Financial Crisis and Stock Return Volatility of the JSE General Mining Index: GARCH Modelling Approach

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Abstract: The aim of this article is to model the return volatility of the JSE mining sector and analyse how changes in the return volatility were affected by the 2008 financial crisis. The GARCH, EGARCH and GJR-GARCH are estimated in mean with the Student's t-distribution. To account for the 2008 financial crisis, the sample period, which included daily stock index returns from July 1995 to June 2018, was divided into three sub-periods. From the results, the best-fit model for the three sub-periods was found to be GJR-GARCH (1, 1). The results revealed that the level of volatility varies across the three sub-periods with the highest reported pre-crisis and the lowest volatility during crisis. This article found that the level of volatility decreased significantly during crisis, but began to rise after the crisis, although not rising to the pre-crisis level. This implies that the crisis increased the mining investors' risk aversion. Fundamentally, the magnitude of the volatility is not similar across three sub-periods. Such variation suggested different reactions of investors to new information. The fluctuation in volatility proved that the 2008 financial crisis affected JSE mining investors' attitudes towards overall risk.

Keywords: Financial crisis; GARCH models; JSE; mining index; risk-return; volatility

JEL Classification: C10; G01; G10

1. Introduction

South Africa (SA) is one of the world leaders in the mining Industry due to her richness in minerals. The abundance of the SA mineral resources attracts foreign investments through the mining stocks registered on the Johannesburg Securities Exchange (JSE). The economy of SA is built on its mineral resources and the mining sector is one of the largest employers of labour (Sorensen, 2011). The SA mining sector has been volatile in recent years and this volatility is a consequence of both endogenous and exogenous factors. One example of these variables triggering the volatility in the mining sector is the high labour costs, which are motivated by the high number of strikes in South Africa (Prno and Slocombe, 2012; Delloite, 2013). Volatility can also be influenced by the disturbance of the global economy and the instability of financial markets (Engle et al., 2012), such as global financial crises. Volatility is one of the most examined concepts in financial application, economics and risk management and, in general, portfolio management. Volatility can be defined as a measurement of dispersion of returns for a given market index or a relative rate at which a market swings around its expected value (Tsay, 2010). This implies that, volatility represents risk that can be taken in order to obtain a reward, as risk and reward are correlated (Neokosmidis et al., 2009). Engle (2001) and

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Gujarati (2004) note that an extended period of wide swing in prices could be followed by a relatively calm period. It means that the variance of financial time series varies over time (Engle 2001, Gujarati 2004)

The mining sector is volatile. The Fraser Institute's 2014 Investment Attractiveness Index, which considers mineral potential and policy perceptions, ranks South Africa in sixty-sixth place, below certain African countries. To have countries such as the Democratic Republic of Congo ahead of South African is considered anomalous (James, 2016). The observed volatility in the SA mining sector portends serious dangers for the investors and the economy since it is an indication of risk (Neokosmidis et al., 2009). In this context, any unidentified volatility may lead to economic losses for investors which will affect the job security in the mining sector. It is argued that the JSE mining sector was affected by the 2008 financial crisis through the flow of foreign portfolio investment. The aim of this article is to model the return volatility of the JSE mining sector and analyse how changes in the return volatility were affected by the 2008 financial crisis. In addition, modelling volatility provides increased insight for an improved method to design an appropriate investment strategy. The article hypothesised that volatility varies over time and, consequently, the volatility is not the same pre-, during and post-crisis.

In modelling volatility, Engle (1982) and Bollerslev (1986) proposed the Autoregressive Conditional Heteroscedasticity (ARCH) and Generalised ARCH (GARCH) models respectively. Thereafter, several extensions of GARCH models have been developed. They include the exponential-GARCH (EGARCH) model proposed by Nelson (1991), the Glosten, Jagannathan and Runkle GARCH (GJR-GARCH) model proposed by Glosten et al. (1993), the Asymmetric Power GARCH (APARCH) model proposed by Ding et al. (1993), introduced since the GARCH model was not able to detect the leverage effect, which occurs when the negative shock in the stock price has a higher impact than positive chock with a change in volatility (Black, 1976). All these GARCH family of models were employed in this study with the aim of identifying the optimum model for measuring volatility of the JSE mining sector pre-, during- and post-crisis periods.

