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The Relationship between Stock Market Volatility and Trading Volume: Evidence from South Africa

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Abstract

This paper revisits the relationship between equity trading volume and returns volatility for the Johannesburg Stock Exchange (JSE) of South Africa using daily data over the period of 6th July 2006 to 31st August 2016. Further, we analyzed an after-crisis period, i.e., 1/04/2008 to 8/31/2016, in order to verify the findings immediately after the sub-prime crisis. EGARCH and Granger causality models were employed to analyse the volume-volatility relationship. Also the level of volatility persistence has been compared before and after the inclusion of trading volume in the volatility model as an exogenous variable. The analysis shows that the JSE exhibits volatility asymmetry implying that the return volatility responds more to the bad news than the good news. The relationship between trading volume and market volatility is found to be positive and contemporaneous supporting the mixture of distribution hypothesis. But lagged volume is found to be statistically insignificant in explaining volatility. We also uncover that the volatility persistence remains high even after the inclusion of trading volume as an explanatory variable in the volatility model. The above set of results also holds for the post-crisis sub-sample. Furthermore, the pairwise Granger causality tests indicate a feedback relationship between volume and volatility only in the case of the sub-sample. But for the full sample we find a unidirectional causality between volume and volatility, with trading volume Granger causes market volatility.

JEL Codes: G110, G120, C580.
Keywords: Asymmetric volatility, Trading volume, EGARCH, South Africa, Volatility persistence.

1. Introduction

Research on market volatility has been a central theme in the finance literature. Within the context of market volatility, another much debated issue in the domain of finance literature is whether rate of information flows into the market have any role in generating market volatility. If the argument of efficient market hypothesis (EMH) put forwarded by Fama (1970) to be believed then the rate of information flow in a competitively traded stock market would not help to predict the stock returns and its volatility. The EMH claims that an efficient market already incorporates

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the available information and therefore investor would not able to make abnormal returns. However, it is reasonable to believe that once the available information is well understood the smart and clever investors can able to predict the market movement. Several studies empirically provide the belief that stock market volatility can be predicted by the available information. But quantifying the rate of information flow is merely difficult. Nonetheless, many scholars believe that *trading volume* can be considered as a proxy for the arrival of information flow into the market. It is argued that trading volume may be higher on the day with larger return innovations and releases of any public information, which eventually may cause the price movements (Clark, 1973; Lamourex and Lastrapes, 1990; Andersen, 1996). Thus, a considerable attention has been given by several scholars to examine the relationship between market volatility and trading volumes. Investigation of this type provides us the idea that how new information impounded in stock prices. The theoretical underpinning of volume-volatility relationship may be directly borrowed from *Mixture of Distribution Hypothesis* (MDH) introduced by Clark (1973), or *Sequential Information Arrival Hypothesis* (SIAH) developed by Copeland (1976).

The MDH postulates that the innovation on returns is a linear combination of the intraday return movements. The intraday return increment incorporates the number of information flows arrived into the market in a given day. Since the intraday price movement is random, daily returns follow a mixture of normally distributed random variables with the information flow into the market as a mixing variable. To sum this up, daily price changes are driven by a set of information flow and the arrival of unexpected news is accompanied by the above average trading activity. This argument was subsequently supported by Epps and Epps (1976), Tauchen and Pitts (1983), Harris (1986), Lamoureux and Lastrapes (1990). The MDH implies a positive contemporaneous relationship between trading volume and equity return volatility. On the other hand, the SIAH of Copeland (1976) questions the instantaneous relationship as predicted by MDH and provides a different explanation. It argues that each trader observes the information signal differently at time and the information may not receive simultaneously, thereby generating a series of incomplete equilibria. Market equilibrium can be established provided that all traders receive same set of information simultaneously. Thus, the shift of new information is not immediate as considered in Clark (1973). Nevertheless, both MDH and SIAH believe that the price volatility of the market can be potentially predictable through the knowledge of trading volume, and that the relationship of volume and volatility is positive.

