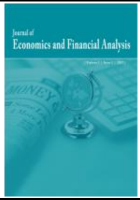
Journal of Economics and Financial Analysis
Type: Double Blind Peer Reviewed Scientific Journal
Printed ISSN: 2521-6627 | Online ISSN: 2521-6619
Publisher: Tripal Publishing House | DOI:10.1991/jefa.v5i2.a46
Received: 06.06.2021 | Accepted: 21.01.2022 | Published: 17.03.2022
Journal homepage: ojs.tripaledu.com/jefa



Country Risk Dynamics and Stock Market Volatility: Evidence from the JSE Cross-Sector Analysis

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Abstract

The rapid integration of the global markets and financial system has increased stock market volatility due to the increased exposure to various risks. Using different GARCH family models, this study investigates the impact of country risk components shocks on stock market return volatility of the Johannesburg Stock Exchange (JSE) and its sectors for the 1996-2018 period. High positive correlations were found among the sectors, which potentially erodes diversification benefits. The research found that the South African stock market volatility is mainly driven by own/internal shocks, while the effect of county risk shocks on stock return volatility differs across the JSE sectors. We found that financial risk shocks negatively transmit to the volatility of oil and gas sector returns, leading to an increase in conditional volatility. Regarding economic risk, we found a statistically significant relationship between economic risk shocks and the entire JSE and financial and oil and gas sectors. The results show that political risk shocks negatively transmit to stock return volatility in the industrial sector, basic materials, consumer goods, financial, and the oil and gas sectors, leading to higher conditional volatility. Thus, the return volatility of most of the JSE sectors is primarily affected by political dynamics, emphasising the role of political instability in destabilising stock market volatility.

Keywords: *Country Risk; Stock Return; Volatility; GARCH Models; JSE, Stock Market Sectors.*

JEL Classification: *D53, E44, G1, L6, I10.*

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1. Introduction

With globalisation, there is a notable increase and broadening of stock markets and international operations, as such, different risk exposures have emerged. Capital markets play a fundamental role in the global economy in assisting firms to raise capital, diversify, gain international presence for investment purposes (Bekiros, Gupta, & Kyei, 2016). From an academic perspective, capital market movements promote the modelling of realistic asset pricing models and enhance market efficiency (Rapach & Zhou, 2013). The rapid integration of the global financial system brought about the increased importance of global stock exchanges. Market integration, on the other hand, introduced different risk exposures to financial markets and economies. For example, continuous stock market adjustment to new information introduces volatility in the market. This volatility is evidenced in the African stock exchanges, which are perceived to be illiquid, more volatile and less developed owing to unstable economic and political environments (Chinzara, 2011). The volatility of stock markets reflects on the future prospects of the firm and the market and as an important indicator to financial practitioners, it helps them in portfolio management, capital budgeting and financing decisions (Bekiros et al., 2016; Suleman, Gupta, & Balcilar, 2017).

The Johannesburg Stock Exchanges (JSE) is one of the oldest surviving stock markets in Africa. Considering market capitalisation, it is the largest and most active exchange on the African continent (Bimha & Nhamo, 2017). The geographic economic data show that since 2013 there has been an increase in volatility of stock price index (measured as a 360-day standard deviation of the return on the national stock market index) on the JSE from 13.38 to 17.94 in 2016 and 14.88 in 2017. Additionally, Gaston et al. (2020) found that the 2008 global financial crisis changed the volatility of the JSE mining signalling a high response of the JSE sectors to global shocks. The volatility on the JSE index is high compared to developed economies standards, such as the USA 11.02; Canada 10.79; Australia 12.43 and India 12.76 in 2017 (Suleman et al., 2017). Thin trading and country-specific risks contribute to index volatility through significant technical imbalances or an imbalance of trade orders in one direction. This has been confirmed by Nhlapho and Muzindutsi (2020) who established the link between country risk components and the JSE all index.

High volatility of the market index points to high levels of uncertainty in the stock price movement and can be linked to various risk factors. Considering risk factors, the political uncertainty eroded business and consumer confidence, including the sentiments on the outcome and possibilities of the controversial land act, which intends to restrict propriety rights for foreigners (Verma, 2014). Unemployment remains high − about 26.7 % in 2017, according to IMF[1]. Inflation also fell into the upper part of the target range (3-6%) and the South African rand counted among the most volatile currencies, fluctuating with up to 8.6 percent against the US dollar between 2017 and 2018. The country also experienced a fall in raw materials prices, decline in Chinese demand and bad harvests that affected the growth of the economy, which averaged 1 percent in 2017 and 2018. Additionally, public debt rose above 50 percent of GDP and a record budget deficit of 4.3 percent was reached in 2017, the highest since 2009. According to the Trade and Development 2018 report[2], FDI decreased by a concerning 41 percent between the years 2016 and 2017. The report points to a decrease in domestic demand as one of the causes of the decline in FDI. South Trade Africa suffers from high crime rates, high civil unrests (demonstrations and strikes) and high levels of corruption. Above all, the lack of precision on policy and structural reforms is also a concern for investors. All these uncertainties may hamper investor potential.

