-RISK ESTIMATION IN EMERGING MARKETS: THE CASE OF THE STOCK MARKET INDEX PORTFOLIO IN SOUTH AFRICA

Lumengo Bonga-Bonga and George Mutema

Department of Economics, University of Johannesburg

Abstract

Accurate modelling of volatility is important as it relates to the forecasting of Value-at-Risk (VaR). The RiskMetrics model to forecast volatility is the benchmark in the financial sector. In an important regulatory innovation, the Basel Committee has proposed the use of an internal method for modelling VaR instead of the strict use of the benchmark model. The aim of this paper is to evaluate the performance of RiskMetrics in comparison to other models of volatility forecasting, such as some family classes of the Generalised Auto Regressive Conditional Heteroscedasticity models, in forecasting the VaR in emerging markets. This paper makes use of the stock market index portfolio, the All-Share Index, as a case study to evaluate the market risk in emerging markets. The paper underlines the importance of asymmetric behaviour for VaR forecasting in emerging markets' economies.

Keywords: Value-at-Risk, volatility, emerging markets

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Introduction

Accurate modelling of volatility in the financial market is important, particularly as it relates to the modelling of Value-at-Risk (VaR) and the forecasting of market risk. The RiskMetrics model to forecast volatility has been the benchmark for estimating VaR in the covariance VaR methodology, and the market risk in the financial sector since its inception by J.P. Morgan in 1994. It is important to note that VaR, which refers to the amount of money a portfolio is likely to lose over some predefined period at a given confidence level, is one of the most important measures of market risk and is widely used by financial institutions, portfolio managers and bank regulators. As far as market risk is concerned, it is defined as the uncertainty of future earnings resulting from changes in market conditions such as the prices of assets and interest rates (Das, 1997).

In order that regulators may monitor bank solvency and systemic risk effectively, they require that banks provide them with measurements of market risk using VaR models. With VaR estimation, financial institutions have a sense of the minimum amount that is expected to be lost with a given probability, α , also known as the level of significance, over a given time horizon, h , usually one day or 10 days. For example, with a $\alpha = 5$ per cent, a one-day VaR of 10 million currency units tells us that for every one out of 20 days, we could expect to realise a loss of at least 10 million. Alternatively, we could say that the maximum loss we could expect on 19 out of 20 days is 10 million.

Following the 1996 amendment to the Basel Accord on Bank Regulation and Supervision, banks are now permitted to use internally developed volatility models to calculate their VaR thresholds, as opposed to the "standardised" RiskMetrics approach which received widespread criticism for being too conservative

(Alexander, 1996). While the amendment was designed to reward those institutions with superior risk management systems, a back-testing procedure (or performance assessment tool) was introduced to assess the quality of the internal models whereby the realised returns are compared with VaR forecasts. If a bank's VaR forecasts from its internal model are violated more than ten times in a financial year, then a penalty is imposed and the bank may also be required to adopt the standardised approach. The imposition of such a penalty is severe, as it has a direct impact on the profitability of the bank through higher capital charge, and may also damage the bank's reputation.

In order to estimate VaR, one needs proper volatility modelling of the asset or portfolio in question. It is the prediction of future volatility that needs to be accurate in order to have a sound VaR model which satisfies regulatory requirements by passing the back-testing check.

The aim of this paper is to assess different models of volatility forecasting for emerging financial markets, in order to determine which volatility model is appropriate for the modelling of VaR in the emerging markets' context. The performance of the proposed models of volatility in forecasting VaR will then be compared to that of the RiskMetrics methodology.

Contrary to the RiskMetrics estimation of VaR that uses a normal distribution hypothesis, the conventional wisdom seems to be that, in the case of emerging markets, it is necessary to use more sophisticated volatility models, as well as non-normal distributions in order to forecast market risk adequately. Some of the return distributions of emerging markets' equity indices may possess "fat tails" (Zangari, 1996). Using data on equity exposure, consisting of the All-Share Index as a stock market index portfolio traded in the Johannesburg Stock Exchange (JSE), this paper compares the performance of the different models of volatility of the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) family, to the RiskMetrics model in modelling the VaR in an emerging market economy. The All-Share Index, as a stock market index portfolio, is made up of all the JSE-listed shares that meet specific criteria, such as size and the extent to which they

are traded. As such, it is a completely diversified portfolio, which means that all the unique risks of the individual shares are cancelled out.