Yet another empirical issue was emerged within the research on volume-volatility relationship after Lamoureux and Lastrapes (1990) examined volume-volatility relationship for 20 actively traded stocks in the US market from 1980 to 1984. Under the assumption that volume is the mixing variable, they included the contemporaneous trading volume as an exogenous variable in the conditional volatility equation. They found a positive relationship between volume and volatility providing strong support to MDH. The empirical debate started after they conclude that the persistence of volatility shocks vanishes once the trading volume included in the volatility equation as an exogenous variable. This conclusion tempts scholars to empirically verify in

several empirical studies relating to the volume-volatility relationship. The empirical findings are at large mixed. The basic objective of the present work is to revisit and verify the aforementioned arguments considering recent data from equity market of an emerging market economy, namely South Africa.

To the best of our knowledge, investigation of this kind has not been done for the South African stock market. For our purpose, we consider recent daily data spanning from 6/07/2006 to 8/31/2016. Research on modeling and forecasting South African stock market volatility has been restricted to primarily univariate models (see, Babikir et al., (2012), Katzke and Garbers (2015), and Kgosietsile (2015) for detailed literature reviews in this regard), barring few cases. First is the work by Chinzara (2011), that analayzed the relationship between macroeconomic and stock market volatilities. The findings show that, volatilities in inflation, gold, and oil prices seem to be less important than the volatility in short-term interest and exchange rates. Then Fedorova et al., (2014) and Cakan and Gupta (2016) respectively looks at the importance of European and US macroeconomic news on South African stock returns volatility, with the former study also looking at the markets of Colombia, Indonesia, Vietnam, Egypt, and Turkey (i.e., the CIVETS). Finally, Balcilar et al., (forthcoming) analyzed the importance of geopolitical risks on the volatility of the South African equity market while analyzing the BRICS countries, i.e., Brazil, Russia, India, China and South Africa.

The paper proceeds as follows: Section 2 presents a review of some of the related literature in this area. The data and empirical methodology are presented in section 3. Section 4 devotes the discussion of empirical findings and finally section 5 concludes the study.

2. Review of Earlier Literature

As mentioned above the theoretical arguments regarding the impact of trading volume on equity market volatility can be understood from the mixture of distribution hypothesis and sequential information arrival hypothesis. A plethora of early research studies attempted to test the nature of volume-volatility relationship and tried to verify these theories. Andersen (1996) produced a modified version of MDH and tested it for five major stocks on the New York Stock Exchange over the period of 1973 to 1991. Their results supported the MDH. Similarly, Gallo and Pacini (2000) investigated this relationship using data of 10 actively traded US stocks for the period of 1985 to 1995 and found that the volatility persistence decreased when the trading volume is included in the volatility equation. Brailsford (1996) examined the volume-volatility relationship for Australian stock market using daily data from the period of 1989 to 1993 and found a positive relationship between these two. He also found that the level of persistence decreases significantly when trading volume was included in the volatility model. Similar finding was seen in Pyun *et* al. (2000) who investigated this relationship for the Korean stock exchange for the period of 1990-1994. Bohl and Henke (2003) investigated this relationship using daily data for 20 Polish stocks listed in the Warsaw Stock Exchange for the period of 1999 to 2000 and found that inclusion of trading volume in the volatility equation reduces the volatility persistence of most of the cases. However, while their findings show strong support in favour of MDH, their

findings also show that the inclusion of trading volume do not produce significant effect on five stocks under investigation. Wang *et* al. (2005) investigated the dynamic relationship between stock return volatility and trading volume for the individual stocks listed in the Chinese stock market. They also documented that the volume effect was positive and significant and the inclusion of trading volume reduced the level of volatility persistence although the GARCH effect was not completely vanished. Alsubaie and Najand (2009) used market indices and firm level daily data for 15 individual firms listed in the Saudi stock market from the period of 1993 to 2005 to test the effect of trading volume on volatility persistence on the conditional volatility model. Their results revealed that with the inclusion of trading volume the persistence level decreased for some of the market indices but not all. However, the results for firm level data indicated that the persistence level is highly decreased for all the firms. Choi *et* al. (2012) investigated the volume-volatility relationship in Korean stock market using daily data for the period of 2000 to 2010 and documented a positive relationship between volume and volatility supporting the MDH.