From the efficient market hypothesis perspective, filtration of negative information to market will be reflected negatively on the performance of the market (Fama, 1965). However, on a good note, South Africa has matured markets and a well-developed democratic space that observes the rule of law more than most of the African countries, which makes it more attractive than other African countries (Bimha & Nhamo, 2017). As such, there is a dynamic progression on country risk adjustment. The developments in country risks and stock market volatility poses questions on the sources of volatility. Previous studies (Erb, Harvey & Viskanta, 1996, Arestis, Demetriades & Luintel, 2001, Aye, Gupta, Hammoudeh & Kim, 2015) on stock market volatility show the role of economic fundamentals on market volatility. Numerous studies examined the effect of stock market volatility on real economy and the drivers of stock volatility at firm level. Næs, Skjeltorp, and Odegaard (2011), Beber, Brandt, and Kavajecz (2011) studied the relationship between stock market and real variables such as GDP but the analysis was not extended to assess the contribution and impact of country risk. Moreover, the response of stock market to real variables and country shocks may vary from sector to sector due to differing sector heterogeneity. Existing literature overlooked the role of dynamics and shocks in country risk components on market volatility. More specifically, the relationship between stock market volatility and country risks components for specific JSE sectors has

[1] IMF. Economic indicators Retrieved 12 February 2018 from: http://hdr.undp.org/en/data

[2] Trade, U.N.C.O., & Development. (2018). World Investment Report 2018.

not been investigated. This study contributes to literature by investigating how the shocks in country risk affect the volatility of different stock market sectors in South Africa. In a way, the study also examines which risk components are more detrimental to the development of a stable and efficient stock market.

2. Empirical Literature

In the literature, despite the tremendous importance of forecasting returns and volatility, predicting financial market movements is extremely challenging due to the existence of stochastic and non-linearity (Bekiros et al., 2016; T. Suleman et al., 2017). A wide assortment of non-parametric and non-linear predictive models with a diversity of predictors ranging from international and domestic macroeconomic, financial, institutional behavioural uncertainty have been used (Aye et al., 2015; Rapach & Zhou, 2013; Suleman et al., 2017). There is mixed empirical evidence on the predictability of returns and volatility. Different studies used a variety of proxies for country risk; the relationship between country risk and stock markets was first investigated by Erb et al. (1996). Subsequent studies, including Hassan, Maroney, El-Sady, and Telfah (2003); Bilson, Brailsford, and Hooper (2002); Suleman and Daglish (2015); Suleman et al. (2017) used risk rating agencies like Moody's, Standard and Poor's, Euro-money, Economic Intelligence Unit, Institutional Investor and ICRGs classifications of country risk into political financial and economic risks components.

Erb, Harvey, and Viskanta (1995) used country's credit ratings provided by ICRG and institutional investor banker's survey to examine the association between stock market returns and country risk. They found that countries with higher credit risk command higher expected returns. Erb et al. (1996) analysed the effects of country risk components and found a positive relationship between risk components and returns. The political risk literature was extended by Bilson et al. (2002) by presenting a return variation model incorporating country risk. They found political risk to be an important determinant of return in the Pacific basin and not important for developed markets. For developed markets, economic and financial risk was found to be more important. Using a panel model and European credit ratings, Ramcharran (2003) concludes that economic, political and credit ratings have a significant impact on equity returns in emerging markets. With the use of GARCHM models and ICRG risk ratings, Hassan et al. (2003) showed that country risk shocks transmit to stock market volatility in MEAF emerging markets. Political risk was found to determine stock market volatility in only three out of ten markets analysed. Suleman and Randal (2016) found predictive power of country risk for volatility in emerging markets while Cermeño and Suleman (2014) found significant persistent conditional volatility and confirmed that stock market volatility increases with country risk.

Financial theory reveals that capital market information has a significant bearing on the economy, financial structure and firm behaviour (Hoshi, Kashyap, & Scharfstein, 1991). Volatility has numerous implications for stock markets and the economy at large. It reveals the persistence of risk (Makoko & Muzindutsi, 2018), which brings about volatility clustering; hence, influencing future volatility anticipation in investors (Engle & Patton, 2004). Future volatility anticipation affects investor behaviour. Volatility can be utilised as a risk measurement (Miah & Rahman, 2016); thus high volatility can be taken as a negative market indicator. Above all, volatility can cause a ripple effect or spillover effects, which may result in the increase in return volatility in financial markets, discouraging investment and bringing about uncertainty (Miah & Rahman, 2016). The understanding of the drivers of volatility is therefore paramount in investment analysis.

In the context of country risk, numerous studies (Bilson et al., 2002; Erb et al., 1996; Ramcharran, 2003) examined the interaction of the absolute risk components and stock returns. They found that high country risk economies earn higher equity returns. The role of these risk components shocks and dynamics on the stock market volatility remains unknown. Makoko and Muzindutsi (2018) document that country risk conditions influencing investor confidence have diverging effects on different sectors of the economy. This was confirmed by Gaston et al. (2020) who found varying level of volatility in the JSE mining index. As such, volatility of the market is determined by the sector the market is categorised into. Cermeño and Suleman (2014) highlights that sectors with high trading frequency and investment injections are associated with higher volatility levels. This implies that different risk factors influence different sectors of the market differently.

