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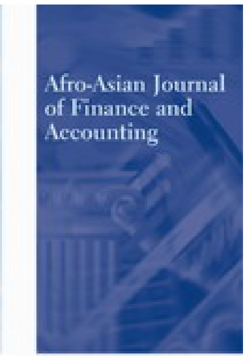

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The relationship between implied volatility and equity returns in South Africa

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Abstract: This study investigates the relationship between implied volatility and stock market returns. Although previous studies on this topic only exist from an international context, this paper presents evidence from South Africa by examining the effect of the South African volatility index (SAVI) on different Johannesburg Stock Exchange (JSE) listed stock indices. The objectives of this study are to determine which GARCH model is most appropriate for modelling volatility in South Africa and whether the SAVI displays any relationship with the returns on equity indices. The study finds that the TGARCH model is the most suitable model for modelling volatility on the JSE. Thereafter, using a TGARCH model, it is observed that the SAVI is significantly positively related to the returns of all the chosen indices and that a leverage effect exists between them. The results provide important insight for investors, risk managers and policymakers.

Keywords: GARCH; implied volatility; returns; South African volatility index; SAVI; volatility modelling.

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1 Introduction

The element of risk in investments is an essential one, and since its quantification by Harry Markowitz, many attempts have been made to eliminate or minimise the amount of uncertainty faced by investors, traders, corporations and governments. The need to hedge against risk has even led to many different asset classes being spawned, all with the sole purpose of operating in a world full of volatility. In emerging markets such as South Africa, this volatility is particularly concerning, and driven mainly by the unstable political and economic climate, and its reliance on dollar-denominated natural resources. The sentiment generated by either economic or political indicators, drives volatility, and if captured, this allows one to ascertain what the consensus is in the market about future financial development. Volatility in itself is complex, with many different types of volatility present in the financial market, such as: historical volatility, realised volatility, conditional volatility, unconditional volatility and implied volatility. Whilst realised volatility measures the dispersion of returns over a pre-specified previous period, conditional volatility measures the variance of returns conditioned upon an information set, and implied volatility represents future expectations of volatility. This study however focuses on implied volatility, as it can be argued that forward-looking measures are most desirable for investors in the financial market.

Measures such as the Volatility Index (VIX), developed by Robert Whaley (1993) for the USA, provide a tangible and quantifiable measure of implied volatility. The VIX attempts to calculate the volatility that investors anticipate by using the weighted prices of all the closest at-the-money call and put options of the S&P500. This measure is therefore forward-looking, and aims to capture changes in market sentiment. Studies such as Arik (2011) found that a high VIX value represents a large amount of investor fear, and thus a higher perceived risk level, whilst low VIX levels indicate investor optimism and corresponds to lower perceived risk.

Given the importance of volatility, this paper aims to contribute to existing knowledge on the relationship between implied volatility and stock index returns. However, this paper will be unique in that it provides evidence from South Africa, by using the South African volatility index (SAVI) Top 40 and stock index returns from the Johannesburg Stock Exchange (JSE hereafter). In South Africa, the SAVI is used as a measure of implied volatility. The SAVI was launched in 2007, and it provides a measure of the three-month market volatility based on the FTSE/JSE Top 40 Index. The objective of this study is to determine the relationship between the SAVI index and the returns of different stock indices listed on the JSE, as well as to ascertain whether the SAVI can be considered a reasonable predictor of implied volatility for equity investors.

The volatility of stock markets is an important factor that is considered by investors when developing investment strategies. The volatility of markets is used to examine the outlook of investors in the market. Investors then formulate investment strategies that they expect to be profitable. This study, therefore, aims to benefit academics, investors, portfolio managers, monetary policymakers, risk management strategists, and all other individuals concerned about the relationship between implied volatility and stock index returns.

2 Literature review

2.1 Theoretical considerations

There are many hypotheses which aim to explain the anticipated relationship between implied volatility and stock returns. The *Leverage Hypothesis* (Black, 1976; Christie, 1982) theorises that as the volatility of profitability in a firm increases, this decreases firm value which also decreases equity value (while increasing debt value relative to firm value). This therefore results in the risk of the company increasing, which thus decreases the share price of the firm, due to the systematic portion of risk that cannot be eliminated through diversification. The leverage hypothesis therefore specifies a negative relationship between volatility and stock returns.

The *Volatility Feedback Hypothesis* (Black, 1976; Pindyck, 1984; French et al., 1987) implies that any shock will impact both current and future volatility of stock returns. Since an increase in volatility causes an increase in the expected return, there will also be a resultant decrease in stock price. The *Intertemporal Capital Asset Pricing Model (ICAPM)* developed by Merton (1973) illustrates that the conditional expected return on a stock is a linear function of two terms, viz. its conditional variance, as well as a hedging variable which is meant to capture the investor's risk aversion, and their desire to hedge future changes in investment prospects. Merton (1980) found that this hedging variable becomes negligible during certain circumstances, in which case the result is a direct correlation between return and the variance component. This therefore implies that investors will require a larger risk premium when the stock market is more volatile, which specifies a positive relationship between volatility and stock returns.

The theory of *Behavioural Finance*, also assumes a negative relationship between stock returns and volatility. The implied volatility index is based on investor sentiment, therefore if investors foresee high volatility (high SAVI values), it is rational for them to not participate in the given market, which results in a decrease in the market returns due to the decrease in demand for the shares (Sewell, 2007). The *Positive Risk-Neutral Relation Theory* was proposed by Banerjee et al. (2007) and it states that it is rational to consider implied volatility as a risk-neutral variable, as it is obtained under the condition of risk-neutral measures. The use of implied volatility in the variance equation can be utilised to identify a positive risk-neutral relation. Barr (2009) found implied volatility to be effective, and to be an upward-biased determinant of intended realised volatility.

