Modelling Return Volatility in the Main Board and the Alternative Exchange of the Johannesburg Stock Exchange: Application of GARCH Models

Katleho Makoko[1], Paul-Francois Muzindutsi[2]

Abstract: Volatility has been a major concern for the stock market because it poses risk challenges to stock markets' investors. This paper estimated and compared the level of volatility in the two boards of the Johannesburg Stock Exchange (JSE) namely, the Main Board and the Alternative Stock Exchange (AltX), in order to establish whether there are volatility spill-over effects between these two boards of the South African stock market. Different GARCH models were used to analyse daily returns for the sample period running from January 2007 to December 2016. Results found that the best volatility capturing model for the JSE Main Board was EGARCH; while the best model for AltX was GARCH (1, 1). The JSE AltX was found to be more volatile than the Main Board and there was no spill-over effect between the two boards. The absence of the spill-over effect is an indication that the risks do not spill-over between the two boards of the JSE. The findings of this study therefore suggest that investors can minimise risk by diversifying their investment between the two major boards of the JSE.

Keywords: Alternative exchange; JSE; GARCH models; return volatility

JEL Classification: G11; G17

1. Introduction

The Johannesburg Stock Exchange (JSE) is a South African stock market comprising of two main boards that run in parallel. The two boards are the JSE Main Board and the JSE alternative exchange referred to as AltX (JSE, 2013). The majority of the companies listed on the JSE, including all of South Africa's largest and most well-known companies, are on the Main Board (JSE, 2013). The JSE AltX was introduced in 2003 to serve as an alternative listing platform for smaller companies that could not be listed on the JSE Main Board (Manikai, 2007). Thus, the JSE AltX provides small to medium sized companies a public listing option with conditions that are less strict than those of the JSE Main Board (Manikai, 2007). Although AltX caters for small companies, it is noticed that a large number of companies suspended on AltX are worth a significant value (Hasenfuss, 2013). As a result, AltX plays a non-negligible role in the South African financial markets and may be volatile as the main board.

JSE investors are exposed to large changes in stock prices and this is observed through the fluctuations of stock returns in the two major indices namely, the JSE main board and the JSE AltX. Fluctuations in stock returns are known as the volatility within the return of stocks which can be defined as a measure deviation from the average return of stocks (Manda, 2010). Stock market volatility can sometime follow the patterns of the business cycle (Manda, 2010); implying that the volatility of the stock market can be linked with changes in economic conditions (Kotze & Joseph, 2009). For example, stock market returns may decrease when a country's economy is in a recessionary phase, whereas the stock return may increase when the economy moves into a recovery phase (Howard, 2011). Stock market volatility can also be caused by investors' confidence, whereby the/a decline in investors' confidence causes stock

[1] North-West University, Kirkland, Washington, E-mail: missmaykok05@gmail.com.
[2] University of KwaZulu-Natal, South Africa, E-mail: muzindutsip@ukzn.ac.za.

market returns to decline (Howard, 2011). A good example is the 2008 financial crisis which resulted in some firms being liquidated due to investor's lost confidence and scepticism with taking on risks and any sort of investments (Howard, 2011).

Considering that the economic and political conditions affecting investor confidence have differential effects on the sectors of the stock market, it can be assumed that volatility may also be asymmetric for all the sectors of the stock market (Khositkulporn, 2013). Thus, stock market volatility is determined by the type of sector the market is categorised into. Sectors with high levels of volatility are often associated with more frequent trade activity and a higher number of investment injections (Ungarino, 2016). This means that the volatility can differ across the different stock market sectors or indices. For example, sectors with new growing stock may be characterised by high volatility; while a sector with matured and stable stocks can be less volatile. This means that indices within a specific stock market may also portray different levels of volatility. However, the volatility may be the same if there is a spill-over effect between the stock market indices. In the context of this study, the JSE main board and the JSE AltX may have different risk exposures resulting in different volatility or have similar volatility if there is a spill-over effect between these two boards of the JSE. Therefore, the motivation behind this study is based on comparing the volatility of the returns in these two indices.