On the other side, there is strand of literature that document little evidence on the effect of trading volume on volatility persistence. For example, Sharma *et* al. (1996) tested for ARCH effect in the stock market return using daily data of New York stock exchange for the period of 1986 to 1989. Their results indicate that trading volume has not able to diminished the volatility persistence completely although trading volume influenced the return volatility positively. Using daily price and volume data of Treasury bond future market over 1984-1989, Najand and Yung (1991) also documented that the level of volatility persistence remain high even after the inclusion of trading volume as an exogenous variable in the volatility model. Huang and Yang (2001) examined the mixture of distribution hypothesis using intraday (5min) data over a period of 1989 to 1993 for Taiwan Stock Exchange. Their findings do not support the MDH and revealed that there was little difference in the volatility persistence before and after inclusion of trading volume as an exogenous variable. Similar findings were documented by Ahmed *et* al. (2005) for Kuala Lumpur Stock Exchange using daily data over a period of 1990 to 2000. However, they found a positive and significant effect of trading volume on the conditional volatility. Darrat *et* al. (2003) investigated it for US stock Market using 5min interval data from the period of April 1, 1998 to June 30 1998. The authors documented a positive correlation between trading volume and volatility for only three out of thirty stocks under investigation. The other twenty seven stocks exhibited no significant correlation. However, they found a lead-lag relation in a large number of stocks. Their findings did not support MDH rather they support SIAH. Pati and Rajib (2010) examined the volume volatility relationship in the Indian Future market and documented that both contemporaneous and lagged trading volume can reduce the volatility persistence but the GRARCH effect do not vanish completely.

Mahajan and Singh (2009) examined the empirical relationship between volume and volatility dynamics using daily data of BSE Sensex of Indian stock market over the period from 1996 to 2006. Their findings support MDH but show that volatility persistent remains significant. Using national equity indices of five developed (G5) markets for the period ranging 2008 to 2010

Sabbaghi (2011) also found that trading volume fails to eliminate the volatility persistence in the aggregate equity index of G5 returns data. Naik and Padhi (2014) investigated the asymmetric volatility and trading volume in the Indian equity market using daily data from January 1997 to May 2013. Their finding supports the validation of MDH but show that GARCH effect remains significant even after the volatility model included the trading volume. Similar findings were documented by Naik and Padhi (2015) who examined the volume volatility relationship for Brazil, Russia, India and China (BRIC) over a sample period from 2008 to 2013.

Our analysis is thus, an extension of the work of Naik and Padhi (2015), discussed above, in the sense that by looking at South Africa in this paper, we complete the analysis for all the BRICS (Brazil, Russia, India, China and South Africa) countries. The BRICS countries have grown rapidly and have become more integrated with the developed world in terms of trade and investment. They account for more than a quarter of the world's land area, slightly less than a half of the world's population, and about one sixts of the world's GDP (Mensi et al., 2014). Understandably, given the financial dependence in the modern globalized world, the current and potential growth of the BRICS countries has important implications for the capitalization of the international equity markets. The BRIC countries are expected to account for more than 40% of the global stock market capitalization by 2030, with China overtaking the United States in equity market capitalization (Mensi et al., 2014). Recently, several studies (see for example Mensi et al., 2014; 2016 and references cited therein), have added South Africa into the BRIC group. This is because of the fact that South Africa has also a fast-growing economy,[1] with rapid financial market development and sophistication. In addition, South Africa is also one of the world's largest exporters of some strategic commodities that include coal, chrome, gold, and iron.[2] Thus, the inclusion of South Africa into the BRICS group provides investment diversification opportunities and, hence, deserves a separate analysis along with the other four members of the BRICS, already dealt with by Naik and Padhi (2015).

3. Data and Empirical Methods

Daily data of closing prices and trading volumes of Johannesburg Stock Exchange (JSE) for the period from 6th July 2006 to 31st August 2016 have been extracted from Google Finance, with the start and end dates being purely driven by data availability on the two variables of interest. The JSE is the largest stock exchange in the African subcontinent and stands the 19th largest stock exchange in the world. In addition, it is ranked 1st in the world in terms of regulation of security exchanges. In order to test the relationship between trading volume and stock return volatility in the post US Sub-prime crisis the study also considered the sub sample period from

[1] South Africa was growing over 5% during 2005 to 2007 until the global financial crisis hit the economy resulting in negative growth rates. But the economy has now revived and growing over 2%.