2. Literature Review

Several empirical studies have been carried out to model stock market return volatility globally and in the JSE using GARCH models. Mangani (2008) used ARCH-type models to explore the behaviours pattern of volatility on the JSE. The results showed the presence of volatility in the market and the effect of shocks on that volatility was symmetric but not a commonly priced factor. Junior et al. (2014) explored the effect of volatility on BRICs countries compared to the industrialised countries (The USA, United Kingdom, Japan and Germany) by applying GARCH, EGARCH and TGARCH models during the 2007-2009 financial crises. They showed that the BRIC's market has less persistence to volatility shocks, less asymmetry, and higher reactions of volatility to market changes as with the developed markets.

The GARCH, EGARCH and GJR GARCH models were used by Oberholzer et al. (2015) to investigate the behaviour of volatility in the five JSE/FTSE stock indices in 2007-2009 and over the full period of 2002-2014. Their results showed that the GJR GARCH model was the best fit in full sample for all indices except the JSE/FTSE Top 40 Index and the crisis period except the JSE/FTSE Fledgling Index (J204) for which the best fit was the EGARCH model. The results also showed evidence of leverage effects in all markets and this indicated that the rise in volatility is of a greater magnitude after a large negative shock, when compared to that of a positive shock.

Chinhamu et al. (2015) used the generalised extreme value distribution (GEVD) and the generalised Pareto distribution (GPD) to examine the properties of the Johannesburg Stock Exchange Mining Index returns. The value-at-risk (VaR) estimates used to compare the ability of the two distributions and results showed that both GEVD and GPD were better than the normal distribution. Similarly, Mathur et al. (2016) modelled the effects of the 2008 financial crisis on the Indian stock exchange. Results of the GARCH-type models showed the prevalence of volatility clustering over the sample period (2001-2012) and higher volatility during periods of financial crisis (2007-2009). In addition, Gil-Alana and Tripathy (2014) reported volatility and a leverage effect in both the nonferrous Indian metals spot and the futures series using GARCH class models. Mwamba et al. (2017) studied daily closing prices of eleven JSE sector indices with the sample period divided into the pre-crisis, crisis and post-crisis periods. The results of the multivariate Dynamic Conditional Correlation GARCH model employed in the study showed that the performances of the portfolios were not the same over the three sub-periods. The risk-based portfolios performed poorly in the pre-crisis period but better than the market portfolios during- and post-crisis.

In summary, the possibility of changing volatility has been elucidated in literature with the prevalence of sub-period analyses. However, a lack of studies was found that employed GARCH, EGARCH and GJRGARCH models in the study of the JSE general mining index volatility before, within and after financial crises. Considering the volatility of the JSE mining sector and its implications for investors and economy, this study combined various GARCH models in order to examine the risk properties of the sector pre-, during- and post-financial crises periods.

3. Methodology and Data

3.1. Data and Sample

This study employed the daily closing price data for the Johannesburg Stock Exchange index in the general mining sector, obtained from the McGregor BFA database. The data was divided into three sub-data sets to take financial crisis into consideration. The sub-periods were pre-crisis, within crisis and post-crisis. The sub-period analyses allowed the research to assess the effects of major events such as liberalisation and financial crises (Obalade, 2019). For the pre-crisis period the study used data from 28th September 1998 to 31st May 2007, 1st June 2007 to 31st December 2009 and 04th January 2010 to 13th September 2018 for pre-, during- and post-crisis, respectively. The number of observations for pre-crisis and post crisis was the same (2165 observations), while within crisis comprised 647 observations. Daily closing index series were converted into compounded returns by taking the first difference of the natural logarithm of the JSE daily general mining indices and this was given by:

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

Where R_t is the return of stock indices at time *t*; P_t is the closing price on day *t* and P_{t-1} is the closing price on previous day and $\ln$ is natural logarithm (Zivot E, et al., 2007; Tsay, 2010).