Given that volatility is measured by different models, which differ according to the data utilised (Brooks, 2014); this study used Generalized AutoRegressive Conditional Heteroscedasticity (GARCH) models (such as ARCH/GARCH, TARCH/GJR-GARCH and EGARCH) to measure the level of volatility within the JSE Main Board and AltX. However, the appropriate GARCH model to be used in measuring volatility has to be determined first (Brooks, 2014). Thus, the specific objectives of this study were to identify the appropriate model in capturing return volatility in each of the two indices; estimate and compare the level of volatility of the JSE Main Board and AltX and establish whether there is a volatility spill-over effect between the two boards of the JSE.

2. Literature Review

The stock market has to consistently adjust in order to reflect the new information and this makes it more volatile. Volatility is highly linked with uncertainty in the movement of the stock returns and as a result investors tend to require higher returns from high volatile stocks (Veronesi, 1999). For example, an investor expects higher returns when investing in bonds than holding cash because of the higher risk associated with bonds (Maurer, 2016). Similarly, investors tend to expect higher returns for investing in stocks than in bonds mainly because stocks drive great uncertainty. The same logic can also be applied to understanding the reason for differences in volatility between sections of the stock market, such that an isolated market index (such JSE AltX) with small companies may be considered to be more volatile than an index (such the JSE main board) with established companies (Maurer, 2016). Thus, it is important to measure the stock market volatility in order to establish the level of risk in each index. The measurement of volatility gives investors an indication of how the market is performing so that they can identify the stock market index to invest in.

Volatility has various implications on return and the investors' behaviours. Firstly, volatility reveals the persistence of risk which results in the implication of volatility clustering which has a great influence on the anticipation of future volatility (Engle & Patton, 2000). Secondly, volatility can be seen as a part of financial market problems by policy makers and financial market participants because it can be utilized as a measurement of risk (Miah & Rahman, 2016). Thirdly, volatility may create a ripple effect, causing an increase in return volatility within financial markets which may discourage investments in the stock market resulting in high uncertainty (Miah and Rahman, 2016). This ripple effect is referred to as spill-over effect, if the volatility spills from one stock market index to another one. The understanding and the measurement of stock market volatility is therefore crucial in investment and risk modelling.

There are different types of volatility such as historical volatility, relative volatility and implied volatility. With the aid of volatility models like the ARCH/GARCH, TARCH and EGARCH models, volatility can be modelled and estimated (Kotze & Joseph, 2009). The first type of volatility is known as historical volatility or realised volatility and this is a volatility that can be noticed and measured on the basis of historical changes in stock prices. Historical volatility looks into how many times a stock's price changes within a year. This type of volatility is often utilized as a comparison of most recent behaviour of prices amongst two securities. The second type of volatility is implied volatility which is seen as an expression of the market's anticipation of future volatility in stock prices (Radtke, 2014). This implies that it is difficult for implied volatility to be calculated from historical prices of stocks because the past movement can be used to anticipate the future movement in stock prices (Figlewski, 2004). Implied volatility is perceived as an effective estimator of future volatility because it performs better than other types of volatility. However, the analysis of implied volatility has been criticised as being subjective and not efficient because all volatility types are made of information regarding future volatility which tends to be greater than the volatility included in implied volatility (Christensen & Prabhala, 1997). Despite these criticisms, the implied volatility continues to be a relevant estimator of risk in stock returns (Giot, 2005; Yan, 2011) and therefore is used in this study.

A common way of measuring volatility includes standard deviation which provides an indication of the likelihood of returns increasing or decreasing sharply in the short term (Carther, 2015). The standard deviation is referred to as a measure of the total risk of a security in a specific period of time (Campbell & Hentschel, 1992; Carther, 2015). One of the challenges with measuring volatility with variance or standard deviation is that prices constantly change due to market circumstances. This means that significant price changes over a short period of time results in high volatility and as results regular price changes constitute high volatility. It is important to accurately measure volatility in order to assist investors with investment decisions (Tothova, 2011). If an incorrect model is used to measure the level of volatility, the conclusion reached may provide misleading information (Engle & Patton, 2000; Tothova, 2011). Thus, volatility modelling involves the identification of the appropriate model to be used in estimating the total amount of return fluctuations (Engle & Patton, 2000).