[2] Though, diamond and gold production may now be well down from their peaks, South Africa is still the sixth in gold production. It is the world's largest producer of chrome, manganese, platinum,vanadium and vermiculite. It is the second largest producer of ilmenite, palladium, rutile and zirconium. It is also the world's third largest coal exporter. South Africa is also a huge producer of iron ore, with it overtaking India in 2012 to become the world third biggest iron ore supplier to China - the world's largest consumer of iron ore. Further details can be found at: https://en.wikipedia.org/wiki/Mining_industry_of_South_Africa.

2008 to 2016. Thus, sample has been sub divided into full sample i.e., 6/07/2006 to 8/31/2016, and sub sample i.e., 1/04/2008 to 8/31/2016. We extracted daily data of FTSE/JSE All Share Index (ALSI) which covers 99 percent of the market capitalization. The daily price indices are then converted into log returns as $RT_t = LnP_t - LnP_{t-1}$, where, RT_t represents stock returns at time t; and P_t and P_{t-1} represent daily closing price indexes at two successive days, t and t-1. Number of share traded has been used as a proxy to incorporate the rate of information flow into the market. Similar approach has been adopted by several previous studies (See Lamoureux and Lastrapes, 1990; Brailsford, 1996; Gallo and Pacini, 2000; Darrat, Rahman and Zhong, 2003; Alsubaie and Najand, 2009; Sabbaghi, 2011 among others). Previous studies have shown the existence of deterministic time trends, both linear and nonlinear, in the volume data (see for example, Gallant et al., 1992; Chen et al., 2001; Gebka, 2012). To control for these trends, and following Gebka and Wohar (2013), we use a detrended measure of volume. Specifically, we consider the natural log of the volume series and remove its trend by regressing it on a constant, *(t/T)* and $(t/T)^2$, where *T* is the total sample size. Then the residual (*e*) of the following regression is considered for the further analysis:

$$\ln(volume) = a + b(t/T) + c(t/T)^2 + e \tag{1}$$

We employ the EGARCH model developed by Nelson (1991) to test whether the return series exhibits volatility asymmetry. Not to be mentioned the advantages of EGARCH model over other volatility model as it explains the leverage effects and the log transformation of conditional variance series guarantee that the forecast of conditional variance is positive. The estimated model has been specified as follows.

$$\begin{aligned} &RT_t = \mu_t + RT_{t-1} + \varepsilon_t \\ &where\ \varepsilon_t = Z_t\sqrt{h_t}\ \ and \\ &\log(h_t) = \omega + \alpha\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \beta\log(h_{t-1}) + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) \end{aligned} \tag{2}$$

The γ coefficient in this model suggests the presence of volatility asymmetry. If this coefficient is statistically different from zero and negative then we can conclude that the bad news or the negative ε_{t-1} generates more volatility than the good news or a positive return shock i.e., a positive ε_{t-1} does. The magnitude of β coefficient provides the degrees of volatility persistence.

The mixture of distribution hypothesis predicts that the GARCH effects would negligible once captured the rate of information flow into the market. Supporting this view Lamoureux and Lastapes (1990) empirically found that the GARCH effects disappear once the volatility model incorporates the rate of information flow arrived into the market. Trading volume has been used as a proxy for rate of information flow. Thus, the EGARCH model has been extended by

incorporating the instantaneous trading volume as an exogenous variable in the variance equation. The specified model therefore becomes as follows.

$$RT_t = \mu_t + RT_{t-1} + \varepsilon_t$$
$$where\ \varepsilon_t = Z_t\sqrt{h_t}\ and$$
$$\log(h_t) = \omega + \alpha\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \beta\log(h_{t-1}) + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \theta Volume_t \tag{3}$$

Najand and Yung (1991), on the other hand, have questioned the strict exogeneity of instantaneous trading volume in the mixture of distribution hypothesis and therefore suggested the lagged trading volume to be included as the exogenous or the predetermined variable in the volatility model rather than the instantaneous trading volume. This led us to also estimate the following variance equation

$$\log(h_t) = \omega + \alpha\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \beta\log(h_{t-1}) + \gamma\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \theta Volume_{t-1} \tag{4}$$

In order to test whether trading volume causes volatility or vice-versa, the following Granger causality models for full sample as well as sub-sample have been tested. To do so we first generated the variance series from our estimated EGARCH (1, 1) model and conducted the Granger causality model. The estimated Granger causality model has been represented in a Vector Autoregression framework as follows.