3.2. Method of Analysis

Before the application of GARCH models, it was necessary to consider if there is an ARCH effect (heteroscedasticity) and autocorrelation in the residual. This study employed Ljung –Box test and Lagrange Multiplier (LM) test by Engle (1983) for the purpose. The observed autocorrelation and ARCH effect presented in the mean were removed (Tsay, 2010) by modelling the AR (Autoregressive) model and using the residual to run GARCH model. This is similar to the modelling of the ARMA-GARCH model (Wurtz, 2009) and this method was used by (Ruppert, 2011). To check the best model, this article employed Akaike information criterion (AIC), Bayesian Information Criterion (BIC) and log likelihood. The preferred model is the one with the smallest AIC and BIC or the highest log likelihood. The daily closing price series for the JSE index was not stationary as it had to be transformed into continuously compounded returns to convert it to stationary. The symmetric and asymmetric GARCH models were used with normal distribution and the parameters were estimated using the method of log likelihood in R software.

3.2.1. GARCH Model

For symmetric modelling, this article used GARCH model introduced by Bollerslev (1986), after the ARCH model by Engle (1982), as it was simple and required a given number of parameters to fit to the data. The general formula of GARCH (p, q) model is:

$$\sigma_t^2 = \alpha_0 + \sum_i^p \alpha_p \epsilon_{t-p}^2 + \sum_j^q \beta_j \sigma_{t-q}^2 \qquad 2$$

where σ_t^2 is the volatility at time t, $\sum_i^p \epsilon_{t-p}^2$ is the previous period's squared error term, and $\sum_j^q \sigma_{t-q}^2$ is the previous period's volatility, while α_0 is a constant term to be estimated. The parameters $\alpha_0, \sum_i^p \alpha_p, and\ \sum_j^q \beta_q,$ should be greater than zero (>0) and to keep the process stationary, the parameter estimates $\sum_i^p \alpha_p + \sum_j^q \beta_q$ should be less than one (<1) and they all should be statistically significant. This is an indication of the presence of volatility clustering in the return data. In the GARCH (p, q) the p and q, determine the order of lags and the majority of studies used GARCH (1, 1) for capturing the ARCH effects and the autocorrelation in the variance (Mangani, 2008; Mandimika & Chinzara, 2010, 2012; Dedi & Yavas, 2016). In this context, the order of lags could be increased when the first order failed and this does not extend further than order two.

3.2.2. Asymmetry Models

The GARCH model failed to capture the leverage effect or asymmetry in volatility (Black, 1976) where positive and negative shocks of similar magnitude have a different impact on stock market volatility (Engle & Ng, 1993). Consequently, the extensions of the GARCH model were developed, such as the asymmetry GJR-GARCH and the E-GARCH models. The EGARCH (p, q) model was introduced by Nelson (1991) to allow for asymmetric effects between positive and negative asset returns. This model is effective in detecting the leverage effect due to its conditional variance which is always positive despite the parameter estimates being all negative, because of its logarithms form. The general formula of the EGARCH model can be expressed as:

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^p \frac{\alpha_i |\epsilon_{t-1}| + \gamma_i \epsilon_{t-1}}{\epsilon_{t-1}} + \sum_{j=1}^q \beta_j \ln(\sigma_{t-j}^2) \qquad 3$$

When $\epsilon_{t-i>0}$ there is good news and this gives $\alpha_i(1+\gamma_i)|\epsilon_{t-1}|$ to the log volatility, while $\epsilon_{t-i<0}$,if there is bad news, and this gives $\alpha_i(1-\gamma_i)|\epsilon_{t-1}|$, where the parameter γ_i indicate the leverage effect of ϵ_{t-i} , and γ_i is expected to be negative (Tsay, 2010; Franke, 2011).