One of the appropriate ways of measuring volatility is to use the conditional variance. There are various models that use the conditional variance to capture whether volatility has increased or decreased. These models include ARCH model introduced by Engle (1982), GARCH model introduced by Bollerslev (1986), TARCH (threshold GARCH) similar to GJR-GARCH (named after the authors Glosten, Jagannathan & Runkle, 1933) and exponential GARCH (EGARCH) models (Brooks, 2008). These GARCH models and their extensions are relevant in modelling volatility because they provide relatively comprehensive ways of estimating volatility in its simplest form (Diebold & Lopez, 1995). GARCH models have proved to be successful in measuring conditional variances (Engle, 2001). The application of ARCH and GARCH models in finance has also been relatively successful because these models treat heteroscedasticity as a variance to be modelled (Engle, 2001). Hence, ARCH and GARCH models have been used in a variety of time series analysis. This study therefore used ARCH/GARCH models and their extensions to compare the return volatility between the two boards of the JSE.

3. Methodology

3.1. Data and Sample Period

This study was conducted using quantitative research with time series that comprises of 2500 daily closing price index for the JSE AltX and the JSE Main Board. The sample period starts from the beginning of January 2007 to the end of December 2016 and excluded South African public holidays and weekends. The sample period was selected based on the availability of data; the JSE AltX data is only available from 2007 because it began trading in 2006. The data for the main board (JSE All Share Index) and JSE AltX were accessed from McGregor Bureau of Financial Analysis (BFA) website. The continuous return was estimated from the share price index as follows:

$$R_t = ln\left(\frac{P_t}{P_{it-1}}\right) \quad (1)$$

Where P_t and P_{t-1} are the closing share price index at the period t and t-1, respectively.

3.2. Model Specification

This study used ARCH/GARCH models to capture stock market volatility of the selected stock market indices. The performance of these models depends on the market, time period and error measures. The GARCH model is often favoured over the ARCH model as it overcomes some limitations such as overfitting and constraints encountered by the ARCH model (Brooks, 2014). ARCH model was introduced by Engle (1982), as a tool to model heteroscedasticity in financial time series. This model contained conditional variance σ_t^2 as well as being described as a linear function of lagged squared residuals ε_t (Hamadu, 2010). The ARCH model is derived for an asset return (R_t) expressed as:

$$R_{t=}\mu + \varepsilon_t \quad (2)$$

WhereR_t is return of an asset at time t.

The conditional variance, σ_t^2 of ε_t is expressed by the following equation:

$$\sigma_t^2 = \mu + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 \quad (3)$$

Where σ_t^2 is the conditional volatility at time t, ε_t^2 is the previous period's squared error term known as ARCH term at time t and α is the ARCH coefficient and μ is the intercept. The conditions for this formula are as follows: conditions:μ> 0 and $\alpha_i \geq 0$ and ε_tI $\emptyset_{t-1}$~ N (0, σ_t^2).

It is essential to notice that in ARCH models, the unconditional distribution of ε_t is clustered all of the time (Engle, 2002). The ARCH model's limitation is the definition and modelling of the persistence of shocks and the problem of modelling asymmetries, which led to the development of generalized ARCH (GARCH) model introduced by Bollerslev (1986). The GARCH model is expressed as follows (Hamadu, 2010):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \, \sigma_{t-j}^2 \quad (4)$$

Where $\sigma_t^2$is the conditional volatility at time t, ε_{t-i}^2 is the previous period's squared error term, and $\sum_j^q \sigma_{t-j}^2$ is the previous period's volatility, and α_i and $\beta_j$are the ARCH and GARCH coefficients, respectively. All α_i and $\beta_j$values should be greater than zero and their summation should be less than one (α_i+ $\beta_j < 1$) to keep process stationary.

The major limitations of GARCH models is that the positive conditional variance though which α_i and β_j should be non-negative. This is known as a non-negativity constraint. GARCH models assume that the influence of updates on the conditional volatility only depend on the magnitude of the coefficients, but not on the sign of the innovation (Hamadu, 2010). Thus, the GARCH model is sometimes unable to provide adequate forecasts that could accurately specify the true volatility measure against which the forecasting performance can be measured (Matei, 2009). Another limitation of the GARCH model is in isolating the leverage effects, which are mostly identified in the financial time series. Leverage effects are characterised by the trend of changes in stock prices that are negatively correlated with stock volatility changes (Matei, 2009). The leverage effect means that stock prices have a lagged and asymmetric response to volatility shocks. This means that the effect of a shock upon the volatility is asymmetric; implying that such shock has a positive and negative impact on lagged residuals. The inability of GARCH to capture the leverage effects led to the extension of GARCH to TARCH (Threshold GARCH), the GJR-GARCH (named after the authors Glosten, Jagannathan & Runkle, 1933) and exponential GARCH (EGARCH) (Brooks, 2008).