$$\text{Volatility}_t = \alpha_1 + \sum_{i=1}^{p}\beta_{1i}\text{Volatility}_{t-i} + \sum_{i=1}^{p}\gamma_{1i}\text{Volume}_{t-i} + \varepsilon_1$$
$$\text{Volume}_t = \alpha_2 + \sum_{i=1}^{p}\gamma_{2i}\text{Volume}_{t-1} + \sum_{i=1}^{p}\beta_{2i}\text{Volatility}_{t-i} + \varepsilon_2 \tag{5}$$

where, α_1 and α_2 are the intercepts, β and γ are the parameters to be estimated, and ε_1 and ε_2 are the white noise error terms, *p* denotes the lag lengths. In these equations equity trading volume Granger causes volatility if either γ_{1i} are jointly significant by testing the null hypothesis that H_0: $\gamma_{11}=\gamma_{12} = \ldots = \gamma_{1p} = 0$. Similarly, volatility Granger causes volume if either β_{1i} are jointly significant.

4. Results and Discussion

The distribution properties of daily return series can be observed from the descriptive statistics presented in table 1. This table presents the summary statistics of our two important variables trading volume and daily closing price index. The detrended volumes and log returns have also been presented in the same table. It can be observed from first panel of the table that the mean value of closing price and trading volumes are positive. However, after the removal of trend in volume the mean value of trend turned to be negative. The standard deviation values are also

indicates that the stock prices and volumes are highly deviated from the mean value. Both the values of skewness and kurtosis indicate non normality of the underlying variables, which have been supported by the highly significant Jarque-Bera statistics. Similar observation can be made from the descriptive statistics of the subsample. However, in this case the mean values of both detrended volume and log return are turned to be positive implying that the price series and the trading volume have increased over time.

In order to establish whether the time series variables are stationary or not the standard procedure of unit root test have been conducted. Table 2 presents results of three unit root tests such as Augmented Dickey Fuller (ADF), Phillips- Perron (PP) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The results show that that both log return and detrended volumes are stationary at level. The results are similar for both full sample and sub-sample.

Table 1: Descriptive Statistics

	Closing Price	Trading Volume	Volume (De-trended)	Ln Returns
Full Sample (6/07/2006 to 8/31/2016)				
Mean	8079.104	226516.2	-0.002	0.0007
Median	7330	139879	0.022	0.000
Maximum	18502	3095788	3.171	0.139
Minimum	1975	1664	-4.470	-0.105
Std. Dev.	3162.879	285071.2	1.042	0.018
Skewness	1.069	3.992	-0.344	0.308
Kurtosis	4.015	26.716	3.763	8.991
Jarque-Bera	597.095***	66721.74***	112.726***	3863.696***
Obs.	2557	2557	2557	2556
Sub Sample (1/04/2008 to 8/31/2016)				
Mean	8474.037	212025.1	0.013	0.0002
Median	7445	135451	0.044	0.000
Maximum	18502	2874997	3.171	0.109
Minimum	3660	1664	-4.374	-0.105
Std. Dev.	3164.536	252679.1	1.009	0.017
Skewness	1.125	3.874	-0.325	0.001
Kurtosis	3.710	26.227	3.742	7.637
Jarque-Bera	501.702***	54011.04***	87.936***	1937.477***
Obs.	2162	2162	2162	2162

Note: *** indicates statistically significant at 1 percent level.

Table 2: Unit Root Tests for Stationary

Full Sample (6/07/2006 to 8/31/2016)			
Tests	Ln Returns	Volume (De-trended)	Critical Value at 0.01
ADF	-32.66***	-14.72***	-3.43
PP	-46.57***	-48.79***	-3.43
KPSS	0.127	0.222	0.739
Sub Sample (1/04/2008 to 8/31/2016)			
ADF	-42.49***	-13.59***	-3.43
PP	-42.57***	-43.12***	-3.43
KPSS	0.279	0.374	0.739

Note: *** indicates statistically significant at 1 percent level.

EGARCH (1, 1) model has been estimated in three different specifications. The specification we estimate the volatility model without incorporating the trading volume. Estimating this specification enable us to know whether the Johannesburg Stock Exchange exhibits volatility asymmetry. After confirm so we next move towards estimating the second specification of our volatility model with augmenting the trading volume as an exogenous variable in the volatility model. Further, as discussed above, we consider the contemporaneous trading volume and lagged trading volume separately and analyze their effects. The analysis has been done for full sample (6/07/2006 to 8/31/2016) as well as sub sample (1/04/2008 to 8/31/2016). The results of full sample are reported in table 3.