2.2 Empirical review

Harvey and Whaley (1991) use transaction data on the S&P 100 index options to ascertain whether volatility implied in OEX option prices can predict future realised index return volatility. Using closing prices to estimate implied volatility, Harvey and Whaley (1991) find that spurious negative serial correlation in implied volatility changes is induced by non-simultaneously observing the option price and the index level. Day and Lewis (1988) also used closing prices to form their volatility estimates. They found that there were unexpected increases in implied volatility around quarterly expiration dates. Canina and Figlewisk (1993) found that for S&P 100 index options, implied volatility was a poor forecast of subsequent realised volatility from 1983 to 1987. In aggregate and across sub-samples separated by maturity and strike price, implied volatility had virtually no correlation with future volatility, and it did not incorporate the information contained in recent observed volatility.

Christensen and Prabhala (1998) used the ordinary least squares (OLS) method and the instrumental variables (IV) framework examine the predictive power of implied volatility on S&P 100 index options, over the period 1983 to 1995. The IV framework was adopted to control for the errors-in-variables problem. Results from both techniques showed that implied volatility outperformed past volatility in forecasting future volatility and even subsumed the information content of past volatility in some specifications. The study also provided evidence of a regime shift following the 1987 stock market crash, where implied volatility was more biased before the crash than after the crash.

Hansen (2001) studied whether the volatility implied by the Danish KFX call and put option prices have the ability to predict future realised index return volatility. The OLS estimates provided evidence that the implied volatility contained information about future volatility. Similar to Christensen and Prabhala (1998), Hansen (2001) used the IV framework to account for errors-in-variables. When measurement errors were controlled for, call option prices contained information about future realised volatility over and above the information contained in historical volatility.

Bali and Peng (2006) use high-frequency data to evaluate the intertemporal relationship between realised volatility and return on the S&P 500 index, over the period of 1986 to 2002. Their use of the GARCH model produced a significantly positive relationship between the conditional mean and the conditional volatility of US market returns. Guo and Whitelaw (2006) conducted a similar study of the intertemporal CAPM model, and found a positive relationship between risk and return as well. The authors argue that other studies that report negative relationships between volatility and return, do so because they did not appropriately account for the risk that is attributed to expected returns from the hedging component, and this therefore results in a bias. A positive relationship between risk and return was also found by Guo and Neely (2008), and Bollerslev et al. (2009).

Panda et al. (2008) investigate the predictive power of implied volatility against the past realised volatility of S&P CNX Nifty4 index option in India from 2001 to 2004. The study found that implied volatility contained more information than past realised volatility. Hence, it is considered as an efficient albeit slightly biased estimator of realised return volatility. From both OLS and IV methods, Panda et al. (2008) observed that past realised volatility did not add any information beyond what is already contained in the implied volatility.

A recent study conducted by Kanas (2012) used the GARCH-M model to study the risk-return relationship for the S&P 500 Index. The study found that a significantly positive relationship exists between risk (measured by the VIX) and returns on the S&P500 Index, if the VIX squared is used as an additional variable in the conditional variance equation. According to Kanas (2012), this relationship is present even after controlling for the Fama and French variables as controls in the study. The results were found to be consistent over both daily and weekly data frequencies, and overall, it was found that their GARCH model which was combined with the volatility index has superior predictive power than the GARCH model without the volatility index, or the volatility index itself.

In contrast, studies such as by Dowling and Muthuswamy (2005), found that the relationship between the Australian Market Volatility Index (AVIX) and the returns of the ASX 200 Index was negative, and that there was no asymmetry present. Sarwar (2012) also found a strong negative relationship between the VIX and the returns on the S&P 100, S&P 500, and S&P 600 over the period of 1992 to 2009. This negative result was also found to increase over the time, and it was found to be stronger when the VIX value was higher (indicating more volatility). Similarly, Antonakakis et al. (2013) found that an increase in the stock market volatility (measured by VIX) and policy uncertainty, resulted in a reduction in stock market returns (measured by the returns of the S&P500). Wang et al. (2014) also found the VIX to be negatively correlated to the returns experienced in the Chinese stock market. These results were echoed in studies by Shaikh and Padhi (2014), Chandra and Thenmozhi (2015), as well as Emna and Myriam (2017) in selected European markets, the USA and India. Shaikh and Padhi (2014) also found the negative relationship to be more prominent when the implied volatility index is higher and more volatile. Thus, the relationship suggested between risk and return is asymmetric. Emna and Myriam (2017) also found asymmetric responses to positive and negative shocks, thus confirming the volatility feedback hypothesis.

With regards to studies conducted in South Africa, Mandimika and Chinzara (2012) analysed the nature and behaviour of volatility, the risk-return relationship and the long-term trend of volatility on the South African equity markets from 1995 to 2009. Three time-varying GARCH models were employed: one symmetric, and two asymmetric. The findings showed that volatility was largely persistent and asymmetric and that the TARCH-M model was the most appropriate model for conditional volatility of the South African stock market. Kenmoe and Tafou (2014) assessed the information content in SAVI implied volatility using daily markets data focused on the FTSE/JSE Top 40 index. Results showed that the RiskMetric approach moved in the oppositely with respect to the SAVI, whereas the GJR-GARCH moved in the same way and was more informative when encompassing regression is considered.

The literature on the subject therefore has mixed results, with some confirming a positive relationship between the VIX and equity returns, whilst others found positive results in different markets. Furthermore, there is no empirical evidence on the JSE to the authors' knowledge, which is a research gap that this study aims to fill.

3 Methodology and data

3.1 Data

This study aims to examine the relationship between implied volatility and the returns of the market as a whole, which is proxied by the returns on the JSE All-Share Index. The JSE Top 40, Midcap Index and Small Cap index are also analysed to evaluate whether the relationship between implied risk and return is affected by the size of a company. The SAVI Top 40 is selected as a measure of implied volatility since it captures investor sentiment in the South African equity market. Whilst this index was formed in 2007, the method of calculation was later changed in 2009, therefore the period of study extends from 1 May 2009, through to 28 April 2019.