The EGARCH model is responsible for capturing the asymmetric responses to a shock. The reason for this is that volatility is allowed to react more accurately to reductions in negatively lagged residuals than consistent increases in positively lagged residuals (Matei, 2009). The EGARCH model was introduced by Nelson (1991) and is expressed as follows (Brooks, 2008):

$$\mathrm{Ln}(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left[\frac{|\varepsilon_{t-i}|}{\sqrt{\sigma_{t-i}^2}} - \sqrt{\frac{2}{\pi}} \right] + \sum_{i=1}^{p} \gamma_i \frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}^2}} + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2) \tag{5}$$

Where the parameter γ_i indicates the leverage effect of ε_{t-i} , and since the relationship between return and volatility is negative, γ_i is expected to be negative (Tsay, 2005).

The EGARCH process is specified in terms of log of the conditional variance which implies that σ_t^2 is always positive and automatically there are no restrictions on the sign model parameters. This model has many advantages over the GARCH model due to it conditional variance which is always positive (because of its logarithms form), even if the parameter estimates are all negative (Brooks, 2014).

Contrary to the EGARCH's exponential form, TARCH model's leverage effect is expressed in a quadratic form. TARCH model has several outcomes on the conditional variance (Matei, 2009). If the impact of the news is asymmetric and the leverage effects exist, the TARCH model takes the form of a standard GARCH model (Matei, 2009). The TARCH is similar to GJR-GARCH model introduced by Glosten et al. (1993) and it is a simple extension of GARCH with an additional term added to account for possible asymmetries. The conditional variance in TGARCH is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2 \tag{6}$$

Where d_t = 1 if ε_t< 0, and d_t = 0 otherwise. A positive coefficient would be obtained when ε_t< 0 and a negative coefficient obtained when ε_t > 0 (Hamadu, 2010).

Each of the aforementioned models was tested in this study to determine the best model fit to estimate return volatility of JSE main board and the JSE AltX. In GARCH modelling, the quality of the results is seen as the chosen model's ability to give a correct approximation of the relationship between the exogenous and endogenous variables, by taking into account the autocorrelations and interaction effects that may exist within the data (Matei, 2009). The model that minimises information criteria (with the lowest AIC and SC values) without the presence of serial correlation was identified as the best model for either JSE Main board or AltX.

4. Empirical Results

For the analysis, the preliminary investigation was conducted through graphical representation. This was followed by the descriptive statistics summary which is made up of heterogeneous variables, the main variable being standard deviation as an effective measure of volatility. Therefore, a higher standard deviation value would indicate higher risk. Correlation analysis was conducted to determine the relation between the two major indices boards. Unit root tests were used to determine stationarity of the variables as GARCH models are applicable for stationary variables (Brooks, 2014). The next step was to test for the ARCH effect, which is essential for the model misspecifications. The model selection test was then conducted to identify the appropriate model for each of the two JSE indices considered by this study. The selected appropriate model, for each index, was then used to estimate and compare volatility of the indices. The final step was to conduct a spill-over effects test to determine whether the two JSE indices affect each other or not. The spill-over effect is essential in establishing whether investors can diversify their portfolios across two indices.

4.1. Descriptive and Correlation Analysis

Graphical analysis[1] shows that the returns of the JSE Main Board and the JSE AltX exhibit more volatility during 2008 and 2010-2014. The JSE AltX appear to have higher return volatility, suggesting that it may be more volatile than the JSE Main Board. Overall, the JSE Main Board experienced steady returns throughout the sample period. Descriptive statistics in Table 1 show that the JSE AltX has a negative average daily return with a slightly higher standard deviation. The higher standard deviation of JSE AltX is more volatile than the JSE Main Board. Over the sample period, the JSE AltX incurs a higher daily loss (minimum) and yields a higher daily return than the JSE main board. This confirms the high level of volatility in AltX price returns shown by its standard deviation. The skewness suggests that returns of both indices are skewed to the left but the skewness is very high in the JSE AltX returns. This is also confirmed by a large value of Kurtosis. Given that the JSE AltX is dominated by small and medium companies this high level of skewness is expected. The correlation between the two indices is positive (0.15511) and implies statistically significance at 0.05 level. This implies that the two indices are positively correlated but the low coefficient value suggests that there may exist diversification opportunities between the two indices.