From table 3 second column, which provides the results of EGARCH model without considering trading volume, it can be observed that the γ parameter representing the volatility asymmetry shows the expected negative sign and highly significant. This implies that effects of negative return shocks are higher than that of positive return shocks as postulated by the leverage effect hypothesis. The α parameter is also positive and statistically significant at 1 percent level implying that once the asymmetric impact is accounted for, the absolute size of innovation is also important. Further the significant and positive coefficient of β indicates the significant GARCH effects. Its value in magnitude is close to 1 indicating high level of volatility persistence. Other diagnostic tests, such as, the statistically insignificant Q(36) and $Q^2(36)$, the statistically insignificant ARCH LM (36) confirm the specification of the model.

Now, turning to column 3 & 4 of table 3 that reports the volume augmented volatility results, similar results have been observed. In this case, the volatility model has been reestimated by incorporating the contemporaneous and lagged volumes in the spirit of Lamoureux and Lastrapes (1990) and Najand and Yung (1991). While doing so we were trying to verify the postulation of mixture of distribution hypothesis (MDH) and sequential information arrival hypothesis (SIAH). Our findings, as reported in table 3, clearly show that the coefficient of θ, which represents the

contemporaneous trading volume, is found to be positive and statistically significant at 5 percent level. Though the lagged volume is coming up with a positive sign it is statistically insignificant at the usual level of significance. Thus this findings support the argument of mixture of distribution hypothesis (MDH). Our finding is consistent with the findings of earlier studies such as Lamoureux and Lastrapes (1990), Anderson (1996), Brailsford (1996), Bohl and Henke (2003), Wang et al. (2005), Alsubai and Najand (2009), Naik and Padhi (2015), and others.

This finding tempts us to conclude that daily trading volume is an important variable in explaining the volatility dynamics in the South African equity market. However, as can be observed from the results that the level of volatility persistence remains high even after incorporating the trading volume. The volatility persistence has been declined in minutely i.e, only 1 percent, from 99 percent to 98 percent, contradicting with findings with Lamoureoux and Lastrapes (1990). Our finding is consistent with the findings of several recent studies such as Ahmed et al. (2005), Sabbaghi (2011), Mahajan and Singh (2009), Naik and Padhi (2015).

Similar results have been observed from the sub sample (1/04/2008 to 8/31/2016) that presented in Table 4. Concentrating on the variance equation, it is evident that the findings are continuous to support the presence of volatility asymmetry of the JSE. In this case also the contemporaneous trading volume has been positively and highly significantly explaining the stock return volatility. The lagged trading volume is also statistically significant but only at the 10 percent level. However, the effect of contemporaneous trading volume may be considered based on the high log likelihood value and the relatively small value of AIC. The level of volatility persistence remains high even after controlling for trading volume. The results of diagnostic tests such as Q(36), $Q_2(36)$ and the ARCH LM (36) indicate that the model specifications are in good fit.

The presence of volatility asymmetry may be well observed from the estimated EGARCH (1, 1) based news impact curves. The news impact curve due to Engle and Ng (1993) graphically represents the impact of positive and negative shocks on volatility. The news impact curves generated from the estimated volume augmented EGARCH (1, 1) model for full sample and sub-sample have been presented in Figure 1 and 2 respectively. As can be seen a clear evidence of volatility asymmetry in response to positive shocks (good news) and negative shocks (bad news) are found. Stock return volatility in JSE responds quickly to the bad news than the good news in the sample period under consideration.

Table 5 reports the results of pair wise Granger causality test at lag 3. The findings indicate that the null hypothesis that "*Volume does not Granger Cause Volatility*" has strongly rejected for both full sample as well as sub-sample. The other null hypothesis that "*Volatility does not Granger Cause Volume*" cannot be rejected at the usual 5 percent level in case of full sample, but, in case of sub-sample it is rejected. Thus, it can be concluded from these results that a feedback relationship between volume and volatility has been observed only after the crisis period. So in general, our results are in line with those obtained by Naik and Padhi (2015) for the

BRIC countries, thus, validating the association of these five emerging countries grouped as the BRICS.