The study uses daily data due to the fact that equity markets typically assimilate information quickly. All price series were then transformed into a compounded returns (or movements for the SAVI) series as presented by equation (1):

$$r_t = 100 \times \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where P_t and P_{t-1} are current and previous stock prices for $t = 1, 2, \cdots, \infty$.

The stationarity of the series is examined using the Augmented-Dickey Fuller (ADF) test. Thereafter, an ARCH-LM diagnostic test is conducted to identify whether the data presents any ARCH effects and heteroscedasticity.

3.2 Methodology

According to Campbell et al. (1997), the risk-return tradeoff exhibits nonlinearity in some input variables. Furthermore, Brooks (2014) states that most financial data exhibits leptokurtosis, and volatility clustering or volatility pooling. These properties cannot be adequately captured by time series models, and thus, volatility models are the most appropriate alternative. As such, a majority of the literature in forecasting volatility employs the generalised autoregressive conditionally heteroscedastic (GARCH) model proposed by Bollerslev (1986). The GARCH model has become a more widely used model than the ARCH model, due to it being more parsimonious and better fitting (Brooks, 2014). Following the development of the GARCH model, a variety of different GARCH models have been developed to forecast volatility more accurately.

The exponential GARCH (E-GARCH) model, proposed by Nelson (1991), models the logarithm of volatility, therefore there is no need to artificially impose non-negativity constraints on the model parameters and an additional variable to account for asymmetries has been added to the conditional variance equation (Brooks 2014). The GJR-GARCH model, proposed by Glosten et al. (1993), is another extension of the GARCH model which includes a dummy variable to account for possible asymmetries in the market. Banerjee et al. (2007) posit that it is rational to consider implied volatility as a risk-neutral variable, as it is obtained under the condition of risk-neutral measures. This being so, the use of implied volatility in the conditional variance equation can be used to identify a positive risk-neutral relation.

Brailsford and Faff (1996) conclude, in their study on Australian equity index data, that the GJR-GARCH model provides better results in forecasting volatility than any other model used. Peters (2001) however, used data on the FTSE100 and DAX 30 indices to examine the performance of four GARCH models (GARCH, EGARCH, GJR-GARCH and APARCH) as well as three distributions namely; normal, student-t and, skewed distributions. The study found that the APARCH and GJR models outperformed the EGARCH model, and that non-normal distributions provided better in-sample and out-of-sample results. On the other hand, Li and Lin (2003) found that the Markov-switching ARCH (commonly referred to as the SWARCH model) framework is a better model than the ARCH and GARCH models when predicting the dispersion of the returns of Taiwan stock indices.

Ezpeleta (2015) found that the performance of EGARCH models can be improved by adding the VIX as an exogenous variable since the VIX captures the characteristics of asset returns. On the other hand, Banumathy and Azhagaiah (2015) found that the basic GARCH and GJR-GARCH model was the most appropriate to model symmetric and asymmetric volatility in the Indian Stock Market. With regard to the Shanghai Stock Exchange, Lin (2018) found that the EGARCH model was the best model to fit and forecast volatility on the stock market. Likewise, Naseem et al. (2018) showed that the EGARCH delivered the most satisfactory model to model the volatility of the Pakistani Stock Exchange. Locally, Kgosietsile (2014) found that the EGARCH model was the most suitable tool to model and forecast the volatility of stock returns from the JSE. Similar findings were reported by Masinga (2015) and Mokoena (2016). Olberholzer and Venter (2015), however, found that the best fitting model was the GJR-GARCH model as it accurately assessed all the indices, except for the JSE Top 40 index.

The preceding empirical review proves that the discussion of which GARCH model is most suited to the South African financial market is continually ongoing, and subject to different views, since the empirical evidence is mixed. An analysis of different GARCH-type models will therefore be conducted in order to determine which GARCH model most accurately predicts the relationship between implied volatility and the returns of selected indices.

For the GARCH, EGARCH, GJR-GARCH and GARCH-M models, the mean equation used in the study will be based on the Fama-French (1993) three factor model. The Fama-French (1993) three factor model accounts for three risk factors, namely; market (MKT), size (SMB), and value (HML) factors. The market risk premium captures the excess returns of the market (all share index) over the risk-free rate of interest (3-month treasury bill rate). The use of the 3-month T-Bill rate is supported by Strydom and Charteris (2013) who conducted a study on the South African risk-free rate anomaly and concluded that the relationship between the risk-free proxies, such as the 3-month T-bill rate, and the minimum required return does not differ in South Africa. Moreover, the size factor captures the excess returns of small stocks over large stocks, whilst the value factor captures excess returns of value stocks over growth stocks. These three variables possess valuable information, regarding the risk present in financial markets, which in turn, influences the investment opportunity set.

The use of the Fama and French (1993), three factor model is largely supported by previous literature. Kelly (2003) indicated that information about inflation and economic growth was included in the SMB and HML – information that is different from information represented by the market factor. Hahn and Lee (2006) found that GDP growth and business cycles were accounted for by SMB and HML. According to Chiah et al. (2016), the three-factor model has therefore become a benchmark model in the asset pricing literature. These mean equations for these GARCH models is therefore summarised in Table 1.