The motivation of this study is to assess the impact of country risky shocks on stock market volatility in different sectors of the JSE. At the international level, available studies examined country risk on the overall stock markets. Against this backdrop, the present paper contributes to the literature in two ways; first, by examining the role of country risk dynamics and shocks on the volatility of the JSE overall market and secondly, the effects of various components of country risk on different sectors of the South African stock market. The present study extends the existing literature y providing a disaggregated analysis of economic, financial, and political risks on stock return volatility. The research shows how the dynamics, shocks, and changes in country risk affect the volatility of the stock market and different JSE sectors.

3. Empirical Approach

3.1. Data and Variables

This study used monthly observations for a 20-year period from 1996 – the post-apartheid era – to 2018. The data were broadly categorised into seven major sectors of the economy, namely the all share, industrials, basic materials, consumer goods, financials, health care and oil and gas. Stock market data were obtained from the JSE through Bloomberg online financial data base. The continuous returns were estimated from the JSE indices as follows:

$$R_t = ln\frac{P_t}{P_{t-1}} \tag{1}$$

where R_t is return at time t, P_t and P_{t-1} are closing prices at periods t and t-1 respectively.

The study used country risk data developed by the ICRG; previous studies have shown that ICRG data predicts risk better than other risk providers (Bekaert & Hoerova, 2014; Hoti, McAleer, & Shareef, 2005; Howell & Chaddick, 1994). The four risk indices provided by ICRG, namely political risk index, financial risk index, economic risk index and composite index were used. According to Howell (2013), in the ICRG approach, political risk provides an assessment of the country's' political stability. The political environment is assessed through 12 risk components, namely government stability, socio economic conditions, law and order, corruption, internal conflict, investment profile, external conflict, military in politics, ethnic tensions, democratic accountability, religious tensions and bureaucracy quality (Howell, 2011). The economic risk rating assesses the country's economic strength and weakness through economic risk components, namely GDP growth, GDP per capita, inflation and budget balance (Howell, 2013). If the weaknesses are outweighed by the strengths, there is low economic risk, and vice versa (Suleman & Randal, 2016). The financial risk measures the country's ability to service its commercial trade and official debt obligations. The financial risk indicators include foreign debt as a percentage of GDP and exports, current account as a percentage of exports, net international liquidity and exchange rate stability. The lower the risk point the higher the risk (Howell, 2011). The composite index constitutes of the weighted average of the three indices (economic, financial and political risk indices) and is calculated as 0.5 (political risk + economic risk + financial risk) (Suleman et al., 2017).

3.2. Model Specification

To analyse the effect of country risk dynamics on the JSE volatility, the study used the GARCH models (EGARCH, T/GJR-GARCH, GARCHM) for JSE sectors. The ARCH models were introduced by Robert F. Engle (1982) and later generalised by Bollerslev (1986). Following the leptokurtosis and asymmetry associated with stock market data, numerous refinements of these models have been made in modelling the conditional volatility (Hassan et al., 2003). Asymmetric volatility refers to a situation where there is an asymmetric relationship between the volatility of stock returns and past returns (Hentschel, 1995). The GARCH models are mostly preferred to the ARCH models because of the ability to deal with overfitting, constraints and the correlation of squares of residuals associated with the ARCH model (Silvennoinen & Teräsvirta, 2009). The GARCH model allows the conditional variance to be dependent upon previous own lags (Brooks, 2014).

The asset return model (R_t) in the general ARCH/GARCH model is derived as:

$$R_t = \mu + \varepsilon_t \tag{2}$$

where R_t is stock return at time t..

The GARCH models are considered to be better in return modelling because they are more parsimonious and avoid overfitting and are less likely to breach the non-negativity constraints. Using time lags on time subscript of the conditional variance equation, in the simplest form, the conditional variance equation of the general GARCH (p, q) is represented as:

$$\sigma_t^2 = w_0 + \sum_{i=1}^{P} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{3}$$

Where; σ_t^2 is the conditional variance, ε_{t-i}^2 the ARCH term, and σ_{t-1}^2 the GARCH term, $\alpha_1, \alpha_2 \ldots \alpha_P$ are parameters of the ARCH component model, $\beta_1, \beta_2 \ldots \beta_q$ are parameters of the GARCH component model, p is the order of the ARCH component model, q is the order of the GARCH component model, w > 0, α ≥ 0 and β ≥ 0 for the conditional variance σ_t^2 to be positive and stationery.

However, the absolute GARCH (p, q) model has a limitation of ignoring the asymmetry usually observed in analysing the response of stock return volatility to various shocks. The impact of shocks on volatility is asymmetric as the negative shock in the stock price tends to have a higher impact on stock return volatility than a positive shock of the same magnitude (Makoko & Muzindutsi, 2018). Another limitation of the GARCH model is the coefficient restriction (non-negativity constraint) (Hentschel, 1995). Nelson (1991) proposed the exponential GARCH (EGARCH) to solve these shortfalls. EGARCH is a general form of the GARCH model that nests all asymmetric and symmetric GARCH models, which depends on the shifts and rotations in the news impact curve (Hentschel, 1995). The news impact curve indicates the effect of the shocks on the conditional standard deviation (Hassan et al., 2003). The general form of the variance equation for the EGARCH model takes the following form:

$$\mathrm{Ln}(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left[\frac{|\varepsilon_{t-i}|}{\sqrt{\sigma_{t-i}^2}} - \sqrt{\frac{2}{\pi}} \right] + \sum_{i=1}^{p} \gamma_i \frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}^2}} \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2) \tag{4}$$

Where; γ_i represents the leverage effect of ε_{t-i} , γi is expected to be negative since the relationship between return and volatility is negative (Ang, Hodrick, Xing, & Zhang, 2009).

