Rupande et al., *Cogent Economics & Finance* (2019), 7: 1600233
https://doi.org/10.1080/23322039.2019.1600233

cogent economics & finance

FINANCIAL ECONOMICS | RESEARCH ARTICLE

Investor sentiment and stock return volatility: Evidence from the Johannesburg Stock Exchange

Lorraine Rupande[1], Hilary Tinotenda Muguto[1] and Paul-Francois Muzindutsi[1*]

Received: 08 November 2018
Accepted: 24 March 2019
First Published: 31 March 2019

*Corresponding author: Paul-Francois Muzindutsi, University of KwaZulu-Natal, School of Accounting, Economics and Finance, Westville campus, Bag X 5400, Durban 4000, South Africa
E-mail: muzindutsip@ukzn.ac.za

Reviewing editor:
Zhaojun Yang, Finance, Southern University of Science and Technology, China

Additional information is available at the end of the article

Abstract: Volatility is an important component of asset pricing; an increase in volatility on markets can trigger changes in the risk distribution of financial assets. In conventional financial theory, investors are considered to be rational and any changes in relevant risk are assumed to be a result of the movement in fundamental factors. However, herein this study, it is hypothesized that there are movements in risk that are driven by volatility linked to sentiment-driven noise trader activity whose patterns are irreconcilable with changes in fundamental factors. This assertion is tested using a daily sentiment composite index constructed from a set of proxies and Generalised Autoregressive Conditional Heteroscedasticity models on the South African market over a period spanning July 2002 to June 2018. The results show that there is a significant connection between investor sentiment and stock return volatility which shows that behavioural finance can significantly explain the behaviour of stock returns on the Johannesburg Stock Exchange. It is, thus, recommended that due to the inadequacies of popular asset pricing models such as the Capital Asset Pricing Model, consideration should be made towards augmenting these asset pricing models with a sentiment risk factor.

ABOUT THE AUTHORS

Lorraine Rupande is a PhD candidate at the University of KwaZulu-Natal in the school of Accounting, Economics and Finance. Her research interests include financial markets, behavioural finance and financial risk management.

Hilary Tinotenda Muguto is a PhD candidate at the University of KwaZulu-Natal under the HEARD division. His research interests include healthcare equity and finance, financial markets, behavioural finance, investment analysis and development economics.

Paul-Francois Muzindutsi (PhD) is an associate professor of Finance in the School of Accounting, Economics and Finance, University of KwaZulu-Natal. His research interests include financial markets, behavioural finance, financial risk management, time series analysis of macroeconomic variables, investment analysis and development economics.

PUBLIC INTEREST STATEMENT

This paper investigates whether stock market return volatility is influenced by market-wide investor sentiment on the South African market. Daily closing prices and dividend yields on the Johannesburg Stock Exchange All Share Index were employed to compute the returns and a composite sentiment index was constructed using a set of seven proxies to measure sentiment over the period spanning July 2002 to June 2018. The Generalised Autoregressive Conditional Heteroscedasticity models were then used to examine the relationship between market returns and investor sentiment. The empirical findings show that there is a significant relationship between market-wide investor sentiment and stock return volatility on the South African market. Thus, although traditional asset pricing models ignore investor behavioural biases, their impact on asset pricing is significant. As such, consideration should be made towards adding behavioural risk factors to the traditional asset pricing models to ensure that financial assets are correctly priced.

Subjects: Behavioural Finance; Corporate Finance; Financial Asset Pricing; Financial Asset Price Discovery; Investment & Securities; Risk Management; Traditional Asset Pricing Models

Keywords: Generalised autoregressive conditional heteroscedasticity model (GARCH); investor sentiment; stock return volatility; noise traders
JEL classification: G11; G12; G14; G40; G41

1. Introduction

Behavioural finance, a new paradigm in finance, continues to burgeon. Introduced as a response to the modern finance theory, behavioural finance replaces the supposition that investors always act rationally when making investment decisions with the idea that investors do not always act rationally as they are prone to various behavioural biases. This replacement has certain consequences for asset pricing; it implies that the mean-variance portfolio theory (Markowitz, 1952) is replaced by behavioural portfolio theory (Shefrin & Statman, 2000). It also implies that the traditional asset pricing models such as the capital asset pricing model (Linter, 1964; Sharpe, 1964) are replaced by behavioural asset pricing models (Statman, 2014). This is because the mean-variance portfolio theory and the traditional asset pricing models are based on the assertion that expected returns are determined by risk and that risk is determined by movements in fundamental factors only. Instead, in addition to the fundamental risk, behavioural portfolio theory and behavioural asset pricing models recognize the impact of behavioural biases on investors' decisions (Kapoor & Prosad, 2017).

The irrational traders identified in behavioural finance are termed as noise traders (Herve, Zouaoui, & Belvaux, 2019). These are the investors whose wants, cognitive errors and emotions affect their preferences for certain stocks (Shefrin & Statman, 1984). Consequently, they irrationally act on noise in their investment decision-making as if it were fundamental information that would allow them to consistently earn abnormal returns on the financial markets (Peress & Schmidt, 2017). In traditional finance, there is an argument that the noise traders are eradicated from the markets by their rational counterparts through the process of arbitrage. The sophisticated institutional investors, considered to be rational, exploit less sophisticated retail investors, considered to be the noise traders (Lin, Sias, & Wei, 2018). The process of exploitation of the mispricing is aided by the increased liquidity that comes with the noise traders (Barrot, Kaniel, & Sraer, 2016). As a result, the presence and the impact of the irrational noise traders on financial markets is considered to be only transient at best. This explains why traditional finance did not take them into account when the framework was constructed.

However, this process of exploitation might not occur as quickly as expected (Lin, Sias, et al., 2018). This means that the noise traders may survive in the market for protracted periods. Further, rational investors demand a risk premium to trade stocks that are prone to noise trading. This is because the unpredictability of the noise traders' beliefs creates a risk—termed as noise trader risk—in the price of the asset that deters rational arbitrageurs from aggressively betting against them. Even if there is some form of mispricing that can be exploited to make a profit, rational investors face the risk that the mispricing might get worse in the short run, triggering margin calls and thereby forcing early liquidation of their positions at a loss (Ljungqvist & Qian, 2016). Only when the premium is high enough will the rational traders bet against the irrational noise traders (Akbas, Boehmer, Jiang, & Koch, 2019). This may also result in noise traders surviving for protracted periods on the financial markets. Add to that, there are limits to arbitrage on most financial markets which prevent sophisticated investors from trading profitably against the irrational noise traders (Chu, Hirshleifer, & Ma, 2017). These include the short-selling constraints in regulation and short-selling risk such as stock loans becoming expensive and being recalled (Engelberg, Reed, & Ringgenberg, 2018).

The trading patterns of noise traders have been found to be linked to the prevailing market-wide sentiment (Brown, 1999). Sentiment is defined as the overall attitude of investors towards particular financial assets or financial markets that is not dependent on the flow of fundamental information (Antoniou, Doukas, & Subrahmanyam, 2015). Noise traders usually enter the market during high sentiment periods because they interpret the high optimism that typifies high sentiment periods as fundamental information instead of a noisy signal that it is (Shen, Yu, & Zhao, 2017). Incorrect assumptions are made about the distribution of returns of financial securities due to a marked overreliance on recent non-fundamental information, all of which results in mispricing (Miwa, 2016). In low sentiment periods, characterized by a negative outlook, the incidence of noise traders on the financial markets is low because these traders are reluctant to take on short positions in their portfolios (Uygur & Taş, 2014). Therefore, mispricing is more likely to occur in high sentiment periods than in low sentiment periods.