Compared to emerging market economies, developed markets are not considerably affected by asymmetric behaviour or any leverage effect in their equity markets. Hagerud (1997) found that few developed market economies show signs of asymmetric volatility clustering and, therefore, VaR forecasting based on asymmetric volatility models, while appropriate for the emerging market, is not applicable to developed market economies. Furthermore, Alexander (2001) contends that the RiskMetrics volatility provides the best option for VaR estimation in a number of developed market economies but not emerging markets' economies. These findings warrant scrutiny for the comparison of the different volatility models used to estimate the VaR for emerging market economies.

The paper is subdivided as follows: the RiskMetrics model, as the benchmark model for volatility and VaR estimation, is discussed in Section 2. Section 3 discusses the GARCH model. In Section 4, the asymmetric E-GARCH model is presented. The focus of this section is on the asymmetric behaviour prevalent in the financial market. Section 5 presents the theoretical background on the VaR concept and Section 6 provides a preliminary analysis of the data with the aim of estimating volatility and calculating VaR, as well as comparing the different VaR estimation models. Section 7 concludes the paper.

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The benchmark model: riskmetrics

RiskMetrics uses the exponentially weighted moving average (EWMA) of historical observations to forecast volatility. Future forecasts are heavily dependent on the most recent data and are not influenced too much by old or very remote historic data. In the EWMA model, the weights decrease exponentially as we move back through time (Morgan and Reuters, 1996: 78). Furthermore, the RiskMetrics model assumes that asset or portfolio returns have a conditional multivariate normal distribution and are generated as follows:

$$r_t = \varepsilon_t \quad (1)$$

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1 - \lambda) r_{t-1}^2 \quad (2)$$

$$\varepsilon_t / \sigma_{t-1} \approx N(0, \sigma^2) \quad (3)$$

λ is a constant parameter called the *decay factor*. Its value is between zero and unity ($0 < \lambda < 1$). The sample mean return, r , is assumed to be zero. This is clear from the expected return from Equation 1. The error term, ε_t , is standard normally distributed. The advantage of the EWMA in estimating volatility is that, if there is a big move in the previous returns, (r_{t-1}^2), this increases the current volatility estimate. The responsiveness of volatility to changes in returns is limited by the size of λ . A high λ close to one produces estimates that are slow to react to new information, and a low λ allocates a greater weight to return when updating volatility and the estimates become highly volatile on successive days.

RiskMetrics uses λ equal to 0.94 and λ equal to 0.97 for daily and monthly volatility updates respectively. These λ values were found to give the closest forecast variance to realised variance after a study of different market variables using the root mean square error (RMSE) criterion (Hull, 2003).

The main characteristic of the RiskMetrics model is that the variance in Equation 2 can be written as an EWMA of the past innovation and return. The reparametrisation of Equation 2 yields:

$$\sigma_t^2 = (1 - \lambda) \sum_{i=1}^{\infty} \lambda^{i-1} r_{t-i}^2 \quad (4)$$

The smaller the smoothing parameter, the greater the weight given to the recent return data.

As it assumes normally distributed returns, the RiskMetrics model completely ignores the presence of “fat tails” in the distribution function even though these are an important feature of financial data.

3 GARCH models

In the case of financial data, large returns are followed by more large returns, and small returns by more small returns. This suggests

that returns are serially correlated. GARCH models have been developed to account for empirical irregularities in financial data. A time series displays conditional heteroscedasticity if it has highly volatile periods interspersed with tranquil periods, so that “bursts” or “clusters” of volatility occur.

In practice, variance rates tend to be mean reverting and the RiskMetrics model’s use of the EWMA does not incorporate mean reversion. The Auto Regressive Conditional Heteroscedasticity (ARCH) models introduced by Engle (1982) are a particular type of the GARCH model. GARCH forecasts are designed to capture the “fat tails” in return distributions. Bollerslev (1986) generalises the ARCH (p) model to the GARCH (p, q) model.