The GJR-GARCH (p, q) model was introduced by (Glosten, 1993) to detect the leverage effect in the market returns data. The general conditional variance of GJR-GARCH (p, q) is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}(\alpha_i + \gamma_{iN_{t-1}})\epsilon_{t-i}^2 + \sum_j^q \beta_j \sigma_{t-j}^2 \qquad 4$$

where N_{t-i} is the dummy variable which can take value one if $\epsilon_{t-1}^2 < 0$; otherwise zero. When $\gamma > 0$, the leverage effect exhibits and propose that the negative shocks will have a larger impact on conditional variance than positive shocks. The parameter estimate should all be greater than zero, and $\alpha + \gamma \geq 0$ provided the model is still admissible despite if $\gamma < 0$ and γ_i is expected to be positive (Brooks, 2008).

4. Results

4.1. Descriptive Statistics

Table 1 shows the descriptive statistics for the returns series of the three sub-periods. These results provide insight on the behaviour of volatility in each sub-period. Standard deviation is a measure of volatility, consequently the higher the variance the higher the volatility. It can be observed from Table 1 that the crisis period has the highest value (0.0328), followed by pre-crisis (0.0252) and post-crisis (0.0195). The positive mean in both pre- and post-crises showed that the general mining index was increasing, while a negative mean during crisis showed a decline in that period (Huang et al., 2014).

Table 1. Descriptive Statistics for the Data

Periods	Obs	Min	Max	Mean	Med	Std dev	Skew.	Kurt.
Pre-Crisis	2165	-0.1488	0.1498	0.0011	0.0005	0.0252	0.4668	4.216
Within	647	-0.1377	0.1538	-0.0001	-0.0006	0.0328	0.1529	2.134
Post-crisis	2165	-0.0897	0.0969	0.0001	0.0002	0.0195	-0.0071	1.716

4.2. GARCH Model Results

Table 2 shows the various GARCH results for the pre-financial crisis sub-period, where the asymmetric GJR-GARCH (1, 1) model was the best fit based on the smallest AIC and BIC and the highest log likelihood. The parameters α_1 and β_1 are positive $(\alpha_1 + \beta_1)$ 0.9766 and is less than one. This shows that the data is stationary and there was a higher volatility in the JSE mining index before the financial crisis. The asymmetric GJR-GARCH (1, 1) is the best, being the one with desired characteristics (AIC and BIC, log likelihood), compared to EGARCH model. The parameters Alpha (α), beta (β) and gamma (γ) are all statistically significant at a 5% level of significance. In addition, the autocorrelations and the ARCH effect observed in the squared residuals as the lags increases were removed.

Table 2. Pre-crisis results for AR1-GARCH models

	AR1-GARCH(1,1)		AR1-EGARCH(1,1)		GJR-GARCH(1,1)	
	Estimate	**p-value**	**Estimate**	**p-value**	**estimate**	**p-value**
Mu	0.0013	0.0041	0.0008	0.0033	0.0009	0.0041
Ar1	0.0577	0.0188	0.0607	0.0041	0.0576	0.0188
Omega	0.0000	0.3991	-0.0217	0.0001	0.0000	0.3991
Alpha1	0.0409	0.0000	-0.0288	0.0389	0.0225	0.0000
Beta1	0.9535	0.0000	0.9965	0.000	0.9541	0.0000
Gamma	-----	--------	0.0975	0.0000	0.0412	0.0048
AIC	-4.6966	-------	-4.6947	------	**-4.7044**	-------
BIC	-4.6835	-------	-4.6789	--------	**-4.6887**	-------
Log	5089.650	-------	5087.999	--------	**5098.864**	------
	GARCH(1,2)		**EGARCH(1,2)**		**GJR-GARCH(1,2)**	
Mu	0.0012	0.0092	0.0008	0.1117	0.0008	0.0606
Ar1	0.0565	0.0129	0.0596	0.0756	0.0569	0.0196
Omega	0.0000	0.1153	-0.0248	0.1316	0.0000	0.6001
Alpha1	0.0519	0.0000	-0.0321	0.0425	0.0273	0.0820
Beta1	0.6661	0.0000	0.8401	0.0000	0.7460	0.0000
Beta2	0.2745	0.0000	0.1560	0.0000	0.1992	0.0000
Gamma	-----	--------	0.1122	0.0001	0.0483	0.0123
AIC	-4.6961	-------	-4.6938	------	-4.7037	-------
BIC	-4.6804	-------	-4.6754	--------	-4.6853	-------
Log	5089.570	-------	5088.052	--------	5098.737	------