The EGARCH process implies that σ_t^2 is always positive since the model is specified in terms of log of σ_t^2 and there are no restrictions on model parameter signs (Brooks, 2019). The Threshold GARCH (TGARCH) model also account for asymmetry. The TGARCH model, also known as GJR-GARCH, expresses the leverage effect in quadratic form in contrary to the exponential form of the EGARCH (Makoko & Muzindutsi, 2018). Extending from the GARCH the TARCH model has an additional term added to consider possible asymmetries. The conditional variance equation in TGARCH process is expressed as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-i}^2 d_{t-1} \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{5}$$

Where $d_t = 1\ if\ \varepsilon_t < 0; and\ d_t = 0\ otherwise$. When γ>0, the leverage effect exhibits that the negative shocks will have a larger impact on conditional variance than positive shocks.

Given that the stock returns may depend on volatility, the GARCH in mean (GARCH-M) model of Robert F Engle, Lilien, and Robins (1987) has been used in the financial literature to capture the potential relationship between risk (measured by conditional variance of returns) and the time-variant expected returns. The GARCH-M model explains the existence of conditional left skewness observed in stock index returns. This is in line with the volatility feedback effect, which dampens the impact of good news and amplifies the impact of bad news (Tan, 2005). The GARCH-M models the conditional mean as a function of the conditional variance and allows the conditional variance h_t to influence the conditional mean return r_t. Stated formally as:

$$r_t = \psi + \delta h_t + {h_t}^{1/2} \epsilon_{t,} \tag{6}$$

where $\epsilon_t \sim IID(0,1)$.

The presence of h_t in the mean equation (Eq. 6) is termed the volatility feedback effect.

The conditional variance assumed to follow the GARCH (p, q) model:

$$h_t = w + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-i} \tag{7}$$

Where, $u_t = r_t - \psi - \delta h_t \; and \; \omega > 0, \beta \geq 0, and \; \alpha > 0.$

Hassan et al. (2003), in examining the impact of country risk on stock market volatility and predictability, extended the Engle et al. (1987) GARCH-M (q, p) model to allow risk components shocks to influence conditional variance. However, the GARCH (p,q) model does not take into account asymmetry found in stock return volatility. As such, the present paper included the asymmetric models (EGARCH and TGARCH) to capture possible asymmetries in return volatility modelling. Following Hassan et al. (2013), the risk shocks were obtained by taking the difference between period t's risk rating and its conditional mean. The shocks were linked to the conditional volatility through the error terms to make them unanticipated. The connection between the conditional mean and risk components allows the market activity and unexpected information on risk components (through the error term) to drive price volatility. This allows measuring the effects of shocks on the risk components on volatility. In addition, the model takes leverage effect into consideration. As shown by Hassan et al. (2003), positive shocks are followed by lower conditional volatility and higher conditional volatility follow negative shocks.

To assess the impact of country risk shocks, the variance models were extended to include exogenous variables of country risk component shocks. The specific variance models estimated take the following forms:

$$\sigma_t^2 = \omega_i + \sum_{i=1}^{p} \alpha_i \, \varepsilon^2{}_{t-i} + \sum_{i=1}^{q} \beta_i \, \sigma_{t-i} + \vartheta_1 \mathcal{F}_{t-1} - \vartheta_2 \rho_{t-1} - \vartheta_3 \lambda_{t-1} \quad (8)$$

$$\mathrm{Ln}(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left[\frac{|\varepsilon_{t-i}|}{\sqrt{\sigma_{t-i}^2}} - \sqrt{\frac{2}{\pi}} \right] + \sum_{i=1}^{p} \gamma_i \frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}^2}} + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2) + \vartheta_1 \mathcal{F}_{t-1} - \vartheta_2 \rho_{t-1} - \vartheta_3 \lambda_{t-1} \quad (9)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-i}^2 d_{t-1} \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \vartheta_1 \mathcal{F}_{t-1} - \vartheta_2 \rho_{t-1} - \vartheta_3 \lambda_{t-1} \quad (10)$$

Where; $\mathcal{F}_{t-1}$;; ρ_{t-1}; λ_{t-1} are exogenous variables for financial, political and economic risk shocks, respectively. ϑ_i; ϑ_2; ϑ_3 are parameters of the country risk component shocks. Equations 8, 9 and 10 represent GARCH, EGARCH TGARCH variance equations, respectively.

GARCH models (EGARCH, TGARCH and GARCHM) were estimated, with normal distribution, for each sector and tested to determine the best-fit model. Following previous studies, including Cermeño and Suleman (2014), Miah and Rahman (2016), Silvennoinen and Teräsvirta (2009), the Akaike info criterion (AIC), Schwarz criterion (SC) and log likelihood were used to select the best model. The best models were identified as ones that minimise the information criteria (lowest AIC and SC) and the highest log likelihood (Andersen, Bollerslev, Diebold, & Ebens, 2001).