The simplest GARCH (1,1) is specified as follows:

$$r_t = \theta X_t + \varepsilon_t \quad (5)$$

$$\sigma_t^2 = \omega + \alpha \sigma_{t-1}^2 + \beta \varepsilon_{t-1}^2 \quad (6)$$

Equation 5 corresponds to the mean equation which is represented as a function of the vector of exogenous variables, X_t , and an error term ε_t . r_t represents the return series. Since σ_t^2 is the one period ahead forecast variance based on past information, it is called the conditional variance. The conditional variance equation specified in (6) is a function of three terms, namely:

- a constant term ω ;
- news about volatility from the previous period, measured as the lag of the squared residual, ε_{t-1}^2 , from the mean equation. It constitutes the ARCH term; and
- the last period’s forecast variance, σ_{t-1}^2 , which constitutes the GARCH term.

In Equation 6, if one assumes that $\alpha + \beta = 1$, $\omega = 0$ and α is replaced by λ , then GARCH (1,1) will be reduced to the Exponentially Weighted Moving Average (EWMA) as expressed in Equation 3. This shows that RiskMetrics models are a particular type of GARCH (1,1).

It is worth noting that contrary to the RiskMetrics model, which is based on the assumption of a constant volatility model with the implication of a constant term structure volatility forecast, with GARCH models the term structure

reflects the mean-reversion of volatility that is the common feature in the financial market (Alexander, 2001: 61).

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Asymmetric GARCH models

Empirical work by Engle and Ng (1993), Black (1976) and Christie (1982) found that stock returns are negatively correlated with changes in conditional volatility, that is, volatility tends to rise in response to bad news (excess returns lower than expected) and to fall in response to good news (excess returns higher than expected). The GARCH models, however, assume that only the magnitude and not the positivity or negativity of unanticipated excess returns determines variance.

It is well established that the volatility of asset prices displays considerable persistence, that is, large movements in prices tend to be followed by more large movements, producing positive serial correlation in squared returns. Thus, current and past volatility can be used to predict future volatility. Empirical works by Black (1976) and Christie (1982) further document and attempt to explain the asymmetric volatility property of individual stock returns. The explanation for this asymmetry is due to leverage. A drop in the value of stock (negative return) increases financial leverage, which makes the stock riskier and increases its volatility.

Bekaert and Wu (2000) show that the leverage effect in equities, as documented by Black (1976) and many others, determines a strong negative correlation between equity returns and volatility and is perhaps the most important source of skewness in equity index returns.

Regarding why asymmetric volatility is more observed in emerging markets compared to established markets, Gokcan (2000) suggests that the extent of volatility is related to the stage of market development. Volatility in emerging markets is large and more persistent than that in developed markets. One explanation is the speed and reliability of information available to investors, which is associated with modes of telecommunication and possible accounting systems in place. For Habib (2002) emerging market economies are subjected to “volatility

contagion” coming mostly from other emerging markets. This volatility contagion accelerates capital withdrawal by speculator investors and hence increases the leverage effect and the persistence of risk in emerging markets. The vulnerability of emerging markets to external shocks is the cause of the pronounced volatility mostly observed during periods of global crisis.

There are quite a number of asymmetric GARCH models among which are the Threshold GARCH (TGARCH) and the Exponential GARCH (EGARCH).

The EGARCH model captures the asymmetric effect and is written as (Engle and Ng, 1993):

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}^2} \right] + \gamma \left[\frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} \right] \quad (8)$$

Where σ_t^2 is the conditional variance and ω , β and α are constant parameters. The asymmetry in the EGARCH model is attributed to the sign of the coefficient γ in Equation 8. This coefficient is usually negative; therefore positive return shocks, ε_{t-1} , generate less volatility than negative return shocks. In the EGARCH model, $\ln(\sigma_{t-1}^2)$ is homoscedastic conditional on σ_t^2 . $\ln(\sigma_{t-1}^2)$ is a linear process and is stationary. The natural logarithm of the conditional variance on the left hand side implies that the leverage effect is exponential rather than quadratic and that a forecast of the conditional variance will be non-negative. The presence of leverage can be tested by the hypothesis that $\gamma < 0$.