The mispricing that occurs in high sentiment periods as a result of the increased incidence of noise traders leads to increased market volatility (Bahloul & Bouri, 2016). According to Devault, Sias, and Starks (2019), sentiment traders shift from safer to more speculative stocks when sentiment increases. Due to herd behaviour, the sentiment-driven noise traders trade in concert, causing trading volumes to increase rapidly, all of which results in increased market volatility (Blasco, Corredor, & Ferrer, 2018; Economou, Hassapis, & Philippas, 2018; Hudson, Yan, & Zhang, 2018). As the incidence of the sentiment traders on the markets increases, mispricing occurs. It would be very profitable for rational arbitrageurs to enter the market to exploit that mispricing. However, they are constrained by noise trader risk and various limits to arbitrage such as short-selling constraints. As a result, overvaluation due to the under-pricing of risk by sentiment traders and the lack of arbitrage activity from the rational traders occurs, leading to the formation of pricing bubbles (Taffler, Agarwal, & Wang, 2017). When sentiment and expectations reverse, these pricing bubbles burst due to the ensuing mass liquidation of portfolios by the sentiment traders. This process induces volatility in the financial markets (Shu & Chang, 2015).

The link between sentiment-driven noise trading and volatility has implications for financial market participants. Traditional asset pricing models assume that the only relevant risk is related to fundamental factors. However, increased volatility on markets as a result of the sentiment-driven noise trading can trigger changes in risk that are irreconcilable with changes in fundamental variables. Therefore, the risk in financial securities can exceed the bounds implied by traditional asset pricing models that assume rationality. There is a need, therefore, to determine whether there is a link between sentiment and stock market volatility so that investors and policymakers can be informed. This is because risk management, portfolio management, policymaking and price discovery are all aspects of financial markets that profoundly depend on the ability of market participants to measure risk. Failure to do so would result in poor risk management, inefficient portfolio strategies, persistent mispricing and poor price discovery.

Accordingly, this study investigated the link between investor sentiment and volatility on the Johannesburg Stock Exchange market using the All Share Index and a composite sentiment index constructed using a set of proxies. It was hypothesised herein that investor sentiment-driven noise trader activity increases financial market volatility on the South African market. The impact of the noise trader activity was expected to be significant and persists for protracted periods of time due to the substantial incidence of sentiment-driven noise traders on the Johannesburg Stock Exchange and various limits to arbitrage. Sentiment-augmented GARCH models were used to test the effect of investor sentiment on the returns in the mean equation and the conditional volatility in the variance equation. The empirical findings from the estimations showed a significant relationship between market-wide investor sentiment and stock return volatility on the South African market.

2. Literature review

As alluded to above, sentiment affects volatility through its influence on noise trading activity on financial markets. This reasoning is consistent with the finding by Liu (2015) that there is an increase in liquidity on the U.S market which is linked to increases in sentiment. As sentiment increases, the incidence of noise traders increases, causing mispricing. Rational arbitrageurs then enter the market to exploit their irrational counterparts. Their trades are essentially contrarian to the irrational traders' bets so the ensuing buying and selling between these two groups create liquidity on financial markets. This is only possible when there are no limits to arbitrage and when the abnormal returns are commensurate to the noise trader risk that the rational investors get exposed to when they enter the market. Alfano, Feuerriegel, and Neumann (2015), however, found that sentiment not only influences unsophisticated noise traders but it also influences informed traders, the investors that are generally assumed to be rational.

Alfano *et al.*'s (2015) results are contrary to the noise trader theory which states that there are noise traders and rational traders; the former trade noise signals while the latter trade on information (Herve et al., 2019). However, many studies have shown that even rational investors demand speculative stocks during high sentiment periods (Devault et al., 2019; Jang & Kang, 2018). Others have also reported herd behaviour among sophisticated institutional traders. For instance, Nofsinger and Sias (1999) found that institutional investors positive-feedback trade more than individual investors and that institutional herding effects prices more than herding by individual investors. This trend-chasing behaviour among institutional investors means that there is a lack of contrarian trades against noise traders. It can lead to extreme volatility on financial markets for protracted periods when sentiment mean-reverts. It is possible that this behaviour is a result of noise trader risk and limits to arbitrage.

Another study by Chau, Deesomsak, and Koutmos (2016) found that there was sentiment-induced buying and selling on the US market. However, their findings further showed that sometimes sentiment-driven investors behave rationally by trading against the herd and sell when financial market assets are overpriced as a result of high optimism that characterises high sentiment periods. Therefore, sentiment-driven noise traders may not be as irrational as originally purported in the noise trader theory. Nevertheless, even if some noise traders sometimes behave "rationally", their effect cannot be substantial as there are also some rational institutional investors with more funds who also behave irrationally in high sentiment periods through herding and feedback trading (Devault et al., 2019). Also, other irrational traders trade in concert in these high sentiment periods. This is consistent with the finding of a deterioration of the risk-return relationship in high sentiment periods due to the impact of less sophisticated noise traders (Antoniou et al., 2015; Kim, Kim, & Seo, 2017; Piccoli, Da Costa, Da Silva, & Cruz, 2018).

The connection between stock market volatility and sentiment-driven noise trading activity has long been established by models developed in behavioural finance (Black, 1986; Campbell & Kyle, 1993; De Long, Shleifer, Summers, & Waldmann, 1990). All these models predict that noise traders have a significant impact on financial markets—both the returns and the volatility thereof. An increased incidence of noise trading activity increases the return volatility as well as contemporaneous returns due to increased mispricing. Further, in the recent agent-based models (Ghonghadze & Lux, 2016; Hessary & Hadzikadic, 2017; Xiao, Wang, & Niu, 2016), noise traders are seen as a source of added volatility in the stock market. This is because the mispricing in the high sentiment periods eventually gets corrected through falling prices and bubble bursts as sentiment mean reverts. The unwillingness by irrational traders to short-sell and the shunning of financial markets result in protracted periods of high volatility on the market.

The predictions of these models are consistent with the findings of a number of authors that have examined the relationship between sentiment and volatility. For instance, Chuang, Ouyang, and Lo (2010) found that changes in investor sentiment, measured by trading volume, significantly affect market volatility on the on the Taiwan Stock Exchange. Bullish sentiment periods had increased trading volume and market volatility, indicative of increased incidence of noise traders in high sentiment periods. Rahman, Shien, and Sadique (2013) also investigated the impact of sentiment-driven noise trading on expected returns and volatility on the Bangladesh stock market. Their results showed that changes in investor sentiment affected the returns and volatility of these stocks. Rahman et al's (2013) findings are consistent with the findings by Uygur and Taş (2014) that sentiment significantly affects conditional volatility on the U.S., Japan, Hong Kong, U.K., France, Germany and Turkey financial markets.