3.3. Pre-Estimation Diagnostic Tests

Diagnostic tests of the residuals were applied prior to estimating the models. The Lagrange multiplier (LM) test suggested by Engle (1982) was used to test for the presence of ARCH effects. The LM test is estimated from an auxiliary regression of the squared residuals from the AR model. The LM test results are presented in Table 1. The p-values of the ARCH effects test results for heteroscedasticity are less than 5 percent for all sectors thus the null hypothesis for homoskedasticity is rejected, implying that the indices are heteroskedastic. In the presence of the ARCH effects the ARCH/GARCH models can be estimated (Wooldridge, 2003). The augmented Dickey-Fuller (ADF) test was used to test for unit root (Dickey & Fuller, 1979). As shown in Table 1, the P-values are all less than 5 percent, hence the null hypothesis for the presence of unit root is rejected. Thus, all variables are stationery at levels, therefore, the GARCH models can be estimated.

Table 1. ARCH effects and Unit root tests

Heteroskedasticity Test: ARCH	*ALL SHARE*	*Basic materials*	*Consumer goods*	*Financials*	*Health*	*Industrials*	*Oil & Gas*
F-statistic	10.532	5.3994	6.7137	24.793	5.6439	9.5567	640.32
Prob. Chi-Sq. (1)	0.0014	0.0211	0.0072	0.0000	0.0184	0.0023	0.0000
ADF Unit root test:							
t-statistic	-28.938	-11.199	-12.660	-11.646	-10.627	-11.809	-12.323
Prob*	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: RTNF-All share; BMINDX-basic materials; CGINDX-consumer goods; FININDX-financials; HLINDX-healthcare; INDINDX-industrials and OILGINDX- oil & gas index.

The residuals plot shown in Figure 1 evidence volatility clustering for all the indices as periods of low volatility are followed by periods of low volatility and high volatility periods followed by high periods of volatility. The behaviour of residuals suggests that the error terms are conditionally heteroscedastic and hence they can be represented by the ARCH/GARCH models (Miah & Rahman, 2016).

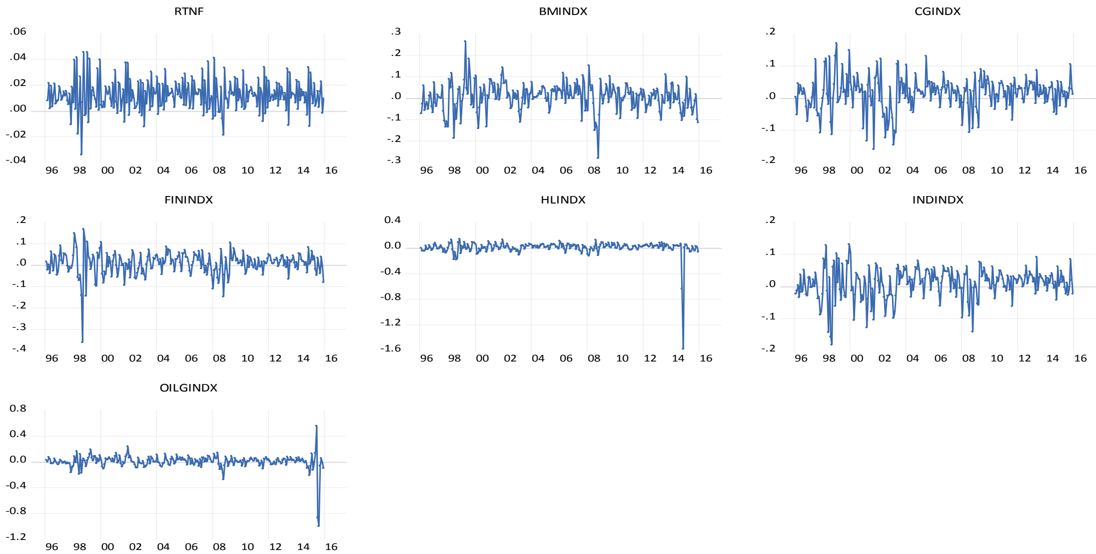

Figure 1. Residuals Plot

4. Empirical Results

4.1. Descriptive Statistics and Correlation Analysis

Table 2 presents the descriptive statistics on monthly returns of the JSE all share index and specific sectors in the market. The table also shows the statistics for country risk and its components (financial risk, economic risk and political risk) together with a summary of risk shocks. As it can be seen from Table 2, the consumer goods sector has a higher average return in the market at 0.0142 followed by the industrials sector at 0.0096, which is above the overall market index with a return of 0.0088. Basic materials and oil and gas sectors offered the lowest average returns over the sample period. The overall returns of the JSE market are much lower than emerging markets average (0.183) and the world index (0.127) (Hassan et al. 2003). Interestingly, as suggested by the capital asset pricing model (CAPM), the overall market has the lowest risk as measured by the standard deviation (0.0466) compared to all market sectors, which explains the essence of diversification; hence, investing in a market portfolio minimises risks without equivalent reduction in returns (Chopra & Ziemba, 2013). Over the sample period, the returns of oil and gas and the health care sectors depict the highest risk as shown by high standard deviations 0.1147 and 0.1221, respectively. Consumer goods and the financial sectors evidenced least risk.