Table 3: Result EGARCH (1, 1) Full Sample

Variables /Parameters	Without Trading Volume	With Trading Volume Augmented	With Lagged Trading Volume Augmented
	Mean Equation		
μ	0.0006	0.0006	0.0006
	[2.294]**	[2.275]**	[2.285]**
RT_{t-1}	0.061	0.063	0.062
	[3.290]***	[3.353]***	[3.329]***
	Variance Equation		
ω	-0.155	-0.162	-0.156
	[-11.287]***	[-11.614]***	[-11.400]***
α	0.099	0.098	0.097
	[11.424]***	[11.085]***	[11.077]***
β	0.990	0.989	0.989
	[671.206]***	[657.930]***	[674.471]***
γ	-0.033	-0.033	-0.033
	[-5.912]***	[-5.766]***	[-5.915]***
θ		0.005	
		[2.179]**	
θ_{-1}			0.002
			[0.879]
Volatility Persistence	99%	98%	98%
Log Likelihood	6927.526	6929.033	6927.770
AIC	-5.418	-5.418	-5.417
SBC	-5.404	-5.402	-5.401
HQC	-5.413	-5.412	-5.411
Q(36)	33.22 (0.60)	33.45(0.59)	33.24(0.60)
$Q^2(36)$	45.45(0.13)	46.09 (0.12)	46.07(0.12)
ARCH LM (36)	45.53 (0.13)	46.41 (0.11)	46.15(0.11)
D-W d statistic	1.957	1.960	1.959
Obs.	2555	2555	2555

*Note: *, ** and *** indicate statistical significant at 0.10, 0.05 and 0.01 level respectively; t-statistics are in brackets; AIC: Akaike Information Criterion; SBC: Schwarz Bayesian Criterion; HQC: Hannan Quinn Criterion and ARCH LM: Autoregressive conditional heteroscedasticitic Lagrange Multiplier; D-W d: Durbin-Watson d statistic.*

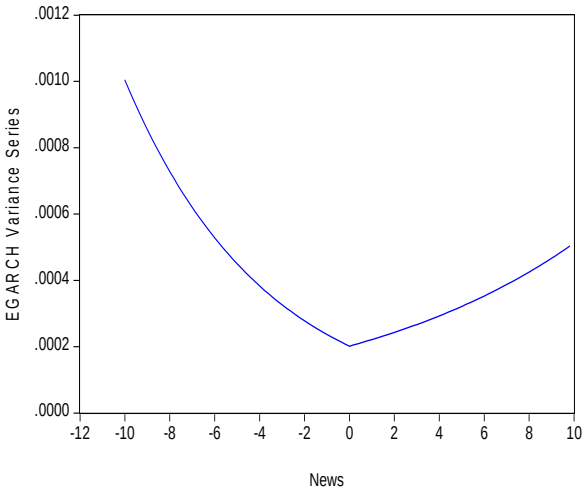

Figure 1: NIC with Trading Volume augmented for Full Sample

Table 4: Result EGARCH (1, 1) Sub Sample

Variables /Parameters	Without Trading Volume	With Trading Volume Augmented	With Lagged Trading Volume Augmented
	Mean Equation		
μ	0.0005	0.0004	0.0005
	[1.676]*	[1.580]	[1.642]
RT_{t-1}	0.043358	0.043	0.044
	[2.110]**	[2.085]**	[2.144]**
	Variance Equation		
ω	-0.202	-0.265	-0.222
	[-6.517]***	[-7.042]***	[-6.721]***
α	0.117	0.126	0.116
	8.857***	[8.711]***	[8.597]***
β	0.986	0.979	0.983
	[326.361]***	[258.646]***	[298.255]***
γ	-0.031	-0.033654	-0.032
	[-4.091]***	[-3.970]***	[-4.143]***
θ		0.013	
		[3.174]***	
θ_{-1}			0.007
			[1.944]*
Volatility Persistence	98%	97%	98%

Log Likelihood	5957.497	5960.898	5958.795
AIC	-5.508	-5.510	-5.508
SBC	-5.492	-5.491	-5.489
HQC	-5.502	-5.503	-5.501
Q(36)	35.016 (0.46)	36.607(0.394)	35.68(0.43)
$Q^2(36)$	39.267 (0.326)	38.377 (0.362)	39.18(0.32)
ARCH LM (36)	37.735 (0.389)	37.205(0.4133)	37.77(0.38)
D-W d statistic	1.912	1.913	1.914
Obs.	2161	2161	2161

Note: *, ** and *** indicate statistical significant at 0.10, 0.05 and 0.01 level respectively. t-statistics are in brackets; AIC: Akaike Information Criterion; SBC: Schwarz Bayesian Criterion; HQC: Hannan Quinn Criterion and ARCH LM: Autoregressive conditional heteroscedasticitic Lagrange Multiplier; D-W d is Durbin-Watson d statistic.