5

Value-at-Risk (VaR) analysis

VaR is one of the most important and widely used statistics that measures the potential risk of economic losses (Campbell et al., 2001). With VaR, financial institutions can get a sense of the likelihood that a loss greater than a certain amount would be realised. VaR is a measure of the maximum potential change in value of a portfolio of financial instruments with a given probability over a pre-set horizon. VaR answers the question “how much can one lose with x per cent probability over a given time

horizon” (Morgan and Reuters, 1996)? Thus a 5 per cent 1-day VaR corresponds to a loss level that one expects to exceed, in normal market circumstances, in one day in twenty, and a 1 per cent 1-day VaR is the loss level that might be seen in one day in a hundred.

There should be a strong relationship between VaR estimates and the absolute value of each day’s profit and loss. Large VaR figures should be accompanied by large profits or losses, while small VaR estimates should be associated with small profit and loss results.

There are different methods used to calculate the VaR of a portfolio or an asset. These methods are the historical simulation, the Monte Carlo simulation and the variance-covariance (analytic VaR) method. Since the advent of RiskMetrics (as a measure of volatility), the VaR calculation based on variance-covariance has become the norm for financial institutions. In the variance-covariance VaR methodology, the only data necessary to compute the VaR of a linear portfolio is a covariance matrix of all the assets in the portfolio, that is, the variances and covariances of the asset returns (Butler, 1999). These can be measured using any of the volatility models, such as EWMA or the family of GARCH models. Due to its popular use for VaR calculation, this article will focus

on the variance-covariance method for VaR calculation by comparing the benchmark model (RiskMetrics VaR) to the VaR measure calculated using other volatility measures such as the GARCH and EGARCH models.

VaR estimation is important as far as the capital requirement of banking institutions is concerned. The 1996 agreement, concluded by the Basel Committee on banking supervision, called the BIS accord, requires banks to hold a certain amount of capital for credit as well as market risk. The agreement calculates capital for the trading book by using a VaR measure. The trading book consists of a number of different instruments that are traded by the bank such as stocks, bonds, forward contracts, and others. Such a trading book is normally re-valued daily.

The Basel Committee agreement sets the capital required to be held by banks to be a certain multiple, k (multiplication factor), times the VaR measure of the instruments held by a given bank. For a bank with excellent well-tested VaR estimation procedures, i.e., the number of exceptions provided by the back-testing is in the green zone, it is likely that k will be set equal to the minimum value of 3. For other banks that fail to meet the requirement of a well-tested VaR estimation, the multiple k may be higher than the value of 3 (see Table 1).

Table 1
The Basel Committee’s three zones

	Number of exceptions (250 days)	Multiplication factor
Green zone	4 or less	3.0
Yellow zone	5	3.4
	6	3.5
	7	3.65
	8	3.75
	9	3.85
Red zone	10 or more	4

Source: Basel Committee on Banking Supervision (1995)

Referring to Table 1 above, the green zone means the models are reliable and can be applied with confidence. The model fails if the following day’s price change is greater than the

VaR calculated. The yellow zone means caution should be applied and further refinements of the model are needed. The red zone means the model is completely flawed and the regulator

will intervene and recommend increasing the scaling factor (Basel Committee on Banking Supervision, 1996). Therefore it is important that banks are always in the green zone in order not to have extra capital set aside for poor models.

Coming up with an excellent, well-tested VaR estimation is therefore a crucial concern for most banks. As stated above, the estimation of the best VaR forecast has to start with the best choice of volatility modelling.

Back-testing is an important procedure used to assess the accuracy of the VaR models. Under the proposed alternative Basel Committee approach, the supervisors will carry out “back-testing”, that is, the comparison of actual trading results with model-generated risk measures. Banks have a choice of two alternative approaches to measure market risk. The first is the internal models approach, where banks are allowed to use proprietary in-house models for measuring market risks, subject to the fulfilment of a number of strict quantitative and qualitative criteria. The second is the standardised approach, where banks measure market risk according to a standardised measurement (RiskMetrics) method.