Table 1. Descriptive Statistics Summary

	Mean	Std.Dev.	Min.	Max.	Skewness	Kurtosis
Mainboard	0.00028	0.013	-0.07581	0.06834	-0.136776	6.49567
AltX	-0.00026	0.017	-0.17984	0.12458	-1.271284	22.2684

4.2. Testing for Unit Root and ARCH Effects

The results of the ADF unit root test, in Table 2, show that both the p-values for both variables are less than 0.05, implying that the null hypothesis for the unit root is rejected. Thus, both AltX and JSE Main Board are stationary at level. This means that it is appropriate to continue with the estimation of GARCH. The results of ARCH effects test for heteroscedasticity show both p-values are less than 0.05, implying that the null hypothesis for homoscedasticity is rejected. Thus, both the AltX and the JSE Main board are heteroscedastic. The presence of ARCH effects means that the GARCH models can be used to estimate the return volatility in the two indices (Wooldridge, 2003).

[1]The graph is not reported in this paper but it can be requested from the corresponding author.

Table 2. ADF Unit root test results

Test	JSE Main board	JSE AltX
ADF unit root	P-value: 0.000	P-value: 0.0411
ARCH effects	P-Value: 0.000	P-Value:0.000

4.3. Model Selection and Volatility Estimation

Using the information criteria, the process of selecting the best model was conducted in two steps. In the first step, the best model was selected from each family of GARCH models based on the maximum number of lags, then the selected models were compared to identify the best model in all GARCH extensions in the second step. Table 3 summarises the information criteria used to select the best model in the second step. This result show that the EGARCH model is the best model for the JSE main board, as it has the lowest AIC and SC values. It is also noted that the best model for the JSE AltX is the TARCH model based on the low SC value but for the lowest AIC value is observed for the GARCH (1,1) model. Therefore, there is a contradiction in the results for the AltX. The Hannan-Quinn (HQ) was used as an additional criteria to confirm the best model and it confirmed that the best model for AltX is the GARCH (1,1). This is also in line with the literature that the SC is likely to be the most accurate in a large sample as it is more consistent than AIC; implying that it picks the correct model in a large sample. Additionally, the coefficient of leverage effects in TARCH model was not statistically significant suggesting that there are no leverage effect in the JSE AltX. This means that there is no difference between negative and positive volatility in the JSE AltX, whereas such difference exists in the JSE main board. This finding means that investors react strongly to bad news, compared to positive news, in the JSE main board. This is in line with the financial literature, which suggests that a negative shock in financial time series tends to cause volatility rise by more than a positive shock of the same magnitude (Brooks, 2014). In addition, the selected models were used to test for the serial correlation and they all confirmed that there was no serial correlation.

Table 3. Results for model selection

Model	JSE Main board		JSE AltX			
	AIC	SC	AIC	SC	HQ	LAG
ARCH	-6.1398	-6.1202	-5.4017	-5.3835	-5.3950	5
GARCH (1, 1)	-6.2056	-6.1943	-5.4447	-5.4326	-5.4402	1
TARCH/GJR	-6.2451	-6.2311	-5.4457	-5.4305	-5.4401	1
EGARCH	-6.2476	-6.2336	-5.4455	-5.4303	-5.4399	1