Table 2 depicts that there is low economic risk (35.12%) and financial risk (37.79%) in South Africa as shown by lower risk ratings (less than 50%). However, South Africa is experiencing an overall increase in risk; for example, in 2003, the average financial risk rating was 33 percent, which increased to 37.79 percent. The descriptive statistics show that South Africa is riskier politically, as depicted by a higher risk rating of 67.79 percent. High political risk can be explained by the recent scandals, changes in government, cabinet reshuffle and presidency changes in the political environment. Overall, the composite country risk rating shows that South Africa is an average risk market with a rating averaging of 52.167 percent over the sample period. On average, there are more negative shocks in financial and economic risks as shown by negative means implying an overall increase in risk levels. The average political risk shock is positive, suggesting an overall improvement or decline in political risk over time; as shown in Figure 1, there is a decline in political risk over the sample period.

Table 2. Descriptive Statistics on Returns of South African Stock Market Sectors

	Sector/Index	Mean	Median	Max.	Min.	Std. Dev.	Obs.
Monthly Returns	All share	0.0088	0.0147	0.1209	-0.2001	0.0466	239
	Basic materials	0.0040	0.0106	0.2636	-0.2818	0.0650	239
	Consumer goods	0.0142	0.0195	0.1694	-0.1596	0.0523	239
	Financials	0.0074	0.0127	0.1671	-0.3619	0.0532	239
	Healthcare	0.0014	0.0152	0.1363	-1.5779	0.1221	239
	Industrials	0.0096	0.0153	0.1309	-0.1825	0.0476	239
	Oil & gas	0.0033	0.0095	0.5587	-1.005	0.1147	239
Risk Rating (%)	CR rating	52.167	51.500	57.500	48.625	2.1095	239
	ER rating	35.117	35.500	38.500	29.000	2.0901	239
	FR rating	37.969	38.000	42.000	31.500	1.9741	239
	PR rating	67.791	67.000	77.000	61.500	3.4023	239
Risk Shocks	CR shock	0.2802	0.4247	4.7662	-3.8217	1.9859	239
	FR shock	-0.774	-0.890	4.2365	-6.0861	1.7794	239
	PR shock	0.5601	0.3708	9.1329	-6.2863	3.2948	239
	ER shock	-0.637	-0.582	3.1322	-6.5340	1.9513	239

Note: CR – country risk, ER – economic risk, PR – political risk and FR – financial risk

Table 3 shows the correlation of monthly returns between indices in the JSE. All the correlations between the indices are positive and statistically significant. The positive correlations imply that there is a direct relationship between the indices, the returns move in the same direction. According to portfolio theory, an optimal portfolio can be created with assets with low correlations. High positive correlations between the consumer goods and basic materials and financials and industrial reduces the benefits of diversification. However, low correlations between health and industrials, industrial and oil and gas, health and oil and gas, financial and oil and gas, consumer goods and oil and gas, consumer goods and health sectors suggest the existence of diversification opportunities that can be exploited by investors. Financial and oil and gas, health and oil and gas, consumer goods and health sectors have the lowest correlations, suggesting the possibility of higher diversification benefits among all sectors. The most striking result to emerge from the correlations analysis in Table 3 is that oil and gas sector has a low correlation with all other sectors in the JSE, signifying diversification benefits in including this sector along with other sectors.

Table 3. Correlation Analysis

	ALL SHARE	**Basic materials**	**Consumer goods**	**Financials**	**Health**	**Industrials**	**Oil &Gas**
ALL SHARE	1.000						
Basic materials	0.754***	1.000					
Consumer goods	0.672***	0.395***	1.000				
Financials	0.763***	0.358***	0.475***	1.000			
Health	0.281***	0.221***	0.171***	0.238***	1.000		
Industrials	0.888***	0.521***	0.743***	0.769***	0.270***	1.000	
Oil & Gas	0.444***	0.484***	0.259***	0.135*	0.142**	0.318***	1.000

Note: ***; **; * Statistical significance at 1%, 5% and 10% levels.

4.2. Analysis of risk shocks and the JSE return volatility

To ascertain the effects of country risk shocks on the overall JSE market and distinct economic sectors, different GARCH family models of equations 7, 8 and 9 were estimated for each sector on the JSE. The selected models (based on the lowest AIC and SC criterion) for each sector are shown in Table 4. The results show that the EGARCH is the best model for the all-share index and consumer goods sector. The TGARCH model was found to be the best for the financial and industrials sectors. For the basic materials, health care and oil and gas sectors, the GARCHM model was selected. The coefficient of leverage γ_i was negative, statistically significant for the all-share index and the consumer goods sector and positive, statistically significant for the financial and industrial sectors. This suggests the existence of differences between negative and positive volatility in these sectors. The implication of these findings is there is a strong reaction to negative news compared to positive news in the JSE all share index, consumer goods, financial and industrial sectors. This is consistent with Brooks (2014) who avers that volatility rises more in a negative shock than a positive shock of the same magnitude. The asymmetric coefficient was insignificant for the basic materials, health care and oil and gas sectors, suggesting nonexistence of differences between negative and positive volatility in these sectors. For the selected models, no serial correlation was found.