Table 1 The mean equation for GARCH models

Type of GARCH	*Mean equation*
GARCH (1,1), EGARCH, GJR-GARCH	$R_t = \mu + \alpha_0 MKT_{t-1} + \alpha_1 SMB_{t-1} + \alpha_2 HML_{t-1} + u_t$
GARCH – M	$R_t = \mu + \alpha_0 MKT_{t-1} + \alpha_1 SMB_{t-1} + \alpha_2 HML_{t-1} + \psi\sigma_{t-1} + u_t$

In Table 1, R_t represents the returns of each stock index. μ is the constant term, whilst u_t is the white noise error term. MKT_{t-1} represents the lagged variable of the market risk premium, which is calculated as the difference between the market return (JSE All Share Index) and the risk-free rate of interest (3-month treasury bill rate). SMB_{t-1} represents the lagged variable of excess returns of small stocks over large stocks, and is calculated by taking the difference between the small cap index and the Top 40 index. HML_{t-1} represents the lagged variable of excess returns of value stocks over growth stocks, and is calculated as the difference between the JSE's Value Style index and the JSE's growth style index.

The use of the lagged variables for the MKT, SMB, and HML factors is supported by Liew and Vassalou (2000). The study conducted by Liew and Vassalou (2000) found that the lagged variables are significant in predicting future changes in the investment opportunity set and are accurate in predicting future economic growth. Moreover, a study conducted by Kanas (2012) found that the lagged variables of MKT, SMB, and HML are significant in capturing information about the fundamental risks of an economy, and therefore, influences the investment opportunity of the country.

The lagged value of the movements in the SAVI will be added as an exogenous variable in each conditional variance equation. The use of the SAVI as a lagged variable in the conditional variance equation is supported by Ezpeleta (2015). Ezpeleta (2015) found that, when modelling stock market volatility, the volatility index contains important information since it is an indication of the general fear in the stock market. Thus, adding the implied volatility index to the variance equation will increase the performance of the different GARCH models. Consistent with Ezpeleta (2015), the conditional variance equations for the various GARCH-type models are specified in Table 2.

For the conditional variance equations in Table 2, ω is the constant term, u_t is the residual from the mean equation (1 or 2 for the GARCH-M) and σ_t^2 represents the estimate of the conditional variance for period t. The parameter δ captures the effect of the exogenous variable SAVI on the conditional variance. The statistical significance of each coefficient is analysed using their relative p-values.

For the EGARCH model, the coefficient γ signifies the asymmetric effects of the shocks on volatility. If the γ coefficient is zero, this would imply that positive and negative shocks of the same magnitude have the same effect on volatility of stock returns. On the other hand, if the relationship between volatility and return is asymmetric, γ is negative. With the GJR-GARCH model, I_{t-1} is a dummy variable that takes the value of one if $u_{t-1} < 0$ and zero if $u_{t-1} > 0$. A positive γ implies that leverage effects are present in the market (Wang et al., 2014).

Table 2 The conditional variance equations after accounting for the SAVI

Model	*Conditional variance equation with SAVI*
GARCH	$\sigma^2 = \omega + \beta u_{t-1}^2 + \alpha\sigma_{t-1}^2 + \delta SAVI_{t-1}$
EGARCH	$\ln(\sigma^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha\left[\frac{\lvert u_{t-1}\rvert}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right] + \delta SAVI_{t-1}$
GJR-GARCH	$\sigma_t^2 = \omega + \beta_0 u_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \gamma\, u_{t-1}^2 I_{t-1} + \delta SAVI_{t-1}$
GARCH-M	$\sigma_t^2 = \omega + \beta u_{t-1}^2 + \alpha\sigma_{t-1}^2 + \delta SAVI_{t-1}$

4 Results

4.1 Preliminary data analysis

Figure 1 is a plot of the transformed time series against the SAVI – the All Share Index return series, the Top 40 Index return series, the Small Cap Index return series, the Mid Cap Index return series. In Figure 1, each return series represents a white noise process as there are no visible trends and, each of the series' frequently crosses its mean values. This may indicate that each of these series is now stationary. To confirm the stationarity of the return series, the Augmented Dickey-Fuller (ADF) test will be conducted later. In addition, in the plotted return series in Figure 1, the series displays a tendency for volatility to occur in clusters. Volatility clustering means that, in the series, there exists periods where there are relatively higher and lower positive movements and periods of relatively lower positive and negative movements. This is a phenomenon commonly observed in financial time series.

Table 3 Descriptive statistics of index returns

	All share index	*Top 40*	*Small cap*	*Midcap*	*SAVI*
Mean	0.0330	0.0324	0.0273	0.0332	–0.0242
Standard deviation	0.9452	1.0335	0.5487	0.7599	2.6893
Skewness	–0.1704	–0.1383	–0.0132	–0.1914	–0.0480
Kurtosis	4.422	4.443	12.09	4.686	10.75
Jarque-Bera	236.5099***	238.6931***	9,140.064***	330.1637***	6,649.726***

Note: ***, **, * denotes significance at 1%, 5% and 10% levels respectively.

Table 3 displays the descriptive statistics of the variables included in the study. It can be observed that during the period of analysis, the Midcap Index earned the highest average return (marginally higher than the ALSI), whilst the Top 40 index experienced the highest level of standard deviation. The Jarque-Bera test for normality, along with the skewness and kurtosis estimates in Table 3, all prove non-normality for each series. This evidence of non-normality, along with the evidence of volatility clustering found in Figure 1 indicates the necessity of ARCH modelling, but this will be tested formally with an ARCH test. The variables included in the study therefore need to be tested for stationarity using the ADF test, the results of which are shown in Table 4.