Table 3. Within-Crisis Results for AR1-GARCH (1, 1) Models

	AR1-GARCH(1,1)		AR1-EGARCH(1,1)		GJR-GARCH(1,1)	
	Estimate	**p-value**	**Estimate**	**p-value**	**estimate**	**p-value**
Mu	0.0010	0.3264	-0.0000	0.9988	-0.0000	0.9822
Ar1	0.0273	0.4158	0.0208	0.5246	0.0268	0.4277
Omega	0.0000	0.6411	-0.0646	0.0000	0.0000	0.7534
Alpha1	0.0878	0.0000	-0.0994	0.0000	0.0000	0.9989
Beta1	0.9033	0.0000	0.9912	0.0000	0.9412	0.0000
Gamma	-----	--------	0.0901	0.0000	0.1141	0.0005
AIC	-4.2703	-------	**-4.3020**	------	-4.2911	-------
BIC	-4.2358	-------	**-4.2605**	--------	-4.2496	-------
Log	1386.453	-------	**1397.699**	--------	1394.165	------
	GARCH(1,2)		**EGARCH(1,2)**		**GJR-GARCH(1,2)**	
Mu	0.0010	0.3802	-0.0000	0.9856	-0.0000	0.9777
Ar1	0.0273	0.4308	0.0208	0.5253	0.0268	0.4260
Omega	0.0000	0.8548	-0.0641	0.0232	0.0000	0.7353
Alpha1	0.0872	0.0094	-0.0982	0.0000	0.0000	0.9998
Beta1	0.9039	0.2554	1.0000	0.0000	0.9415	0.0000
Beta2	0.0000	1.0000	-0.0087	0.0343	0.0000	0.9998
Gamma	-----	--------	0.0890	0.0000	0.1134	0.0002
AIC	-4.2660	-------	-4.2975	------	-4.2869	-------
BIC	-4.2245	-------	-4.2491	--------	-4.2385	-------
Log	1386.045	-------	1397.236	--------	1393.8	------

In addition, Table 3 shows the financial crisis results where the asymmetric EGARCH (1, 1) model was the best fit model (considering the model selection criteria). The leverage term represented by the gamma coefficient showed a positive sign which violated the expected negative sign of leverage term under EGARCH. As α_1+γ<0, the EGARCH (1 1) model was rejected in favour of the GJR-GARCH (1 1). The parameters α_1 and β_1 under GJR-GARCH (1 1) are positive, statistically significant, and close to unity $(\alpha_1 + \beta_1$ =0.9412). This showed that there is a higher volatility clustering in the JSE mining index within the financial crisis but the volatility is less than the pre-crisis period. The gamma is statistically significant with an appropriate positive sign. The autocorrelations and ARCH effect present in the squared residuals were removed and, as a result, the model is of good fit.

Table 4 revealed that the symmetric GJR-GARCH (1, 1) model was the best fit in a post-financial crisis. The parameters α_1 and β_1 were positive and significant as $\alpha_1 + \beta_1$=0.9733. This showed that there was a higher volatility clustering in the JSE mining index (post-crisis) and the model was stationary. The asymmetric GJR-GARCH (1, 1) model was the best fit compared to the EGARCH model, by comparing the model with the smallest AIC and BIC and the highest logarithm. The parameter Alpha was significant but negative as shown in Table 3, while beta and gamma were positive and statistically significant at 5% level of significance. After fitting the model, autocorrelations and ARCH effect were checked to ensure that the model was of good fit.