Abdelhédi-Zouch, Abbes, and Boujelbène (2015) also found a determinant role of investor sentiment in the amplification of volatility during the subprime financial crisis in the U.S. This was a period characterised by very high sentiment due to the positive outlook on financial markets. Naik and Padhi (2016) and Kumari and Mahakud (2016) found that sentiment influences the conditional volatility on the Indian market. The latter study also found that the relationship between stock return volatility and sentiment was persistent, suggesting that investor sentiment in India does play a significant role in determining the stock market volatility. Ya'cob and Ya'cob (2016) found that sentiment predicts volatility on the Malaysian stock market. This remained significant even when they adjusted for financial crises. Bahloul and Bouri (2016) found that sentiment is positively related to price volatility on thirteen major futures markets in the U.S. and that sentiment destabilised these markets.

A study by Dai and Yang (2018) examined the link between investor sentiment and feedback trading, a phenomenon defined as a trading strategy that involves buying when prices rise and selling when they fall in the market. The study found that that positive feedback traders are more likely to trade when sentiment is relatively high. This finding is consistent with earlier findings by Kurov (2008) and Chau, Deesomsak, and Lau (2011) that the intensity of positive feedback trading was linked to the prevailing sentiment, consistent with the notion that feedback trading is driven by expectations of noise traders on the U.S. market. Per Charteris and Rupande (2017), positive feedback trading perpetuates trends and is thus destabilising, as it drives prices away from their fundamental value and contributes to volatility. Thus, positive feedback trading amplifies volatility on markets in high sentiment periods when the incidence of these feedback traders is high.

Despite all this evidence of investor sentiment's impact on markets, no uncontroversial measure of investor sentiment exists. This could be because sentiment is related to these fundamental factors in that sentiment-prone investors also react to fundamental information but only do so irrationally or to the noise surrounding those fundamental factors (Shleifer & Summers, 1990). Also, the extensive debate about which group between individual investors (Frazzini & Lamont, 2005; Schmeling, 2007), institutional investors (Devault et al., 2019; Hong & Stein, 2007) or both (Nofsinger & Sias, 1999; Verma & Soydemir, 2009) are prone to sentiment biases has not been resolved yet. There are groups of authors that argue that sentiment-driven investors are irrelevant (Black, 1986) while some argue that they have a positive impact (Tetlock, 2007) and others have identified their negative impact on markets (Da, Larrain, Sialm, & Tessada, 2015; De Long et al., 1990). All of this contention has undermined the progress towards the development of a much-needed sentiment measure.

3. Data and description of the variables

In this study, we employed daily closing prices, dividend yields and volume turnover on the JSE All Share Index (JSEALSI) from McGregor BFA database (July 2002—April 2018). Daily data was preferred to weekly and monthly frequency because modelling volatility is more accurate with high-frequency data. The total daily return on the JSEALSI, Rt, was computed using Pt, the closing price on day t, P_{t-1}, the closing price on the previous day and D_t, the dividend payment on day t. The dividend payment estimated by multiplying the JSEALSI dividend yield on day t, DY_t, by P_t. Rt was then determined as:

$$R_t = \ln\{[P_t + ((DY_t * P_t)/100)]/P_{t-1}\} * 100 \quad (1)$$

Owing to the absence of an uncontroversial measure of sentiment, a new sentiment measure (InvSent) was constructed using daily data on the exchange rate between the South African Rand and the US dollar (Exch), the prime rate (Prime), the 90-day Treasury bill rate (Treasury), the repo rate (Repo), the trading volume of the JSEALSI (Volume), the volume-weighted average price changes on the JSEALSI (Vwap) and the SAVI index (Savi). The choice of proxies was governed by the availability of data—most series employed in literature are only available in monthly, quarterly and annual frequencies. Principal component analysis (PCA) was then employed to derive a sentiment index from the fitted proxies. This procedure was chosen to construct the composite sentiment index because it allowed for the reduction of the dimensionality of the dataset, which helped in increasing interpretability without information loss in the determination of whether sentiment influences volatility on the South African market (Jolliffe & Cadima, 2016). Also, given that there are seven imperfect sentiment proxies, it was pertinent that focus is only on their common component—considered to be sentiment—instead of what these series measure.

The PCA technique uses orthogonal transformation to translate a set of correlated series into an array of linearly uncorrelated ones (Jolliffe & Cadima, 2016). For rotation, the Varimax rotation was used to rotate the PCA matrix in order to maximise the variance of the loadings. According to Baker and Wurgler (2006), some sentiment proxies take longer to reveal sentiment than others so, to account for this, an index with the first principal components of the current values as well as the one-period lagged values was constructed. Subsequently, the correlation between the first stage index and the current and lagged values of each of the proxies was examined. A composite index, InvSent, was then defined as the first principal component of the correlation matrix of the factors —each corresponding proxy's current or lagged value, whichever had a greater correlation with the first-stage index as:

$$\begin{aligned} Sentiment_t = {} & \theta_1 Exch_{t-1} + \theta_2 Exch_t + \theta_3 Prime_{t-1} + \theta_4 Prime_t + \theta_5 Treasury_{t-1} + \theta_6 Treasury_t \\ & + \theta_7 Repo_{t-1} + \theta_8 Repo_t + \theta_9 Volume_{t-1} + \theta_{10} Volume_t + \theta_{11} Vwap_{t-1} \\ & + \theta_{12} Vwap_t + \theta_{13} Savi_{t-1} + \theta_{14} Savi_t \end{aligned} \tag{2}$$

$$\begin{aligned} InvSent_t = {} & \theta_1 Exch_{\,t-1/t} + \theta_2 Prime_{\,t-1/t} + \theta_3 Treasury_{\,t-1/t} + \theta_3 Repo_{\,t-1/t} + \theta_3 Volume_{\,t-1/t} \\ & + \theta_3 Vwap_{\,t-1/t} + \theta_3 Savi_{\,t-1/t} \end{aligned} \tag{3}$$

Where: θ_i represent the factor loadings on the first principal components of the proxies—lagged and contemporaneously.

4. Method of analysis

To test the impact of sentiment on conditional volatility, the GARCH (1.1), the GJR-GARCH (1.1) of Glosten, Jagannathan, and Runkle (1993) and the E-GARCH (1.1) of Nelson (1991) were employed. Of note, the GARCH models were estimated following unit root and stationarity tests using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, respectively. The lag order of (1.1) was used as most empirical work in South Africa has shown that it captures the ARCH effects and the autocorrelation in the variance (Dedi & Yavas, 2016; Mandimika & Chinzara, 2012; Mangani, 2008). In cases where these first order models failed to capture the inherent ARCH effects and autocorrelation, higher order models were used.

Although the simple GARCH (1, 1) model has been most successful in the estimation of in-sample parameters and out-of-sample volatility forecasts (Hurditt, 2004), it fails to capture asymmetry in volatility (Chinzara & Aziakpono, 2009). This is where positive and negative shocks of equal magnitude have a different impact on stock market volatility, termed the leverage effect (Black, 1976). This has led to extensions such as the GJR-GARCH and the E-GARCH being developed to deal with this asymmetry as negative shocks provide higher volatility than positive shocks of the same magnitude (Engle & Ng, 1993). The GJR GARCH adds a multiplicative dummy variable to check whether there is a statistically significant difference when shocks are negative.