Table 4. Analysis of Risk Shocks and SA Stock Market Return Volatility

INDEX	**ALL SHARE**	**FINANCIALS**	**INDUSTRIALS**	**BASIC MAT.**	**HEALTHCARE**	**OIL & GAS**	**CONS GDS**
Coef.	***MODEL 1***	***MODEL 2***	***MODEL 3***	***MODEL 4***	***MODEL 5***	***MODEL 6***	***MODEL 7***
	EGARCH	*TGARCH*	*TGARCH*	*GARCHM*	*GARCHM*	*GARCHM*	*EGARCH*
$\boldsymbol{\alpha}$	0.3132* (1.9707)	0.0668 (0.6441)	0.0950* (2.4657)	0.1697*** (3.4227)	0.1400 (1.5351)	0.3181*** (3.2040)	0.1335*** (2.9536)
$\boldsymbol{\beta}$	0.6427*** (5.643)	0.6548*** (10.3403)	0.7289*** (10.7700)	0.4782*** (3.0747)	0.4633*** (5.7840)	0.6687*** (5.9520)	0.8478*** (21.1363)
$\boldsymbol{\gamma}$	-0.2800*** (-3.3610)	0.2508** (2.9300)	0.1490** (2.5601)				-0.1742*** (-5.5965)
$\boldsymbol{\vartheta_1}$	-0.0290 (-0.9128)	-8.3330 (-0.8701)	-1.5000 (-0.4439)	-2.3000 (-0.1816)	0.0010 (1.7344)	-0.0001* (-2.0000)	-0.0201 (-3.7952)
$\boldsymbol{\vartheta_2}$	0.0838 (0.8054)	-0.0003* (-2.3070)	-0.0002*** (-3.3678)	-0.0006*** (-4.1710)	-0.0014 (-1.7252)	0.0005*** (2.9580)	-0.1337*** (-4.0189)
$\boldsymbol{\vartheta_3}$	-0.2092* (-2.1060)	-0.00040** (-2.2789)	-0.0028 (-1.4225)	-0.0001 (-0.2801)	0.0016 (1.0926)	0.0008*** (4.6528)	0.0527 (1.0053)
$\boldsymbol{\alpha+\beta}$	0.955	0.7216	0.8239	0.6479	0.6033	0.9868	0.9813

Note: The table shows the GARCH models' results, α & β are arch and garch coefficients. ϑ_1, ϑ_2 and ϑ_3 are coefficients of financial, political and economic risk shocks respectively. Z-statistics are given in parenthesis below the coefficients, *; **and *** represents significant at 10%, 5% and 1% level respectively.

Volatility and Internal/Own Shocks

The parameters of the ARCH $({\varepsilon^2}_{t-1})$ and GARCH (h_{t-1}) components are positive and statistically significant for the JSE all share index (model 1) and the sectors within the South African market except for the health care sector (model 5), which shows the GARCH effect only. Significance of α and β coefficients shows the existence of the ARCH and GARCH effects in the South African stock market, implying that stock market volatility is driven by own/internal shocks. The significant ARCH term denotes that previous day's JSE return information has a statistically significant influence on the current volatility of the JSE stock returns. For the health care sector, the arch term is insignificant, thus previous days' health care sector information on return does not transmit to the current return volatility of the health care sector. The coefficient of the GARCH term (h_{t-1}) is positive and statistically significant for the JSE overall market and for all the sectors in the South African stock market as shown in Table 4. The significant GARCH parameter implies that previous day's volatility of the JSE overall market and JSE sectors stock returns internally influence current volatility of the stock market. The results are consistent with Hassan et al. (2003) who found the presence of GARCH and ARCH effects in a sample of Middle East and North African countries.

4.3. Country Risk Shocks and Stock Return Volatility

To assess the impact of country risk shocks on stock market volatility, the GARCH models were extended to include exogenous variance regressors (financial, political and economic risk shocks). As shown in equations 8, 9 and 10 the shocks were determined by the difference between the risk measure and its conditional mean. The results are presented in Table 4. $\vartheta_1, \vartheta_2 \; and \; \vartheta_3$ are coefficients of financial, political and economic risk shocks respectively. If the shocks in financial, political and economic risk rating are negative, the shock term $f(\varepsilon_{t-1})$ would be positively affected and followed by a higher conditional volatility(σ_t). Conversely, for a positive shock in risk ratings (country becomes safer) the shock term will be affected negatively and would result in lower conditional volatility (Hassan et al., 2003).

Table 4 shows that the financial risk shock coefficient (ϑ_1) is negative and insignificant for the JSE all-share index and other sectors except the oil and gas sector, with a significant coefficient. A negative coefficient implies that the shock parameter will be affected positively and result in a higher conditional variance. The results suggest that the JSE stock market and sectors are not significantly affected by financial risk shocks; this is supported by studies that suggest that the South African market was among the markets that were not significantly affected by the world financial crisis (Agyei-Ampomah, 2011). However, there is a statistically significant relationship for the oil and gas sector, suggesting that financial risk shocks negatively transmit to the returns volatility, leading to an increase in conditional volatility.

Regarding political risk shock, the coefficient ϑ_2 is negative and statistically significant for financials (model 2), industrials (model 3), basic materials (model 4), oil and gas (model 6) and consumer goods (model 7) sectors. The results suggest that political risk shocks negatively transmit to the volatility of returns in the financial, industrial, basic materials, oil and gas and the consumer goods sectors, leading to higher conditional volatility. The implication is that dynamics in politics largely affect the return volatility of these sectors as the returns of these sectors are more responsive to the political environment. For the JSE all share index (model 1) and the health care sector (model 5) we did not find any significant statistical differences suggesting a slow response to political shocks on the overall stock market and the health care sector. For the JSE overall market, the results are inconsistent with Bilson et al. (2002) and Ramcharran (2003) who found political risk to be an important determinant of return volatility in emerging markets; suggesting that different sectors within the market can be affected differently from the overall market.