The bank for international settlements (BIS) accord imposes a penalty on institutions whose VaR models perform poorly. Banks generally back-test risk models on a monthly or quarterly basis to verify accuracy. In these tests, banks observe whether trading results fall within pre-specified confidence bands as predicted by VaR models. The Basel Committee recommends that back-testing be conducted based on a 1-day holding period even though the capital that a bank is required to hold against its market risk is based on VaR with a ten-day holding period (Basel Committee on Banking Supervision, 1995).

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Data analysis, methodology and empirical results

It is important to note that the selection and estimation of an excellent, well-tested variance-covariance VaR model involves different steps.

The following steps are pursued:

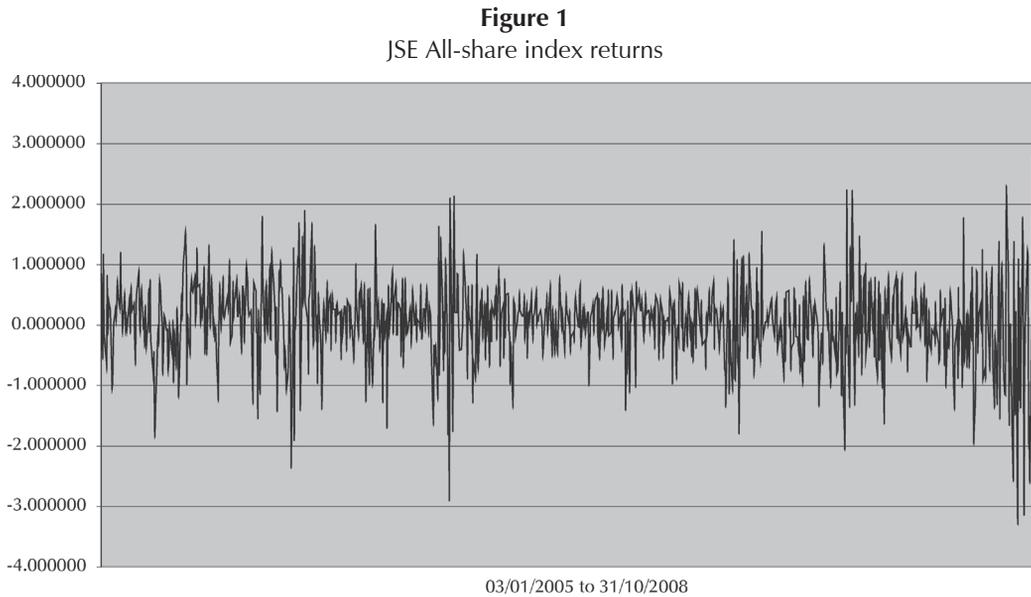
- i. Selection and estimation of the best volatility model;
- ii. Calculation of the VaR of an asset or portfolio for each day on a rolling basis. The rolling VaR is obtained by multiplying the daily volatility by the multiplication factor for the desired level of confidence (the multiplication factor is 1.645 for the 95 per cent confidence level and 2.33 for the 99 per cent confidence level) obtained from the cumulative probability distribution function for a standardised normal distribution;
- iii. Comparison of the VaR calculated for each day to the following day's price change. If the following day's price change is larger, then that day is an exception. The best VaR method should minimise the number of exceptions. Table 1 provides the guidance for a well-defined VaR model.

The empirical analysis presented in this section assumes that a financial institution holds a position on the All-Share Index, a stock market index portfolio traded on the JSE. This paper assesses which of the volatility models – RiskMetrics, GARCH and EGARCH – provides a better estimation of the VaR. The assessment criterion for the best VaR estimation is based on the back-testing procedure. Data used are the daily returns on the All-Share Index obtained from the I-Net Bridge bank of data and cover the period from 3 January 2005 to 31 October 2008, a total of 993 observations. While the first 743 observations are used for in-sample forecasting of volatility, the last 250 observations are used for an out-sample forecast of volatility as well as VaR calculation and the back-testing procedure. A total of 250 observations are used for the out-sample volatility forecast and VaR calculation to conform to the regulator's recommendations. As in Table 1, regulators recommend using the last 250 days of the data observations to back-test the 1 per cent 1-day VaR (Alexander, 2001: 276).