Here in this study, we chose the GARCH models instead of other alternatives because, in the finance literature, it is now widely accepted that volatility is best modelled through GARCH type of models. These models estimate the variance of the next forecasted return based on past forecast errors as well as past estimates of volatility (Bose, 2007). The superiority of these models over some of the historical and stochastic volatility models have been proven in the literature (see Alberg, Shalit, & Yosef, 2008; Hien & Thanh, 2008; Lim & Sek, 2013; Liu, Lee, & Lee, 2009; Matei, 2009). According to Matei (2009), GARCH models provide better quality volatility forecast relative to any other alternative model. This has been aided by the constant refining and evolving of the GARCH models to improve their performances in forecasting volatility by solving the inefficiencies of the previous versions.

In these GARCH models, the sentiment index, ΔInvSent, was introduced into the mean and variance equations to capture the role of investor sentiment in explaining the returns and volatility of the JSE ALSI. The persistence of serial correlation in the data was tested using the Ljung-Box and the ARCH-LM (Engle & Ng, 1993) tests before estimating the GARCH models for correct specification, and after the estimation for model adequacy checks. The GARCH models follow the same mean equation with the conditional variance nested in the mean so as to capture the risk-premium on the JSEALSI returns. This allows for any direct feedback between the mean and conditional variance to be observed (Brooks, 2014). The mean equation was specified as:

$$y_t = \mu + \alpha y_{t-1} + \nu\varepsilon_{t-1} + \delta h_{t-1} + \theta\Delta InvSent_t + \varepsilon_t \tag{4}$$

Where: y_t represents the index returns, δ denotes the risk premium, α captures the effect of past returns, ν captures the effect of past shocks and $\Delta InvSent_t$ represents the changes in investor sentiment in the mean and conditional variance equation. The conditional variance for the GARCH (1.1), GJR-GARCH (1.1) and the E-GARCH (1.1) are modelled as follows, respectively:

$$h_t = \omega + \alpha\varepsilon^2_{t-j} + \beta h_{t-i} + \varphi\Delta InvSent_t \tag{5}$$

$$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-j} + \gamma\varepsilon^2_{t-1} d_{t-1} + \varphi\Delta InvSent_t \tag{6}$$

$$log(h_t) = \omega + \alpha\left[\left|\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} - E\left(\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}}\right)\right|\right] + \gamma_k\frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} + \beta h_{t-i} + \varphi\Delta InvSent_t \tag{7}$$

Where: h_t is the conditional variance in all models. The leverage effect in Equation (6) is denoted by a positive γ. However, since the non-negativity constraints may still be violated under the GJR-GARCH model, the condition for non-negativity where $\omega > 0$, $\alpha > 0$, $\beta \geq 0$, and $\alpha + \gamma \geq 0$ has to be satisfied. The model is still admissible, even if $\gamma < 0$, provided that $\alpha + \gamma \geq 0$. With the E-GARCH in Equation (7), there is no need to artificially impose the non-negativity constraints as it models conditional variance in logs. The log of conditional variance makes the leverage effect exponential instead of quadratic, and therefore, the estimates of the conditional variance are guaranteed to be non-negative.

However, the following conditions still need to be met where $\omega_0 > 0$, $\alpha_j + \beta_i < 1$. The leverage effect under the E-GARCH is shown when $\gamma < 0$. Equations (5–7) were estimated and compared under all the three error distribution assumptions—normal distribution, Student's t-distribution and the generalized error distribution (GED). The best model was selected based on Akaike's Information Criterion (AIC), Schwarz's Bayesian Criterion (SBIC), Hannan and Quinn's Criterion (HQ) and the log-likelihood (LL). That is, the best model minimised the information criteria and maximised the LL (Brooks, 2014). The results from the estimated models are reported in the section below.

5. Results and discussion

The composite sentiment index, InvSent, yielded by the principal component analysis approach in Equation (3) has certain desirable qualities. Firstly, all the seven proxies enter the final equation with the expected sign—negative for those that decrease with sentiment and positive for those that increase with sentiment. Secondly, all of them enter the equation with the expected timing in reflecting sentiment. Thirdly, the creation of the index eradicates some extreme values in some of the proxies such as the Trading volume and VWAP, for instance. This is important because, according to Baker and Wurgler (2006), for the proxies to work as predictors, their levels of extremity must be matched by extremity in the returns. This would not have been the case if the component analysis procedure had not been used.

The stationarity tests in Table 1 above report the order of integration of the two series—investor sentiment, INVSENT, and the returns on the JSEALSI. Given that the sentiment index is I(1), there is need to first adjust it by differencing it once as using it in the GARCH models in its current form would lead to spurious estimation outputs. Of note, the sentiment series exhibited the presence of structural breaks. However, as shown in Figure 1 below, these disappeared when the series was first differenced.

The Ljung-Box[1] statistic for each of the series was significant, signifying temporal dependencies in the first moment of the distribution of these series, thus warranting the addition of an autoregressive component in the mean equation to whiten the error term. The Ljung-Box statistic for the squared residuals and the ARCH-LM test show that ARCH effects are present. This means that the second moments of the series are time-varying and follow an autoregressive process, giving rise to volatility clustering (Brooks, 2014). This is also evident in Figure 2 where most clustering occurred during the financial crisis period (2007 to 2010).

Table 2 shows the information criteria results from the three GARCH specifications—estimated with and without a sentiment factor. Overall, the sentiment-augmented models are better in terms of the information criteria relative to the models without the sentiment variable. Among the three sentiment augmented models, the information criteria show that the E-GARCH-M under the students' t-distribution best models the JSEALSI conditional volatility. However, the model results in Table 3 shows that the sentiment-augmented E-GARCH-M does not fully capture volatility clustering as volatility is explosive. That is, the model fails to satisfy the stationarity condition

Table 1. Stationarity and unit root tests

Test			InvSent	Returns
ADF	Level	Intercept	−1.278567	−7.393972***
		Trend & Intercept	−1.554497	−7.436071***
	First Difference	Intercept	−30.21930***	−25.25799***
		Trend & Intercept	−30.22304***	−25.25483***
KPSS	Level	Intercept	6.272597	0.298158***
		Trend & Intercept	0.371005	0.252076***
	First Difference	Intercept	0.076525***	0.095160***
		Trend & Intercept	0.057498***	0.071248***
Order of integration			**I(1)**	**I(0)**

Figure 1. Multiple breakpoint tests of ΔInvSent.