Consistent with Ramcharran (2003) regarding economic risk rating, the coefficient of economic risk shock (ϑ_3) is negative and statistically significant for the all share index and financial sector. The negative and statistically significant coefficient implies that the shock term would be affected positively and result in a higher conditional variance. Economic risk shocks are negatively transmitted to the return volatility on the South African stock market (all share) and financial sector. Economic risk shock is a significant determinant of stock return volatility. However, for the oil and gas sector, the parameter (ϑ_3) is positive and statistically significant, suggesting lower return volatility transmitted from economic risk shocks to the oil and gas sector. For the basic materials, industrials, consumer goods and health care sectors, no statistical relationship was found, suggesting that these sectors do not significantly respond to shocks in economic risk ratings. We conclude that volatility of the JSE all share index, financial and oil and gas sectors is significantly affected by the economic risk shocks. Industrials, financials, consumer goods, oil and gas and basic materials sectors are affected by political risk shocks. The oil and gas sector is significantly affected by shocks in all the risk components (financial, economic and political risk); this can be explained by the nature of the industry, international outlook and price changes are easily transmitted to local volatility (Regnier, 2007). Narayan and Narayan (2007), Yang, Hwang, and Huang (2002), Guo and Kliesen (2005) in modelling oil prices in different markets, reveal that oil prices are more volatile than all other commodities. Interestingly, the volatility of the health care sector was found not to be driven by all the risk shocks. The health care sector does not respond to country risk shocks. Wagstaff (2007) documents that any shocks in the health care sector are more likely to trigger intervention and assistance from the government and non-governmental organisation. Households are less likely to smooth changes in health-related matters; shocks resulting from the health issues are more likely to be passed through to consumption-related changes, hence; less response from risk factors. (Acemoglu, Finkelstein, & Notowidigdo, 2013; Wagstaff & Lindelow, 2010). This suggests that risk shocks in the health care sector are passed to other sectors of the economy.

Engle and Bollerslev (1986) show that the persistence of the shocks in volatility depends on the sum of $\alpha + \beta$ parameters in the GARCH-M (1, 1) model. For $\alpha + \beta = 1$ the forecast conditional variance persists over all finite horizons and an infinite variance for the unconditional distribution $f(\varepsilon_{t-1})$ (Hassan et al.,2003). The persistence of shocks lasts longer as the summation of $\alpha\ and\ \beta$ approaches unit. The results in Table 4 show that the summation of the parameters $\alpha + \beta$ is statistically less than unity in all the seven models, implying that the shock effects decay over time. The summations of $\alpha + \beta$ are approaching one in all the models, suggesting that the shocks in volatility persist for long periods in the JSE all share and all the sectors. The $\alpha + \beta$ parameter is higher for oil and gas, consumer goods, industrials and the all share index (0.9868; 0.9813; 0.823983 and 0.955, respectively) providing evidence of considerable persistence in volatility for longer periods in these sectors than the financial, basic materials and health care sectors.

5. Summary and Conclusions

The aim of this paper was to analyse the impact of country risky dynamics on the return volatility of the JSE all share index and sectors for 1996-2018 period. The study used the GARCH family models. The results indicate that the volatility of the JSE stock market and its sectors are driven by own internal shocks (previous day's return information and previous day's volatility on the indices). The descriptive statistics depict that the consumer goods sector has higher average returns compared to all sectors and the overall market index. Consistent with the market models the overall JSE all share index was found to be less risky than all the sectors on average as depicted by lower standard deviations. Country risk component trends indicate that political risk is the dominant risk in South Africa, as shown by higher risk ratings.

The study found that the JSE and its sectors are not too responsive to financial risk shocks, except the oil & gas sector with a statistically significant relationship, suggesting that financial risk shocks negatively transmit to the volatility of oil & gas sector returns. Regarding political risk, the study found that political risk shocks negatively transmit to the volatility of returns in all the sectors except the health care sector. This implies that dynamics in politics largely affect the return volatility of most of the sectors on the JSE. This suggests that risk-averse investors should be more cautious in investing in these industries in periods of high political instability. For the JSE all share and health care indices, the study did not find any significant statistical differences, suggesting a slow response to political shocks. In light of economic risk, we found evidence that economic risk shocks are negatively transmitted to the return volatility on only three indices, the JSE all share, financial and the oil and gas sectors. Across the JSE all sectors, political risk was found to be the dominant risk, whose shocks were found to impact negatively on more sectors of the economy than financial and economic risk shocks. To improve the stability of stock markets, policy makers should pay more attention to political stability so that investors are not scared away. The oil & gas sector was found to be highly sensitive to all risk components (financial, economic and political). The industrial, basic materials and consumer goods sectors evidenced low response and exposure to country risk components. The implication of these findings to investors and fund managers is that, considering risk management, these sectors will be a good target to diversify their portfolios in managing financial, economic and political risk. The results show that the health care sector is not sensitive to country risk shocks; for investors this could be a good target to stabilise returns. Political risk was found to be the most dominant on JSE sectors, implying that investors investing on the JSE should pay more attention to the political landscape and management of political risk. With respect to volatility persistence in the JSE, the oil and gas, consumer goods, industrials and the all share index showed considerable persistence in volatility for longer periods than the basic materials, financials and health care sectors.

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