Figure 1 below highlights the volatility clustering of the All-Share Index returns. The increase in volatility observed at the end of the sample period (around October 2008) is attributed to the increase in emerging financial

markets risks as a result of the global financial market turmoil. The time-varying volatility and the mean-reverting property of the variance

rates described in Figure 1 provide an insight for the use of some family classes of GARCH techniques for volatility estimation.



Source: Author's construction from data

The in-sample estimation of the GARCH model of volatility is reported in Table 2. The best fit for the GARCH model is obtained from an AR(2)-GARCH(1,1) where the mean and variance equations are represented as in equations 5 and 6, respectively. The vector X_t contains r_{t-1} and r_{t-2} , the first and second lag of returns on the All-Share Index. The estimation of the AR(2)-GARCH(1,1) shows that the coefficients of the mean and variance equations are statistically significant. The paper used the standard criteria of the Box-Jenskin procedure, which suggests an

AR(2) representation for the mean equation. According to the Box-Jenskin procedure, the autocorrelation and partial autocorrelation functions of a variable should suggest the structure of the autoregressive model. The goodness of fit of this model is confirmed with the plot of the correlogram of the residuals of the fitted model (not shown here). The Ljung-Box Q-statistics of the residuals of the fitted model indicated that the residuals autocorrelation and partial autocorrelation are not statistically significant.

Table 2
Estimation of a AR(2)-GARCH(1,1) variance equation

	Coefficients	Std. error	z-statistic	Probability
r_{t-1}	0.251696	0.048610	5.177847	0.0000
r_{t-2}	-0.100064	0.042914	-2.331742	0.0197
Variance equation				
ω	0.00615	0.00362	1.697153	0.0897
\mathcal{E}_{t-1}^2	0.08076	0.03134	2.576235	0.0100
σ_{t-1}^2	0.85145	0.05949	19.31165	0.0000

R-squared	0.04530	
Adjusted-squared	0.03835	
Durbin-Watson statistics	2.03193	

Likewise, the estimation of the EGARCH model is obtained from the AR(2)-EGARCH(1,1). Table 3 reports the estimation of the variance equation of the EGARCH model as in Equation 8. The estimated coefficients of the variance

equations are all statistically significant. Furthermore, the estimated coefficient of γ is negative. This indicates that there is a leverage effect with negative return shocks generating more volatility than positive return shocks.

Table 3
Estimation of a AR(2)-EGARCH(1,1) variance equation

Coefficient	Estimate	Standard error	Z-statistics	Probability
ω	-0.6430	0.300668	-2.138753	0.0325
α	0.16290	0.066781	2.439321	0.0147
β	0.94492	0.028636	32.99787	0.0000
γ	-0.1046	0.034457	-3.037118	0.0024

RiskMetrics volatilities are computed with the aid of Equation 4 with the value of λ equal to 0.94.

As far as the accuracy of the volatility forecast is concerned, Table 4 shows that the in-sample forecast obtained from an EGARCH model

performs better than the rest of the models. Nevertheless, the performance of the GARCH model is very close to the EGARCH model. The criterion used for the comparison of the different volatility models is the root mean squared error (RMSE).