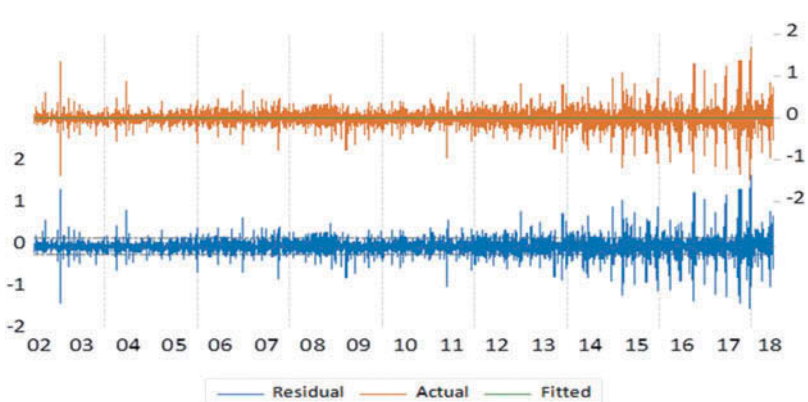
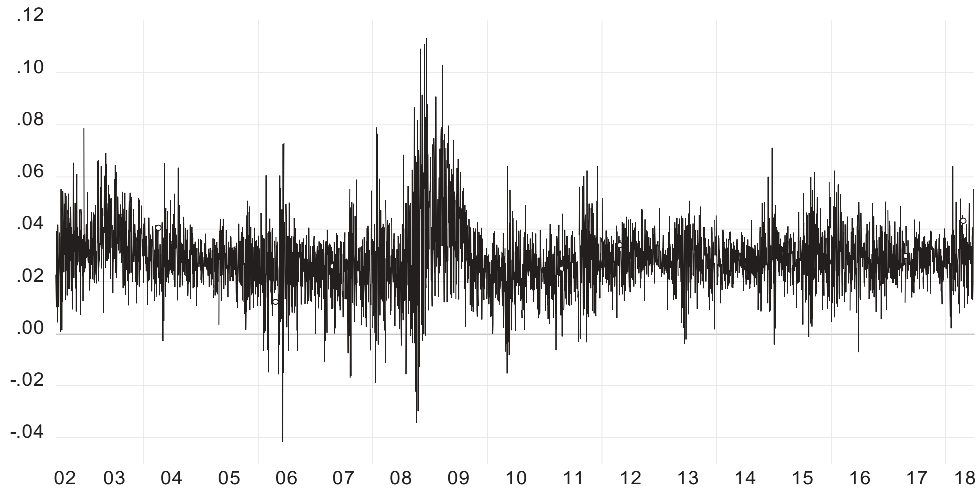


Figure 2. The JSEALSI returns.



where α + β <0. This finding, similar to what Mandimika and Chinzara (2012) found on the JSE, implies that a shock to the returns will persist indefinitely into the future. Given the explosive volatility in the E-GARCH-M specification, the appropriate model based on information criteria and the log likelihood is the GJR-GARCH-M as it satisfies the stationarity conditions.

The sentiment-augmented GJR-GARCH-M mean equation was, therefore, modelled as an ARMA (1.1) so as to deal with autocorrelation in the mean equation. The results show that the JSEALSI returns can be explained by its own past values, indicative of momentum and mean reversion in stock trading, and past unexpected shocks, as both the ARMA(1.1) coefficients were statistically significant. This shows the importance of past returns and unexpected shocks in explaining the JSEALSI returns. In the mean equation, the results show a statistically significant and positive coefficient of risk aversion, δ. This implies that an increase in risk measured by the conditional variance leads to an increase in the mean return. These results are consistent with the theory of a positive risk premium on stock index returns (Brooks, 2014), which shows that risk was priced over the sample period. The evidence of a positive risk premium is statistically strong given the magnitude of the coefficient.

Of note, the higher premium observed for the sentiment-augmented GJR-GARCH model implies that the component of volatility that is sentiment-driven or sentiment-related is also priced on the South African market. This means that investors on the JSE may use volatility and changes in sentiment to forecast the movements in returns. It should, however, be noted that the statistically significant positive risk premium is on total risk and not systematic risk, the latter being the component of risk that is rewarded for in accordance with modern portfolio theory. The coefficient of risk aversion, the risk premium, accounts for total risk and therefore may not be correlated with returns in accordance with CAPM (Gitman, Juchau, & Flanagan, 2015). This implies that risk premiums under the CAPM will increase with increasing risk avoidance as investors are assumed to be risk-averse. Therefore, investors on the JSE need to hold well-diversified portfolios for higher premiums.

The pricing of volatility is contrary to the findings of most South African studies such as Mangani (2008), Chinzara and Aziakpono (2009), Makhwiting, Lesaoana, and Sigauke (2012), Mandimika and Chinzara (2012) and Kgosietsile (2015). The difference in results could be explained by the different sample periods used. For instance, Mangani (2008) used data from 1973–2002, Chinzara and Aziakpano (2009) used 1995–2007, Mandimika and Chinzara (2012) used 1995–2009, Makhwiting et al. (2012) used 2002–2010 and Kgosietsile (2015) used 2007–2013. This study used much more recent data than all the above studies which could explain the difference in results. Mangani (2008) used data from 1973—April 2002 before the change in the implementation of the FTSE

Table 2. Information criteria results from the various GARCH specifications

	GARCH-M	GARCH-M (ΔINVSENT)	GJR-GARCH-M	GJR-GARCH-M (ΔINVSENT)	E-GARCH-M	E-GARCH-M (ΔINVSENT)
AIC	−6.3298	−6.3554	−6.3430	−6.3698*	−6.3448	−6.3750#
SC	−6.3172	−6.3397	−6.3288	−6.3525*	−6.3306	−6.3577#
HQ	−6.3254	−6.3499	−6.3379	−6.3637*	−6.3397	−6.3688#
LL	12 674	12 724	12 701	12 754*	12 705	12 764#

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

Table 3. Results from the various GARCH specifications

	GARCH-M	GARCH-M (ΔINVSENT)	GJR-GARCH-M	GJR-GARCH-M (ΔINVSENT)	E-GARCH-M	E-GARCH-M (ΔINVSENT)
MEAN EQUATION						
AR(1)	0.9950***	0.9948***	0.9955***	0.9950***	0.9954***	0.9934***
MA(1)	−0.9680***	−0.9679***	−0.9588***	−0.9585***	−0.9517***	−0.9504***
δ	24.2605***	25.1123***	18.0445***	18.5677***	23.5280***	23.8149***
θ	–	−0.0059***	–	−0.0058***	–	−0.0060***
VARIANCE EQUATION						
ω	1.80E-06***	2.20E-06***	1.89E-06***	2.13E-06***	−0.3389***	−0.4230***
α	0.0877***	0.1056***	0.0398***	0.0457***	0.1789***	0.2197***
β	0.8991***	0.8778***	0.8938***	0.8766***	0.9784***	0.9731***
γ	–	–	0.1063***	0.1218***	−0.0870***	−0.1033***
ϕ	–	−4.5E-05***	–	−4.8E-05***	–	−0.6911***
α + β	0.9861	0.9834	0.9336	0.9223	1.1573	1.1928

global classification system by the JSE in June 2002 which induced a significant decline in the number of stocks constituting the JSE All Share Index (ALSI) as the market capitalization formula changed (JSE, 2018). Also, the study period like Chinzara and Aziakpano (2009) does not include the financial crisis period where volatility was significantly greater than most years in South African history which is included in this study. Instead, these studies account for the low volatility periods such as the post-apartheid era where there was financial liberalisation, high growth rates among other innovations, hence low volatility.

The difference in results could also be explained by the fact that this study adjusted the returns for dividends. This approach was taken because dividends are a significant contributor to returns as they represent a large portion of the historic total return for shares. Huxley (2007) found that high dividend yield shares were less volatile, thus, the exclusion of dividends may affect the results obtained. Brooks (2014) also documented that excluding dividends not only distorts the real value of the shares but may also provide an inappropriate measure of risk. The lower frequency data used by studies such as Mangani (2008) and the normal distribution assumption used by some studies to model the error term could explain the difference in results. This is because financial time series data is not always normally distributed hence using the incorrect error distribution assumption may result in misspecification (Mandimika & Chinzara, 2012).