Figure 1 Time series plot of logged returns of the indices against the SAVI (see online version for colours)

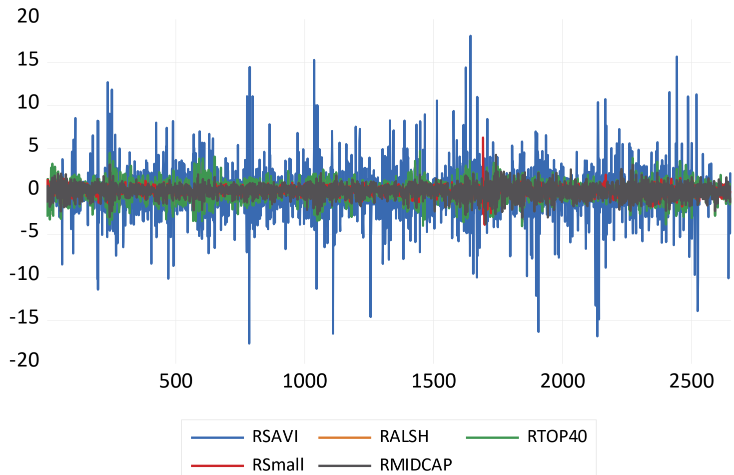

Table 4 ADF test results

Index	*ADF test statistic (levels)*
All Share Index	–52.38444***
Top 40 Index	–53.00417***
Small Cap Index	–46.48645***
Midcap Index	–48.29548***
SAVI	–56.24994***

Notes: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively.

Table 5 ARCH effect test

	F-statistic
All Share Index	26.08241***
JSE Top 40 Index	25.08248***
Small Cap Index	68.24781***
Midcap Index	44.35232***

Notes: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively.

The result in the preceding table provides evidence that each of the variables included in the study are all stationary in their level form. These can therefore be used in the test of whether there are ARCH effects present in the data, the results of which are shown in Table 5.

The results in Table 5 show that ARCH effects are present in the data. Therefore, this confirms that each index consists of ARCH effects and heteroskedasticity. Consequently, to model the relationship between the movements in the SAVI and the returns of the different indices, GARCH type models need to be used.

4.2 *Superior GARCH model*

The methodology section of the article showed four possible variants of GARCH modelling that can be employed in the analysis. The information criteria for each of these GARCH models can be found in Table 6.

Table 6 Information criteria for GARCH models

	GARCH(1,1)	*EGARCH(1,1)*	*TGARCH(1,1)*	*GARCH-M(1,1)*
		All share index		
LL	–3,421.870	–3,413.296	*–3,397.409*	–3,420.242
AIC	2.588581	2.582110	*2.570875*	2.588107
SBIC	2.606339	2.599868	*2.590852*	2.608084
HQIC	2.595009	2.588538	*2.578106*	2.595338
		Top 40 index		
LL	–3,655.975	–3,647.613	*–3,631.948*	–3,654.696
AIC	2.765264	2.758953	*2.747885*	2.765053
SBIC	2.783022	2.776711	*2.767863*	2.785031
HQIC	2.771692	2.765381	*2.755117*	2.772285
		Small cap index		
LL	–1,927.154	–1,927.550	*–1,926.036*	–1,926.148
AIC	1.460493	1.460792	*1.460405*	1.460489
SBIC	1.478251	1.478550	1.480382	1.480467
HQIC	1.466921	1.467220	1.467636	1.467721
		Midcap index		
LL	–2,880.374	–3,017.836	–2,878.774	*–2,853.338*
AIC	2.179905	2.283650	2.179452	*2.160255*
SBIC	2.197663	2.301408	2.199430	*2.180233*
HQIC	2.186333	2.290078	2.186684	*2.167487*

Notes: 1. LL represents Log-Likelihood; AIC, SBIC and HQIC represent the Akaike, Schwartz and Hannan-Quinn Information Criterion.
2. The selected model for each criteria is highlighted in italics.

The results in Table 6 indicate that the log-likelihood (LL) statistic, AIC, SBIC and HQIC for the All Share, Top 40, and Small Cap indices suggest that the TGARCH (1,1) model exhibits superior performance when modelling volatility. However, the results for the Mid Cap index do not concede the TGARCH (1,1) model to be the best model as the

LL, AIC and SBIC and HQIC suggest that the GARCH-M (1,1) is the best model. Similar inconsistencies are present in the small cap index, however given the sample size, AIC and LL will demonstrate the most correct findings therefore suggesting TGARCH (1,1) model as the superior one. Nevertheless, to achieve consistency, the TGARCH model is used to examine the relationship between the returns of the indices and the changes in the SAVI, as the TGARCH model is the most common superior model amongst the observed indices. The superiority of the TGARCH model for modelling the volatility of the JSE is supported by Kgosietsile (2014), Masinga (2015) and Mokoena (2016).

4.3 TGARCH regression results

Table 7 shows that the mean equation presents positive intercepts for the constant terms (μ) for all 4 indices. However, the intercept is only significant for the small cap and mid cap indices, illustrating the presence of excess returns for these indices. Thus, investors can earn higher market returns by incorporating companies that form part of the Small Cap and Mid Cap indices into their portfolio. Moreover, the ability to earn a return that is in excess of the market depicts and inefficient market. Hence, the JSE demonstrates inefficient behaviour, which is in line with the findings of Obalade and Muzindutsi (2018). The market risk premium term (α_0) accounts for the likelihood that the indices returns may rely on the volatility of the market returns (Kgosietsile, 2014). Although the MKT coefficient is negative for the All Share and Top 40 indices, the coefficient is only statistically significant for the Small Cap and Mid Cap returns. The positive and significant parameters suggest a strong risk-return relation, and therefore, indicate that the inclusion of the Fama and French (1993) factors is robust. The findings are confirmed above by the observation of excess returns. That being, in order to earn excess returns, there should be a strong risk-return relationship. Thus, the more risky the investment the higher the return on that investment, which is appealing to risk taking investors as appose to risk-averse investors (Cheteni, 2016). Accordingly, it will be beneficial for risk tolerant investors to incorporate small cap and mid cap stocks into their portfolio as it will elevate their returns.