Table 4. Post-Crisis Results for AR1-GARCH (1, 1) Models

	AR1-GARCH(1,1)		AR1-EGARCH(1,1)		GJR-GARCH(1,1)	
	estimate	p-value	estimate	p-value	estimate	p-value
Mu	0.0002	0.5024	-0.0000	0.6166	-0.0000	0.9582
Ar1	0.0187	03555	0.0187	01476	0.0209	02850
Omega	0.0000	05754	-0.0362	0.0000	0.0000	0..9192
Alpha1	0.0389	0.0026	-0.0382	0.0000	0.0027	0.9700
Beta1	0.9531	0.0000	0.9954	0.0000	0.9706	0.0000
Gamma	-----	--------	0.0511	0.0000	0.0425	0.0041
AIC	-5.1958	-------	-5.2024	------	**-5.2044**	-------
BIC	-5.1827	-------	-5.1866	--------	**-5.1886**	-------
Log	5629.505	-------	5637.558	--------	**5639.745**	------
	GARCH(1,2)		**EGARCH(1,2)**		**GJR-GARCH(1,2)**	
Mu	0.0002	0.5023	-0.0000	0.8378	-0.0000	0.9125
Ar1	0.0186	0.3574	0.0200	0.3106	0.0210	02815
Omega	0.0000	0.3056	-0.0363	0.0275	0.0000	0.1948
Alpha1	0.0389	0.0000	-0.0381	0.0000	0.0028	06348
Beta1	0.9526	0.0000	1.0000	0.0000	0.9683	0.0000
Beta2	0.0004	0.8074	-0.0046	0.0239	0.0024	0.1448
Gamma	-----	--------	0.0509	0.0000	0.0424	0.0000
AIC	-5.1949	-------	-5.2013	------	-5.2034	-------
BIC	-5.1791	-------	-5.1830	--------	-5.1850	-------
Log	5629.461	-------	5637.45	--------	5639.683	------

The results revealed the presence of volatility clustering and a leverage effect in all sub-periods. The summation of parameters (α_1, β_1) was less than 1 and this showed that the volatility was higher and the leverage effect was indicated by parameter $\hat{\gamma}$ (Brooks, 2008; Tsay, 2010). Based on summation of (α_1, β_1), the volatility was higher in a pre-crisis period (0.9766), followed by the crisis period (0.9412) and the post-crisis period (0.9733) respectively. The positive sign and statistical significance of $\hat{\gamma}$ in the three periods showed that the leverage effect existed, consequently the negative shocks will have a larger impact on conditional variance than positive shocks of a similar magnitude.

5. Concluding Remarks

The main focus of this article was to assess the volatility in the Johannesburg Stock Exchange (JSE) index especially in the general mining sector by using symmetric and asymmetric GARCH models. The data used was the daily closing prices for the Johannesburg Stock Exchange index in general mining. The data was divided into three sub-data sets to account for financial crises. The asymmetric GARCH models were the best models to fit the return series data throughout. This is consistent with the findings of Oberholzer et al. (2015) where the asymmetric GJR-GARCH model was the best fit for four of the five JSE/FTSE stock indices in full sample and during financial crises. The selection of the asymmetry models in all sub-periods suggested that the negative shock caused volatility to increase by more than a positive shock of similar magnitude pre- during- and post crises periods. In this context, the leverage effect was found to be a common feature of the SA general mining index. This is consistent with the findings of Makoko & Muzindutsi (2018) where the JSE All Share index was found to be characterized by the leverage effect. This suggests that mining index tend to portray the behavior of the overall JSE which affirms the importance of the mining sector in the development of the South African equity market.

The GJR-GARCH (1, 1) model was found to be the best model for modelling the JSE general mining index. The same asymmetry model was selected between crisis and other periods, however, the magnitude of volatility was found to be different across the three sub-periods. The results revealed that the level of volatility varied across the three periods with the highest reported pre-crisis and the lowest volatility during crises. This finding correlated with that of Mwamba et al. (2017) where the levels of volatility differ over three sub-periods. The results suggested that the level of volatility decreased significantly during a crisis, but began to rise after a crisis, although it failed to rise to the pre-crisis level.

In principle, the magnitude of the asymmetry term is usually not similar across three sub-periods. Such variation suggested different reactions of investors to new information. The fluctuation in volatility showed that the 2008 financial crisis affected JSE mining investors' attitudes towards overall risk. Hence, future research can explore whether this effect of financial crisis on investors' attitudes towards risk was only limited to the mining sector or it was the same across all JSE sectors.

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