Table 4
In-sample performance of the volatility models

Model	RMSE
EGARCH	0.008162
GARCH	0.008178
RiskMetrics	0.013075

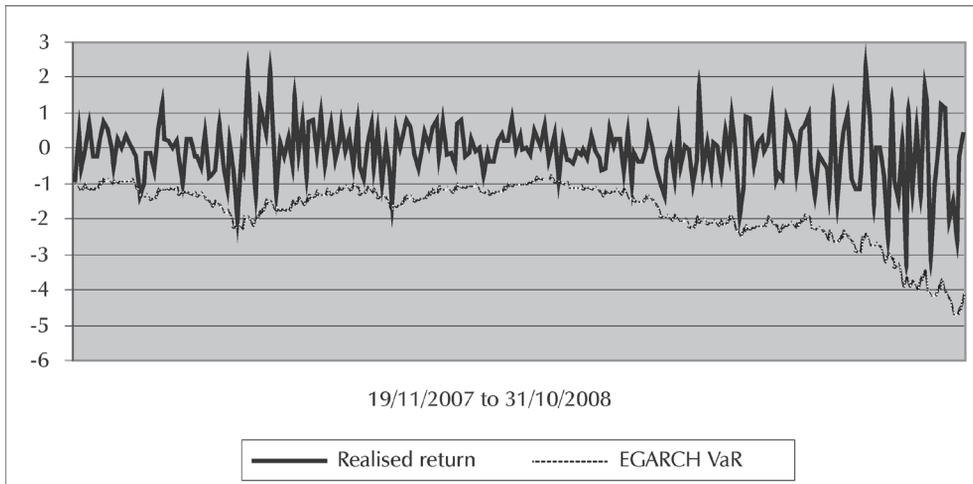
The last step of this analysis consists of forecasting the one-day VaR from each of the three volatility models using a 99 per cent confidence level. As stated earlier, 250 observations are needed for VaR calculation and the back-testing of each model. Observations from 19 November 2007 to 31 October 2008 (a total of 250 observations) are used for out-of-sample forecast of the RiskMetrics, E-GARCH and GARCH volatility models as well as the

VaR estimation. The one-day time horizon and the 99 per cent level of confidence used in the VaR estimation conform to the regulation of the Basel Committee. Figures 2, 3 and 4 depict the trends of the estimated VaR obtained from EGARCH, RiskMetrics and GARCH volatility measures, respectively. In the same figures, VaR estimations are compared with the realised returns of the All-Share Index. The comparison of the VaR estimation and the realised returns

provides the back-testing mechanism, whereby the violation of the model occurs when the negative value of the return on the index exceeds the VaR estimation. Back-testing is relevant for gauging the reliability of the VaR model. The results of the VaR back-testing as in Figure 2, Figure 3 and Figure 4 are summarised in Table 5. The results of the VaR back-testing show that there is no violation for the VaR obtained from the GARCH model and only one violation for the VaR obtained

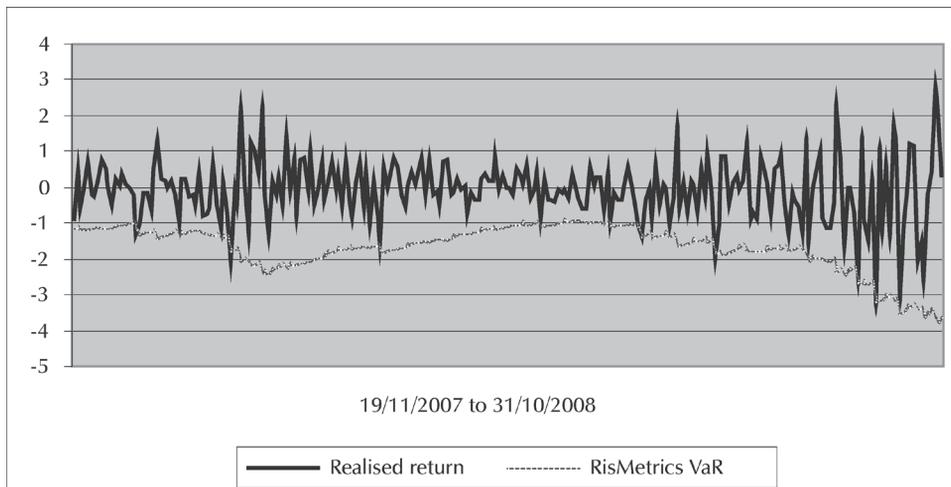
from the EGARCH model. This indicates that the two models perform well as the number of violations is limited to the green zone. The VaR values obtained using the RiskMetrics model show a total of 5 violations. This number of violations puts the VaR obtained using RiskMetrics into the yellow zone. With this outcome caution should be exercised in applying the RiskMetrics volatility measures when estimating VaR for a position held in the All-Share Index.