Table 7 Coefficient estimates of mean equation for the estimated TGARCH model

	All share	*Top 40*	*Small Cap*	*Midcap*
μ	0.013086	0.012273	0.037888***	0.034505**
	(0.808506)	(0.694874)	(4.025411)	(2.530092)
α_0	–0.004370	–0.025291	0.095353***	0.085860***
	(–0.134067)	(–0.716425)	(4.509469)	(3.141796)
α_1	–0.003392	–0.009220	0.046866**	0.001817
	(–0.103655)	(–0.259173)	(2.124887)	(0.069776)
α_2	0.047554*	–0.066697**	0.018030	0.015955
	(–1.648774)	(–2.121797)	(1.212408)	(0.700013)

Notes: ***, **, * denotes significance at a 1%, 5% and 10% levels respectively.
Z statistics are represented in brackets.

The SMB coefficient (α_1) is positive for the Small Cap and Mid Cap indices whereas it is negative for the All Share and Top 40 indices, only the Small Cap returns are found to be significant. This indicates that, due to their relatively undiversified nature and their reduced ability to absorb negative financial shocks, companies included in the Small Cap index are more sensitive to risk factors associated with company size. This is confirmed by the excess returns and the strong risk-return relationship found for the Small Cap index. Excess returns can only be earned if there is a strong risk-return relation and if the index is found to be volatile, such is confirmed by the SMB coefficient of the Small Cap index (Guo and Whitelaw, 2006). The HML coefficient (α_2) is negative and significant for Top 40 indices. This finding of a significant, negative relationship between the HML factor and index returns suggests that there is no evidence of a value effect being present in the South African market.

Table 8 Coefficient estimates of conditional variance

	All share	*Top 40*	*Small Cap*	*Midcap*
ω	0.015766***	0.019567***	0.007999***	0.088312***
	(7.229217)	(7.370248)	(4.705547)	(8.104877)
β_0	–0.015599**	–0.014890**	0.056766***	0.131341***
	(–2.411499)	(–2.309800)	(6.734786)	(6.114974)
β_1	0.945698***	0.944080***	0.903599***	0.679433***
	(134.8417)	(128.7985)	(81.95373)	(26.85331)
γ	0.102073***	0.102888***	0.023231*	0.080100**
	(7.691270)	(7.997106)	(1.719481)	(2.405224)
δ	0.013508***	0.016912***	0.003512***	0.020192***
	(5.238435)	(5.607325)	(3.765517)	(11.18534)

Notes: ***, **, * denotes significance at 1%, 5% and 10% levels respectively. Z statistics are represented in brackets.

It is evident from Table 8 that the constant (ω), ARCH term (β_0) and GARCH term (β_1) for the four indices are highly significant. This implies that the previous day's volatility has a significant explanatory power on current volatility, due to the influence of lagged conditional variance (β_1) and lagged squared disturbance (β_0) on the current conditional variance (σ^2). Thus, if investors examine historical information/pricing of the SAVI, excess returns can be earned as seen above for the small cap and mid cap indices. Furthermore, the large z-statistics of β_1 suggests that there is considerable volatility clustering in the four indices, with JSE All Share Index depicting the highest prominence of volatility clustering. This is confirmed by studies conducted by Samouilhan (2007) and Louw (2008), which also found volatility clustering on the JSE.For each index, the addition of the β_1 coefficient with its respective β_0 coefficient takes a value that is less than one. This finding is indicative that there is a low degree of persistence in shocks to volatility, short memory in the conditional variance and a stationary variance. In other words, shocks to volatility decay over time (Frimpong and Oteng-Abayie, 2006).

The significant negative asymmetry coefficient (γ) of the all share, top 40, small cap and mid cap indices demonstrate the presence of leverage effects in these three indices. This suggests that the all share, top 40, small cap and mid cap companies' equity market value has increased (Chelley-Steeley and Steeley, 2005). Thus, the companies associated with the indices are volatile, as the presence of a leverage effect results in elevated volatility levels (Maiti and Balakrishnan, 2020). Finally, the parameters associated with the SAVI (δ) are found to be positive and statistically significant for all four indices. This suggests a positive relationship between implied volatility and returns of the All Share, Top 40, Small Cap and Mid Cap indices. This positive relationship may be attributed to the risk-return trade-off, which suggests that an increase in a security's risk results in a corresponding increase in its returns. As such, an increase in the volatility (which measures risk) of a market leads to a complementary increase in returns of stocks listed in that market (Ghysels et al., 2005).

This positive association between implied volatility and stock market returns is consistent with the findings of Sehgal and Vijayakumar (2008) and Kanas (2012). The statistical significance of the coefficients illustrates that volatility measured by the SAVI does significantly contribute to the returns of each index being measured therefore, the SAVI and the various indices cannot be looked at in isolation as the contributing factors must be considered by market participants to ensure profound decisions are made.

5 Conclusions

The relationship between implied volatility and stock market returns has been the centre of debate between research scholars since the interception of equity market risk measures, commonly known as volatility indices. The debate has become more profound in developing countries as the extent to which implied volatility effects developing countries stock market returns, has not been fully perused, especially in South Africa. In an attempt to contribute to the debate, the study examines the impact of the SAVI on different JSE-listed stock indices, namely; All Share, Top 40, Small Cap and, Medium Cap. The findings of the study demonstrate that the TGARCH model, with the SAVI as an exogenous variable, is better suited to model volatility on the JSE. Moreover, the SAVI is significantly positively related to the returns of all the JSE-listed indices and that a leverage effect exists between them. The results are consistent with the findings of studies from developing economies and are important for investors and policymakers. Thus, the study shows that South African investors possess inadequate judgments as the JSE-listed indices are significantly influenced by the SAVI. Accordingly, South African investors are encouraged to enhance their judgement, expand their knowledge on investment decision making, develop a responsibility to invest individually, and refrain from irrationally following the general market. The study further highlights the need for South Africa's regulatory agencies to take active part to improve its risk management policies in order to achieve a healthier and stable development of the South African market. The study is subjected to daily closing prices and limited GARCH-type models. Further research can explore data frequency and GARCH-type models that has not be used in this study. These include, but are not limited to hourly, monthly, quartile and yearly data frequency and APARCH GARCH-type model.