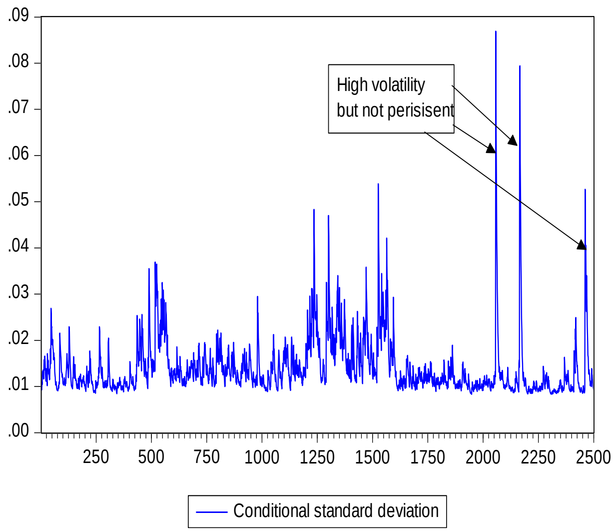
The volatility results, in Table 4, show that all coefficients are statically significant at 0.05 significance level. The summation of the coefficients show that Main Board sums up to 0.765785, while AltX sums up to 0.964. This means that estimated model are not explosive (stationary) as both summations are less than one. The results reveal that JSE AltX is more volatile than the JSE Main board because 0.794241 is greater than 0.990516. For the JSE main board the coefficient for a leverage effect (γ_1) is negative and significant. This is in line with the literature as the negative coefficient for leverage effect means that the error term is negative and the coefficient is multiplied by a negative value thus resulting in a positive effect on conditional variance. Although the JSE AltX has a higher total conditional volatility a higher GARCH coefficient in the JSE main board (β_1= 0.986665) provides evidence of a considerable persistence in the volatility. Thus, the presence of volatility seems to be more persistent in the JSE main board than the JSE AltX. This is also confirmed by the conditional variance figures (1 a & b), which show that, the JSE AltX has a higher volatility than the JSE main board but the persistence of volatility seems to last longer in the JSE main board. This great volatility in the AltX is due to the fact that it is a small, emerging and fast growing board. This is an indication that the JSE AltX is riskier than the JSE all share index, implying that the JSE AltX should offer a higher risk premium than the JSE main board.

The results of the EGARCH-M and GARCH-M, with a risk premium factor, confirm that the JSE AltX offers higher risk premium than the JSE main board.

Table 4. Volatility Determination

Main Board: EGRACH (1, 1)	AltX: GRACH (1, 1)
Coefficients	**Coefficients**
$\alpha_0 =$ -0.184608*	α_0=1.70E-05*
α_1= 0.081651*	α_1= 0.23093*
β_1= 0.986665*	β_1= 0.73305*
γ_1= -0.117923*	

*Significant at 0.05 significant level



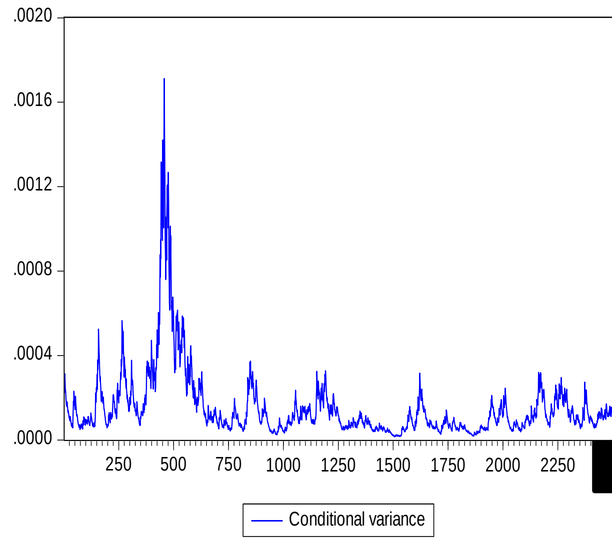


Figure 1. a): Implied Volatility of AltX **Figure 1.b). Implied Volatility of Main Board**

The spill-over test was conducted in order to establish whether Main Board and AltX affect each other or not. Results show that the volatility return in JSE AltX has no significant effect on the conditional variance of the JSE main board and the volatility return in the JSE main board has a significant effect on conditional volatility of the JSE AltX. Thus, there is no spill-over effect between the two indices. The dynamic conditional correlation (DCC) also confirmed that there is no condition correlation between the volatility return of the two indices. In the context of diversification, the absence of spill-over effect implies that investors can invest in the JSE AltX companies to diversify the risk associated with companies in main board.