In the conditional variance equation, it can be noted that all the parameters are statistically significant. This indicates that the current volatility can be explained by past shocks, α, volatility in the previous period, β, and changes in investor sentiment, φ, with previous period volatility explaining most of the volatility. Although the volatility of the sentiment-augmented GJR-GARCH-M is stationary, $\alpha + \beta$ is close to one, which means that volatility is highly persistent. A shock in current volatility will influence the expectation of volatility many periods in the future. Further, the results from Table 3 show that the leverage effect is significantly positive for the sentiment-augmented GJR-GARCH-M model. This means that negative shocks increase volatility more than positive shocks of the same magnitude. This was also evidenced by Chinzara and Aziakpano (2009), Makhwiting et al. (2012) and Kgosietsile (2015) on the South African market. The leverage effect is slightly higher in the sentiment-augmented GJR-GARCH-M model, indicating that changes in sentiment amplify the effect of negative shocks. However, the difference is minute.

It is interesting to note that changes in investor sentiment have a negative effect on both the returns and conditional volatility. This is because changes in investor sentiment reflect mean reversion of sentiment. As sentiment mean-reverts, noise traders exit the market, which means that their incidence and impact on the market reduces, resulting in low volatility on the market. When sentiment is high, there is increased mispricing in the market- precisely, overvaluation- however, when sentiment mean-reverts, expectations fall. This results in a fall in the prices and consequently the returns. This is consistent with a study by Stambaugh, Yu, and Yuan (2012) on the US market and Dalika and Seetharam (2015) on the South African market.

Model diagnostic checks on the selected model showed an improvement in normality. Furthermore, all the mean and variance equations have no serial correlation and heteroscedasticity based on the Ljung-Box[2] statistics and the ARCH-LM tests, respectively. Although this study augments the model with a sentiment variable, the findings are consistent with Mandimika and Chinzara's (2012) who found that a GJR-GARCH better models conditional variance on the JSE.

6. Concluding remarks

This study analysed the dynamics of investor sentiment and volatility on the JSE by using the GARCH-M specifications augmented by a sentiment factor under the three error distribution assumptions using daily data over the period 2002–2018. The results show that the JSEALSI returns can be modelled as an ARMA (1.1) process, implying that the effect of past returns and past shocks to the conditional mean will dissipate after a single period. Also, the results show significant evidence of a positive risk-return relationship on the JSE, showing that volatility is a priced factor on the JSE. The results show the presence of volatility persistence and leverage effects. Concerning investor sentiment, the results show that it is a significant factor in explaining the returns and the conditional variance on the JSE. Overall, the most appropriate model for modelling volatility for the JSEALSI series was the GJR-GARCH-M with an investor sentiment factor. This affirms the importance of investor sentiment on the JSE.

The study's findings bear implications for investors and policymakers. For investors, the fact that volatility is priced, including the sentiment-driven component, means that their strategies should include a sentiment factor when measuring the total risk. Given the significant positive risk-premium, investors need to hold well-diversified portfolios to be rewarded for the component of risk borne which is systematic risk as per CAPM. For policymakers, volatility persistence may have a negative impact on the functioning of markets and the pricing of assets. This impact may be amplified by changes in investor sentiment, leading to capital outflows and financial instability as investors seek better quality markets. Therefore, policymakers need to not focus only on established fundamental drivers of volatility but also on investor sentiment. The significant leverage effects imply that policymakers need to pay more attention to negative shocks and changes in investor sentiment as volatility is amplified.

The study has certain limitations in its scope. For instance, it employed a broad market index in the determination of the influence that investor sentiment has on volatility. However, sentiment may affect the volatility and returns of different companies differently. Future research may try to look at the effect of investor sentiment on individual shares or a portfolio of similar shares. The study also used proxies to measure sentiment due to the unavailability of direct measures such as sentiment surveys on the South African market. However, proxies are indirect measures. The study is also limited to the South African market, especially in terms of the constructed sentiment index. As a result, its generalisability to other African stock market or other emerging market is also limited. However, it can easily be replicated in those markets to see whether similar conclusions would be reached at.

Future studies may employ a Markov-switching GARCH to determine the effect of sentiment-driven noise trading on the South African market. Other studies may also attempt to construct new sentiment-augmented multifactor models and test their performance against the traditional models to determine whether the explanatory power increases. It is possible that a better model in terms of asset pricing may be developed. This would aid the price discovery processes and increase the efficiency of markets. Future studies may also attempt to determine whether investor sentiment can be used to predict phenomena that comes with extreme volatility on financial markets such as financial crises and price bubble bursts. An ability to predict these events before they occur may help in controlling their effects or in stopping them from happening altogether.

Funding
The authors received no direct funding for this research.

Author details
Lorraine Rupande[1]
E-mail: rupandel@ukzn.ac.za
Hilary Tinotenda Muguto[1]
E-mail: mugutoh@ukzn.ac.za
Paul-Francois Muzindutsi[1]
E-mail: muzindutsip@ukzn.ac.za
ORCID ID: http://orcid.org/0000-0002-4819-8218
[1] The University of KwaZulu-Natal, School of Accounting, Economics and Finance, Westville campus, Bag X 5400, Durban 4000, South Africa.

Citation information
Cite this article as: Investor sentiment and stock return volatility: Evidence from the Johannesburg Stock Exchange, Lorraine Rupande, Hilary Tinotenda Muguto & Paul-Francois Muzindutsi, *Cogent Economics & Finance* (2019), 7: 1600233.

Notes

1. The test results: LB (36)—1297***, LB^2 (36)—6728*** and ARCH LM—0.23*** .
2. The test results: LB (36)—36.5, LB^2 (36)—36.9 and ARCH LM—0.23 (All are insignificant).

References

Abdelhédi-Zouch, M., Abbes, M. B., & Boujelbène, Y. (2015). Volatility spillover and investor sentiment: Subprime crisis. *Asian Academy of Management Journal of Accounting & Finance*, *11*(2), 1–37.
Akbas, F., Boehmer, E., Jiang, C., & Koch, P. D. (2019). *Overnight returns, daytime reversals, and future stock returns: The risk of investing in a tug of war with noise traders* (Working Paper, pp. 1–57). Cambridge, MA: Social Science Research Network. doi:10.2139/ssrn.3324880
Alberg, D., Shalit, H., & Yosef, R. (2008). Estimating stock market volatility using asymmetric GARCH models. *Applied Financial Economics*, *18*(15), 1201–1208. doi:10.1080/09603100701604225

Alfano, S. J., Feuerriegel, S., & Neumann, D. (2015). Is news sentiment more than just noise? *Twenty-Third European Conference on Information Systems*, Münster, Germany, (pp. 1–16). Conference Proceedings.

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2015). Investor sentiment, beta, and the cost of equity capital. *Management Science*, *62*(2), 347–367. doi:10.1287/mnsc.2014.2101

Bahloul, W., & Bouri, A. (2016). The impact of investor sentiment on returns and conditional volatility in US futures markets. *Journal of Multinational Financial Management*, *36*(1), 89–102. doi:10.1016/j.mulfin.2016.07.003

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, *61*(4), 1645–1680. doi:10.1111/j.1540-6261.2006.00885.x

Barrot, J. N., Kaniel, R., & Sraer, D. (2016). Are retail traders compensated for providing liquidity? *Journal of Financial Economics*, *120*(1), 146–168.

Black, F. (1976). Studies of stock price volatility changes. *American Association of Business & Economics Statistics*, *5*(2), 177–181.