References

Antonakakis, N., Chatziantoniou, I. and Filis, G. (2013) 'Dynamic co-movements of stock market returns, implied volatility and policy uncertainty', *Economics Letters*, Vol. 120, No. 1, pp.87–92.

Arik, A. (2011) *Modeling Market Sentiment and Conditional Distribution of Stock Index Returns under GARCH Process*, Doctoral dissertation, The Claremont Graduate University, California.

Bali, T.G. and Peng, L. (2006) 'Is there a risk–return trade-off? Evidence from high-frequency data', *Journal of Applied Econometrics*, Vol. 21, No. 8, pp.1169–1198.

Banerjee, P.S., Doran, J.S. and Peterson, D.R. (2007) 'Implied volatility and future portfolio returns', *Journal of Banking & Finance*, Vol. 31, No. 10, pp.3183–3199.

Banumathy, K. and Azhagaiah, R. (2015) 'Modelling stock market volatility: evidence from India', *Managing Global Transitions: International Research Journal*, Vol. 13, No. 1, pp.27–41.

Barr, K.J. (2009) *The Implied Volatility Bias and Option Smile: Is there a Simple Explanation?*, Doctoral Dissertation, Iowa State University, Lowa.

Black, F. (1976) 'Studies of stock price volatility changes', *Proceedings of the Business and Economics Section of the American Statistical Association*, pp.177–181.

Bollerslev, T. (1986) 'Generalized autoregressive conditional heteroskedasticity', *Journal of Econometrics*, Vol. 31, No. 3, pp.307–327.

Bollerslev, T., Tauchen, G. and Zhou, H. (2009) 'Expected stock returns and variance risk premia', *The Review of Financial Studies*, Vol. 22, No. 11, pp.4463–4492.

Brailsford, T.J. and Faff, R.W. (1996) 'An evaluation of volatility forecasting techniques', *Journal of Banking & Finance*, Vol. 20, No. 3, pp.419–438.

Brooks, C. (2014) *Introductory Econometrics for Finance*, 3rd ed., Cambridge University Press, UK.

Campbell, J.Y., Lo, A.W. and MacKinlay, A.C. (1997) *The Econometrics of Financial Markets*, Princeton University Press, Princeton.

Canina, L. and Figlewisk, S. (1993) 'The information content implied volatility', *Review of Financial Studies*, Vol. 6, No. 3, pp.659–681.

Chandra, A. and Thenmozhi, M. (2015) 'On asymmetric relationship of india volatility index (India VIX) with stock market return and risk management', *Decision*, Vol. 42, No. 1, pp.33–55.

Chelley-Steeley, P.L. and Steeley, J.M. (2005) 'The leverage effect in the UK stock market', *Applied Financial Economics*, Vol. 15, No. 6, pp.409–423.

Cheteni, P. (2016) 'Stock market volatility using GARCH models: evidence from South Africa and China stock markets', *International Business and Economics Research Journal*, Vol. 14, No. 2, pp.367–386.

Chiah, M., Chai, D., Zhong, A. and Li, S. (2016) 'A better model? An empirical investigation of the Fama–French five-factor model in Australia', *International Review of Finance*, Vol. 16, No. 4, pp.595–638.

Christensen, B.J. and Prabhala, N.R. (1998) 'The relation between implied and realized volatility', *Journal of Financial Economics*, Vol. 50, No. 2, pp.125–150.

Christie, A. (1982) 'The stochastic behavior of common stock variances: value, leverage, and interest rate effects', *Journal of Financial Economics*, Vol. 10, No. 4, pp.407–432.

Day, T. and Lewis, C. (1988) 'The behaviour of the volatility and the information content of sock index option', *Journal of Financial Economics*, Vol. 52, No. 1, pp.103–122.

Dowling, S. and Muthuswamy, J. (2005) *The Implied Volatility of Australian Index Options* [online] https://ssrn.com/abstract=1435309 (accessed 29 March 2018).

Emna, R. and Myriam, C. (2017) 'Dynamics of the relationship between implied volatility indices and stock market indices: the case of European stock markets', *Asian Economic and Financial Review*, Vol. 7, No. 1, pp.52–62.

Ezpeleta, E.V. (2015) *Modelling Volatility for the Swedish Stock Market*, Masters Dissertation, Uppsala University, Sweden.

Fama, E.F. and French, K.R. (1993) 'Common risk factors in the returns on stocks and bonds', *Journal of Financial Economics*, Vol. 33, No. 1, pp.3–56.

French, K., Schwert, W. and Stambaugh, R. (1987) 'Expected stock returns and volatility', *Journal of Financial Economics*, Vol. 19, No. 1, pp.3–29.

Frimpong, J.M. and Oteng-Abayie, E.F. (2006) 'Modelling and forecasting volatility of returns on the Ghana stock exchange using GARCH models', *American Journal of Applied Sciences*, Vol. 3, No. 10, pp.2042–2048.

Ghysels, E., Santa-Clara, P. and Valkanov, R. (2005) 'There is a risk-return trade-off after all', *Journal of Financial Economics*, Vol. 76, No. 3, pp.509–548.

Glosten, L.R., Jagannathan, R. and Runkle, D.E. (1993) 'On the relation between the expected value and volatility of the nominal excess return on stocks', *The Journal of Finance*, Vol. 48, No. 5, pp.1779–1801.

Guo, H. and Neely, C.J. (2008) 'Investigating the intertemporal risk-return relation in international stock markets with the component GARCH model', *Economics Letters*, Vol. 99, No. 2, pp.371–374.

Guo, H. and Whitelaw, R.F. (2006) 'Uncovering the risk-return relation in the stock market', *The Journal of Finance*, Vol. 61, No. 3, pp.1433–1463.

Hahn, J. and Lee, H. (2006) 'Yield spreads as alternative risk factors for size and book-to-market', *Journal of Financial and Quantitative Analysis*, Vol. 41, No. 2, pp.245–269.