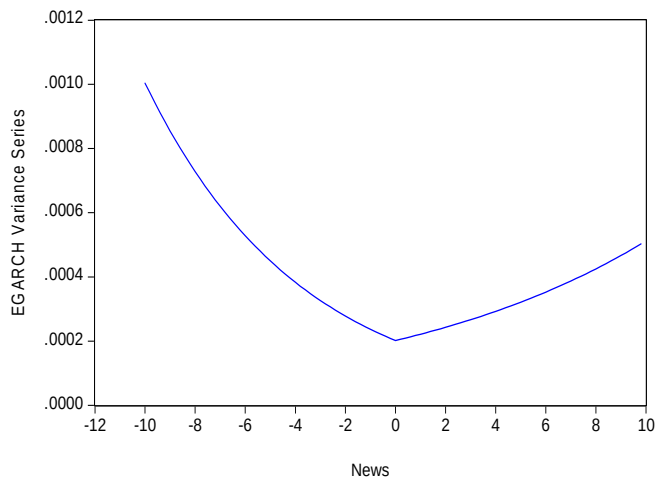

Figure 2: NIC with Trading Volume augmented for Sub Sample

Table 5: Granger Causality between Volume and Volatility at 3 lags

Null Hypothesis	Obs.	F-Stat	Prob.
Full Sample			
H_0: VOLUME does not Granger Cause VOLATILITY	2552	5.615	0.000
H_0: VOLATILITY does not Granger Cause VOLUME		1.675	0.170
Sub Sample			
H_0: VOLUME does not Granger Cause VOLATILITY	2158	7.583	0.000
H_0: VOLATILITY does not Granger Cause VOLUME		3.702	0.011

5. Conclusion

The primary object of the paper was to examine the impact of equity trading volume on return volatility in the South African equity market JSE. While doing so we have reexamined the volume volatility relationship and verify the mixture of distribution hypothesis. We have also tested whether the GARCH effect vanish after incorporating the instantaneous rate of information in the volatility model. To accomplish the research objective daily data of stock index and trading volume in Johannesburg Stock Exchange over a period from 6th July 2006 to 31st August 2016 have been obtained. EGARCH and Granger causality models have been employed for the analysis. The results may be summarized as follows.

First, we confirm that the Johannesburg Stock Exchange exhibits volatility asymmetry implying that equity market volatility respond more quickly to the bad news or negative shocks rather than the good news or positive shocks. This also confirms and supports the conclusion leverage effect hypothesis. *Second,* it was found that the contemporaneous trading volume has a positive and statistically significant impact on equity return volatility implying that trading volume may be one of the important factors in explaining volatility. This finding supports the validity of mixture of distribution hypothesis. However, this study contradict with the conclusion of Lamoureoux and Lastrapes (1990) which states that volatility persistence disappears if the trading volume is incorporated in the volatility model. Our finding shows that the level of volatility persistence remains high even after incorporating the trading volume in the volatility model. Thus, it can be concluded that equity trading volume can provide substantial information for volatility dynamics. However, it may not fully explain the volatility since the GARCH effect remains significant even with the inclusion of equity trading volume as an explanatory variable in the conditional volatility model. *Third,* the Granger causality results indicates that these is a bi-directional relationship between trading volume and volatility only for the sub-sample i.e. sample considered after the sub-prime crisis. For the full sample volume causes volatility was found.

While our analysis provides substantial knowledge about the behavior of the South African stock market, thus benefiting both investors and policy makers, there is scope for further research in this area. The findings from this study are based on the available daily data and a well-established EGARCH model. However, a prospective future study of volume-volatility relationship for this market can be to consider the high frequency intraday or minute-to-minute data by employing some of the recently developed volatility models so as to provide more in-depth conclusions, and also to verify if our results continue to hold.

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