Black, F. (1986). Noise. *Journal of Finance*, *41*(3), 528–543. doi:10.1111/j.1540-6261.1986.tb04513.x

Blasco, N., Corredor, P., & Ferrer, E. (2018). Analysts herding: When does sentiment matter? *Applied Economics*, *50*(51), 5495–5509. doi:10.1080/00036846.2018.1486999

Bose, S. (2007). Understanding the volatility characteristics and transmission effects in the Indian stock index and index futures market. *ICRA Bulletin, Money & Finance*, 139–162.

Brooks, C. (2014). *Introductory econometrics for finance*. Cambridge, United Kingdom: Cambridge Books.

Brown, G. W. (1999). Volatility, sentiment, and noise traders. *Financial Analysts Journal*, *55*(2), 82–90. doi:10.2469/faj.v55.n2.2263

Campbell, J. Y., & Kyle, A. S. (1993). Smart money, noise trading and stock price behaviour. *The Review of Economic Studies*, *60*(1), 1–34. doi:10.2307/2297810

Charteris, A., & Rupande, L. (2017). Feedback trading on the JSE. *Investment Analysts Journal*, *46*(3), 235–248. doi:10.1080/10293523.2017.1342319

Chau, F., Deesomsak, R., & Koutmos, D. (2016). Does investor sentiment really matter? *International Review of Financial Analysis*, *48*(1), 221–232.

Chau, F., Deesomsak, R., & Lau, M. C. (2011). Investor sentiment and feedback trading: Evidence from the exchange-traded fund markets. *International Review of Financial Analysis*, *20*(5), 292–305. doi:10.1016/j.irfa.2011.06.006

Chinzara, Z., & Aziakpono, M. J. (2009). Dynamic returns linkages and volatility transmission between South African and world major stock markets. *Studies in Economics and Econometrics*, *33*(3), 69–94.

Chu, Y., Hirshleifer, D., & Ma, L. (2017). *The causal effect of limits to arbitrage on asset pricing anomalies* (No. 24144, pp. 1–61). Cambridge, MA: National Bureau of Economic Research, Inc.

Chuang, W. J., Ouyang, L. Y., & Lo, W. C. (2010). The impact of investor sentiment on excess returns: A Taiwan stock market case. *International Journal of Information & Management Sciences*, *21*(1), 13–28.

Da, Z., Larrain, B., Sialm, C., & Tessada, J. (2015). *Price pressure from coordinated noise trading: Evidence from pension fund reallocations* (Working Paper No. 22161, pp. 1–48). Cambridge, MA: National Bureau of Economic Research, Inc.

Dai, Z. M., & Yang, D. C. (2018). Positive feedback trading and investor sentiment. *Emerging Markets Finance & Trade*, *54*(10), 2400–2408. doi:10.1080/1540496X.2018.1469003

Dalika, N., & Seetharam, Y. (2015). Sentiment and returns: An analysis of investor sentiment in the South African market. *Investment Management & Financial Innovations*, *12*(1), 267–276.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, *98*(4), 703–738. doi:10.1086/261703

Dedi, L., & Yavas, B. F. (2016). Return and volatility spillovers in equity markets: An investigation using various GARCH methodologies. *Cogent Economics & Finance*, 4(1), 1–18. doi:10.1080/23322039.2016.1266788

Devault, L., Sias, R., & Starks, L. (2019). Sentiment metrics and investor demand. *Journal of Finance*, *74*(2), 985–1024.

Economou, F., Hassapis, C., & Philippas, N. (2018). Investors' fear and herding in the stock market. *Applied Economics*, *50*(34), 3654–3663. doi:10.1080/00036846.2018.1436145

Engelberg, J. E., Reed, A. V., & Ringgenberg, M. C. (2018). Short-selling risk. *Journal of Finance*, *73*(2), 755–786. doi:10.1111/jofi.12601

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *Journal of Finance*, *48* (5), 1749–1778. doi:10.1111/j.1540-6261.1993.tb05127.x

Frazzini, A., & Lamont, O. A. (2005). *Dumb money: Mutual fund flows and the cross-section of stock returns* (NBER Working Paper No 11526, pp. 1–35). Cambridge, MA: National Bureau of Economic Research.

Ghonghadze, J., & Lux, T. (2016). Bringing an elementary agent-based model to the data: Estimation via GMM and an application to forecasting of asset price volatility. *Journal of Empirical Finance*, *37*(1), 1–19. doi:10.1016/j.jempfin.2016.02.002

Gitman, L. J., Juchau, R., & Flanagan, J. (2015). *Principles of managerial finance*. Sydney, Australia: Pearson Higher Education.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, *48*(5), 1779–1801. doi:10.1111/j.1540-6261.1993.tb05128.x

Herve, F., Zouaoui, M., & Belvaux, B. (2019). Noise traders and smart money: Evidence from online searches. *Economic Modelling*, 1–25. Elsvier B.V. doi:10.1016/j.econmod.2019.02.005

Hessary, Y. K., & Hadzikadic, M. (2017). Role of behavioural heterogeneity in aggregate financial market behavior: An agent-based approach. *Procedia Computer Science*, *108*(1), 978–987. doi:10.1016/j.procs.2017.05.254

Hien, M. T. T., & Thanh, T. (2008). *Modelling and forecasting volatility by GARCH-type models: The case of Vietnam stock exchange*. Doctoral Dissertation, University Of Nottingham, United Kingdom. pp. 1–97.

Hong, H., & Stein, J. C. (2007). Disagreement and the stock market. *Journal of Economic Perspectives*, *21*(2), 109–128. doi:10.1257/jep.21.2.109

Hudson, Y., Yan, M., & Zhang, D. (2018). *Herd behaviour & investor sentiment: Evidence from UK mutual funds* (Working Paper, Social Science Research Network). Elsevier. doi:10.2139/ssrn.3222312

Hurditt, P. (2004). An assessment of volatility transmission in the Jamaican financial system. *Journal of*

Business, Finance & Economics in Emerging Economies, *1*(1), 1–28.

Huxley, T. H. (2007). *The high dividend yield return advantage: An examination of empirical data associating investment in high dividend yield securities with attractive returns over long measurement periods* (Working Paper, pp. 1–18). New York: Tweedy Browne Company LLC. doi:10.1094/PDIS-91-4-0467B

Jang, J., & Kang, J. (2018). Probability of price crashes, rational speculative bubbles, and the cross-section of stock returns. *Journal of Financial Economics*, *132*(1), 222–247. doi:10.1016/j.jfineco.2018.10.005

Johannesburg Stock Exchange. (2018, August 17). Headline – All Share (J203). [Internet]. Retrieved from https://www.jse.co.za/services/market-data/indices/ftse-jse-africa-index-series/headline

Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. Philosophical transactions of the royal society. *Mathematical, Physical and Engineering Sciences*, *374* (2065), 1–16. doi:10.1098/rsta.2015.0202

Kapoor, S., & Prosad, J. M. (2017). Behavioural finance: A review. *Procedia Computer Science*, *122*(1), 50–54. doi:10.1016/j.procs.2017.11.340

Kgosietsile, O. (2015). Modelling and Forecasting the Volatility of JSE Returns: A Comparison of Competing Univariate GARCH Models. Witswatersrand University, South Africa. Doctoral Dissertation, 1–55.