Hansen, C.S. (2001) 'The relation between implied and realised volatility in the Danish option and equity markets', *Accounting & Finance*, Vol. 41, No. 3, pp.197–228.

Harvey, C.R. and Whaley, R.E. (1991) 'S&P 100 index option volatility', *The Journal of Finance*, Vol. 46, No. 4, pp.1551–1561.

Kanas, A. (2012) 'The risk-return relation and VIX: evidence from the S&P500', *Empirical Economics*, Vol. 44, No. 3, pp.1291–1314.

Kelly, P.J. (2003) 'Real and inflationary macroeconomic risk in the Fama and French size and book-to-market portfolios', paper presented at the *2003 EFMA Conference*, Helsinki.

Kenmoe, S.R.N. and Tafou, C.D. (2014) *The Implied Volatility Analysis: The South African Experience*, arXiv preprint, arXiv:1403.5965.

Kgosietsile, O. (2014) *Modelling and Forecasting the Volatility of JSE Returns: A Comparison of Competing Univariate GARCH Models*, Unpublished Masters Dissertation, University of Witwatersrand.

Li, M.Y.L. and Lin, H.W.W. (2003) 'Examining the volatility of Taiwan stock index returns via a three-volatility-regime Markov-switching ARCH model', *Review of Quantitative Finance and Accounting*, Vol. 21, No. 2, pp.123–139.

Liew, J. and Vassalou, M. (2000) 'Can book-to-market, size and momentum be risk factors that predict economic growth?', *Journal of Financial Economics*, Vol. 57, No. 2, pp.221–245.

Lin, Z. (2018) 'Modelling and forecasting the stock market volatility of SSE composite index using GARCH models', *Future Generation Computer Systems*, Vol. 79, No. 3, pp.960–972.

Louw, J.P. (2008) *Evidence of Volatility Clustering on the FTSE/JSE Top 40 Index*, Masters dissertation, University of Stellenbosch, Stellenbosch.

Maiti, M. and Balakrishnan, A. (2020) 'Can leverage effect coexist with value effect?', *IIMB Management Review*, Vol. 32, No. 1, pp.7–23.

Mandimika, N.Z. and Chinzara, Z. (2012) 'Risk–return trade-off and behaviour of volatility on the south African stock market: evidence from both aggregate and disaggregate data', *South African Journal of Economics*, Vol. 80, No. 3, pp.345–366.

Masinga, Z.C. (2015) *Modeling and Forecasting Stock Return Volatility in the JSE Securities Exchange*, Masters Dissertation, University of Witwatersrand, South Africa.

Merton, R. (1980) 'On estimating the expected return on the market: an exploratory investigation', *Journal of Financial Economics*, Vol. 8, No. 4, pp.323–361.

Merton, R.C. (1973) 'An intertemporal capital asset pricing model', *Econometrica: Journal of the Econometric Society*, Vol. 41, No. 5, pp.867–887.

Mokoena, T. (2016) *The Ability of GARCH Models in Forecasting Stock Volatility on the JSE Limited*, Unpublished Masters Dissertation, University of Johannesburg, South Africa.

Naseem, S., Mohsin, M., Zia-ur-Rehman, M. and Baig, S.A. (2018) 'Volatility of pakistan stock market: a comparison of GARCH type models with five distribution', *Amazonia Investiga*, Vol. 7, No. 17, pp.486–504.

Nelson, D.B. (1991) 'Conditional heteroskedasticity in asset returns: a new approach', *Econometrica*, Vol. 59, No. 2, pp.347–370.

Obalade, A.A. and Muzindutsi, P.F. (2018) 'Are there cycles of efficiency and inefficiency? Adaptive market hypothesis in three African stock markets', *Frontiers in Finance and Economics*, Vol. 15,No. 1, pp.185–202.

Olberholzer, N. and Venter, P. (2015) 'Univariate GARCH models applied to the JSE/FTSE stock indices', *Procedia Economics and Finance*, Vol. 24, No. 1, pp.491–500.

Panda, S.P., Swain, N. and Malhotra, D.K. (2008) 'Relationship between implied and realized volatility of S&P CNX Nifty Index in India', *Frontiers in Finance & Economics*, Vol. 5, No. 1, pp.85–105.

Peters, J.P. (2001) *Estimating and Forecasting Volatility of Stock Indices using Asymmetric GARCH Models and (Skewed) Student-t Densities*, University of Leige, Working Paper, Belgium.

Pindyck, R. (1984) 'Risk, inflation, and the stock market', *American Economic Review*, Vol. 74, No. 3, pp.335–351.

Samouilhan, N. (2007) 'The persistence of SA equity volatility: a component ARCHperspectiv', *Journal of the Study of Economics and Econometrics*, Vol. 31, No. 1, pp.99–117.

Sarwar, G. (2012) 'Intertemporal relations between the market volatility index and stock index returns?', *Applied Financial Economics*, Vol. 22, No. 11, pp.899–909.

Sehgal, S. and Vijayakumar, N. (2008) 'Determinants of implied volatility function on the NIFTY index options market: evidence from India', *Asian Academy of Management Journal of Accounting and Finance*, Vol. 4, No. 1, pp.45–69.

Sewell, M. (2007) *Behavioural Finance*, University of Cambridge, UK.

Shaikh, I. and Padhi, P. (2014) 'Inter-temporal relationship between India VIX and Nifty equity index', *Decision*, Vol. 41, No. 4, pp.439–448.

Strydom, B. and Charteris, A. (2013) 'The South African risk-free rate anomaly', *African Journal of Business Management*, Vol. 7, No. 28, pp.2807–2816.

Wang, Y.C., Tsai, J.J. and Lu, W. (2014) 'The impact of volatility index on China's stock market', *Journal of Business & Economics*, Vol. 6, No. 1, pp.23–46.