Figure 2
E-GARCH VaR back-testing



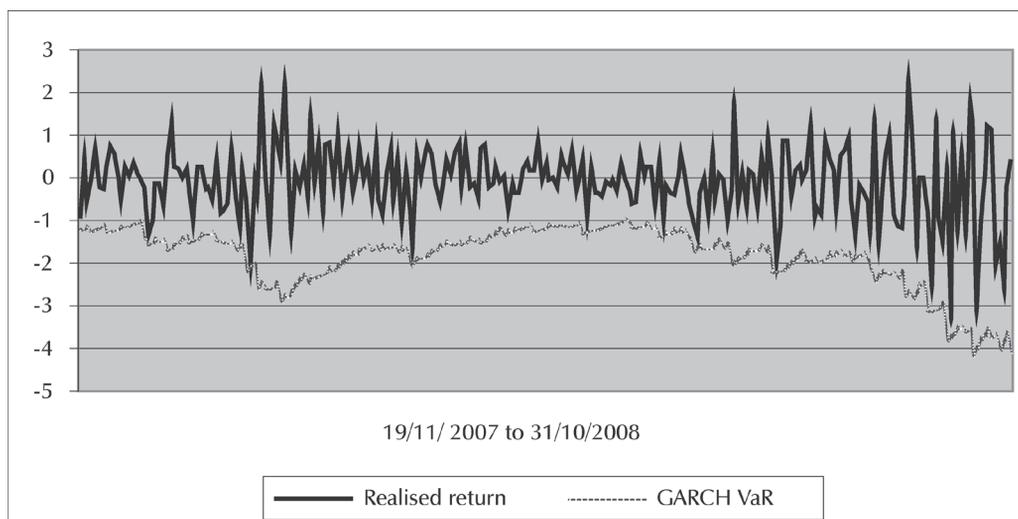
Source: own estimation

Figure 3
RiskMetrics VaR back-testing



Source: own estimation

Figure 4
GARCH VaR back-testing



Source: own estimation

Table 5
Back-testing results

	Number of exceptions	Multiplication factor	RiskMetrics violation	GARCH violation	EGARCH violation
Green zone	4 or less	3.0		0	1
Yellow zone	5	3.4	5		
	6	3.5			
	7	3.65			
	8	3.75			
	9	3.85			
Red zone	10 or more	4			

The results reported in Table 5 show that while the multiplication factor that applies to the VaR values obtained for the GARCH and EGARCH volatility measures is 3.0, this factor should increase to 3.4 for the VaR obtained using the RiskMetrics volatility methodology. This indicates that capital requirement should increase when use is made of the RiskMetrics methodology for the estimation of the VaR for a position held in the JSE All-Share Index.

These findings should indicate that conditional heteroscedasticity, the presence of changing volatility, should be taken into account for an appropriate estimation of VaR,

under the variance-covariance method, in emerging markets. Furthermore, the asymmetric behaviour of volatility remains an essential element for volatility forecasting in emerging markets, though this paper shows that the symmetric model performs as well as the asymmetric model. This is probably due to the relative calmness of the JSE during most of the sample periods of the analysis, except the last period in our sample, namely October 2008. This period has been characterised by global financial turmoil that impacted on emerging financial markets.

7

Conclusion

This article evaluated the performance of the widely used RiskMetrics model to forecast volatility and ultimately calculate VaR, to other models of volatility such as the symmetric and asymmetric GARCH models. Use was made of a stock market index portfolio, the JSE All-Share Index, a market index traded in the JSE, for this end. The stock exchange chosen is an emerging market's exchange. Our analysis shows that the EGARCH and GARCH models provide the best models for volatility forecasts and VaR estimation compared to the RiskMetrics model. These findings show that the assumptions of conditional heteroscedasticity as well as asymmetric volatility should be taken into account when estimating the VaR in emerging markets. The findings of this paper are relevant for a position held in the JSE All-Share Index for a period from 3 January 2005 to 31 October 2008. Nevertheless, we suggest that for further research, other portfolios, such as portfolios made up of bonds and equity assets, be considered.

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