Kim, J. S., Kim, D. H., & Seo, S. W. (2017). Individual mean-variance relation and stock-level investor sentiment. *Journal of Business Economics and Management*, *18*(1), 20–34. doi:10.3846/16111699.2016.1252794

Kumari, J., & Mahakud, J. (2016). Investor sentiment and stock market volatility: Evidence from India. *Journal of Asia-Pacific Business*, *17*(2), 173–202. doi:10.1080/10599231.2016.1166024

Kurov, A. (2008). Investor sentiment, trading behavior and informational efficiency in index futures markets. *Financial Review*, *43*(1), 107–127. doi:10.1111/fire.2008.43.issue-1

Lim, C. M., & Sek, S. K. (2013). Comparing the performances of GARCH-type models in capturing the stock market volatility in Malaysia. *Procedia Economics & Finance*, *5* (1), 478–487. doi:10.1016/S2212-5671(13)00056-7

Lin, C. B., Chou, R. K., & Wang, G. H. (2018). Investor sentiment and price discovery: Evidence from the pricing dynamics between the futures and spot markets. *Journal of Banking & Finance*, *90*(1), 17–31. doi:10.1016/j.jbankfin.2018.02.014

Lin, M., Sias, R. W., & Wei, Z. (2018). *The survival of noise traders: Evidence from peer-to-peer lending* (Research Paper No. 18–22). Georgia: Georgia Tech Scheller College of Business. doi:10.2139/ssrn.3185608

Lintner, J. (1964). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets: A reply. *Review of Economics & Statistics*, *1*(1), 222–224.

Liu, H. C., Lee, Y. H., & Lee, M. C. (2009). Forecasting China stock markets volatility via GARCH models under skewed-GED distribution. *Journal of Money, Investment & Banking*, *7*(1), 1–23.

Liu, S. (2015). Investor Sentiment and Stock Market Liquidity. *Journal of Behavioural Finance*, *16*(1), 51–67. doi:10.1080/15427560.2015.1000334

Ljungqvist, A., & Qian, W. (2016). How constraining are limits to arbitrage? *Review of Financial Studies*, *29*(8), 1975–2028.

Makhwiting, M. R., Lesaoana, M., & Sigauke, C. (2012). Modelling volatility and financial market risk of shares on the Johannesburg Stock Exchange. *African Journal of Business Management*, *6*(27), 8065–8070. doi:10.5897/AJBM11.2525

Mandimika, N. Z., & Chinzara, Z. (2012). Risk-return tradeoff and behaviour of volatility on the South African Stock market: Evidence from both aggregate and disaggregate data. *South African Journal of Economics*, *80*(3), 345–366. doi:10.1111/saje.2012.80.issue-3

Mangani, R. (2008). Modelling return volatility on the JSE securities exchange of South Africa. *African Finance Journal*, *10*(1), 55–71.

Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, *7*(1), 77–91.

Matei, M. (2009). Assessing volatility forecasting models: Why GARCH models take the lead. *Romanian Journal of Economic Forecasting*, *12*(4), 42–65.

Miwa, K. (2016). Investor sentiment, stock mispricing, and long-term growth expectations. *Research in International Business & Finance*, *36*(1), 414–423. doi:10.1016/j.ribaf.2015.10.003

Naik, P. K., & Padhi, P. (2016). Investor sentiment, stock market returns and volatility: evidence from National Stock Exchange of India. *International Journal of Management Practice*, *9*(3), 213–237. doi:10.1504/IJMP.2016.077816

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Journal of the Econometric Society*, *21*(1), 347–370. doi:10.2307/2938260

Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *Journal of Finance*, *54*(6), 2263–2295. doi:10.1111/0022-1082.00188

Peress, J., & Schmidt, D. (2017). *Noise traders incarnate: Describing a realistic noise trading process* (Centre for Economic Policy Research Working Paper No. DP12434, pp. 1–73). London: Social Science Research Network.

Piccoli, P., Da Costa, N. C., Jr, Da Silva, W. V., & Cruz, J. A. (2018). Investor sentiment and the risk-return trade-off in the Brazilian market. *Accounting & Finance*, *58*(1), 599–618.

Rahman, M. A., Shien, L. K., & Sadique, M. S. (2013). Swings in sentiment and stock returns: Evidence from a frontier market. *International Journal of Trade, Economics & Finance*, 4(6), 347–363. doi:10.7763/IJTEF.2013.V4.315

Schmeling, M. (2007). Institutional and individual sentiment: Smart money and noise trader risk? *International Journal of Forecasting*, *23*(1), 127–145. doi:10.1016/j.ijforecast.2006.09.002

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*, *19*(3), 425–442.

Shefrin, H., & Statman, M. (2000). Behavioural portfolio theory. *Journal of Financial & Quantitative Analysis*, *35*(2), 127–151. doi:10.2307/2676187

Shefrin, H. M., & Statman, M. (1984). Explaining investor preference for cash dividends. *Journal of Financial Economics*, *13*(2), 253–282. doi:10.1016/0304-405X(84)90025-4

Shen, J., Yu, J., & Zhao, S. (2017). Investor sentiment and economic forces. *Journal of Monetary Economics*, *86* (1), 1–21. doi:10.1016/j.jmoneco.2017.01.001

Shleifer, A., & Summers, L. H. (1990). The noise trader approach to finance. *Journal of Economic Perspectives*, 4(2), 19–33. doi:10.1257/jep.4.2.19

Shu, H. C., & Chang, J. H. (2015). Investor sentiment and financial market volatility. *Journal of Behavioral*

Finance, *16*(3), 206–219. doi:10.1080/15427560.2015.1064930

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*(2), 288–302. doi:10.1016/j.jfineco.2011.12.001

Statman, M. (2014). Behavioural finance: Finance with normal people. *Borsa Istanbul Review*, *14*(2), 65–73. doi:10.1016/j.bir.2014.03.001

Taffler, R. J., Agarwal, V., & Wang, C. (2017). *Asset pricing bubbles and investor emotions: An empirical analysis of the 2014–2016 Chinese stock market bubble*. Behavioural Finance Working Group Meeting, Queen Mary University, London.pp. 1–50.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance*, *62*(3), 1139–1168. doi:10.1111/j.1540-6261.2007.01232.x

Uygur, U., & Taş, O. (2014). The impacts of investor sentiment on returns and conditional volatility of international stock markets. *Quality & Quantity*, *48*(3), 1165–1179. doi:10.1007/s11135-013-9827-3

Verma, R., & Soydemir, G. (2009). The impact of individual and institutional investor sentiment on the market price of risk. *Quarterly Review of Economics & Finance*, *49*(3), 1129–1145. doi:10.1016/j.qref.2008.11.001

Xiao, D., Wang, J., & Niu, H. (2016). Volatility analysis of financial agent-based market dynamics from stochastic contact system. *Computational Economics*, *48*(4), 607–625. doi:10.1007/s10614-015-9539-y

Ya'Cob, N., & Ya'cob, M. (2016). *The Determinants of Stock Market Volatility: Macroeconomic Fundamentals and Investor Sentiment*. Doctoral Dissertation, University Of Malaya, Malaysia. pp. 1–234.

Yu, J., & Yuan, Y. (2011). Investor sentiment and the mean-variance relation. *Journal of Financial Economics*, *100*(2), 367–381. doi:10.1016/j.jfineco.2010.10.011