5. Discussion of Results

From the output of results, JSE AltX is more volatile than JSE Main board, suggesting that the JSE AltX has higher risk exposure than the JSE main board. This is expected as the AltX comprises of small and medium companies, which are seeking high growth and have high return volatility (Mele, 2008). Based on the concept of high risk-high return (Howard, 2011), AltX may offer investors more return than the main board index. Our findings suggest there exists a weak correlation between the JSE AltX and Main board, despite being part of the same stock market. This implies that the JSE AltX provides South African investors with an opportunity to diversify within the JSE. This is true as the diversification is only valid when the investors securities are not perfectly correlated (van Heerden, 2015) and this seems to be the case between these two indices of the JSE.

With selection of the best GARCH model, our results confirmed that the model can change with the data. The EGARCH model was found to be the best model for the JSE Main Board, while GARCH (1,1) model proved to the best model for the JSE AltX. These two models are often regarded as the best among the GARCH models. GARCH model is often regarded as the best model as it has the potential of removing the leverage effect. The study by Hansen et al. (2014) also regarded the GARCH model as the best model. Other studies (Lamoureux & Lastrapes, 1990; Andersen & Bollerslev, 1998) also found that the GARCH model tends to perform better than other models. Similarly, the current study affirmed that the GARCH model largely defines time variation in the volatility structures and that it has the best empirical properties. According to Hamadu (2010), EGARCH model is the best model for measuring volatility in the presence of leverage effect. Other studies that found the EGARCH to be the best model include Malmsten (2004) and Teräsvirta & Zhao (2011). Thus, we can conclude that GARCH model suitability is mainly a function of the nature of the data.

Our results revealed that there is a presence of leverage effect in the JSE main board, which suggests that South African investors tend to react more to a negative movement in share return than a positive movement of the same magnitude (Silvennoinen & Teräsvirta, 2007). However, this is not the case in the JSE AltX. This difference in the reaction to negative volatility reinforces the diversification opportunity between the indices meaning that the presence of the JSE AltX expands the investors' horizons to broaden their investment base. This is also confirmed by the absence of spill-over effect between the two indices. If the theory associating high risk with high return holds, then the high level of risk observed in the AltX presents a good opportunity for investors with high risk appetites. The JSE AltX is therefore an excellent platform for investors who have knowledge of the stock market conditions and are willing to accept the possible high risk in return for higher rewards associated with investing in growing and volatile companies such as those of the AltX.

6. Concluding Remarks

The ultimate goal of this paper was to employ various GARCH models to capture and compare the level of return volatility in the two major boards of the JSE, namely; the main board composed of stable companies with high value and the JSE AltX, comprises of small and medium companies. Prior expectation suggests that the two indices may have a similar/different volatility and a volatility spill-over between them may exist. Models such as, ARCH, GARCH, TGARCH and EGARCH were applied in order to test this expectation within the JSE Main board and AltX. For the main board, the best model to capture volatility was EGARCH; while GARCH (1, 1) was the best model for the JSE AltX. The results of the estimated volatility revealed higher volatility in the JSE AltX than the JSE main board. Contrary to prior expectation, the return volatility in the JSE AltX was found to have no spill-over effects on the JSE main board and vice versa. This finding implies that diversification opportunities exist between these two major boards of the JSE.

Exploring the various features of the volatility process is essential for financial and portfolio diversification research. Changes within the volatility processes tend to be isolated because of time-varying, increasing conditional moments which are essential but challenging to estimate. The presence of leverage effects in the JSE main board confirms the financial theory that investors tend to react more strongly to negative news than to positive news. A negative volatility within the JSE main board attracts investors' attention but such attention seems to be less when there is a positive volatility. The absence of leverage effects in the JSE AltX means that the sensitivity of investors in small and medium firms tend to differ from that of investors in well established firms of the JSE main board. Our findings showed that the JSE AltX has high risk and offer higher risk premium than the JSE main board suggesting that investors are encouraged to invest in the JSE AltX for higher returns but must however be prepared to bear the risk associated with such higher returns. Our findings also suggest that investors can diversify their portfolios within the South African stock market as the risk within two JSE indices seems to be uncorrelated. Thus, the JSE AltX should be nurtured as it gives South African investors an opportunity to reduce risk associated with investing in the JSE main board.

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