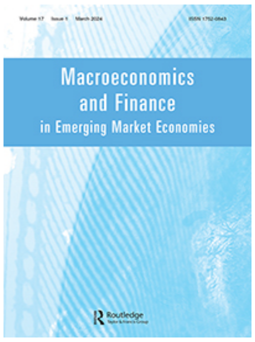

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Revisiting the dynamic stock return–volume relationship in South Africa: a non-parametric causality in quantiles approach

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ABSTRACT
The study investigates the dynamic relationship between trading volume and stock returns on the JSE. The results show prima facie evidence of causality from returns to trading volume in the middle quantiles of the conditional distributions in stable periods as well as the full sample, and this causal relationship disappears during the in-crisis and the post-COVID periods. Second, it is observed that the highest impact occurs in the middle of the conditional distribution but not necessarily the median. Third, across all the samples used in the study, no evidence is found of causality from trading volume to return.

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COVID-19; causality in quantiles; JSE; volume–return relationship; pandemic

1. Introduction

Various studies have been done on the association between stock prices and trading volume. The seminal work by Karpoff (1987) provides empirical and theoretical insights on this important relationship as well as the importance of understanding this relationship. Some of the earliest studies looked at the relationship between trading volume and changes in stock prices (Clive. Granger and Morgenstern 1963), the relationship between the absolute value of price changes and trading volume (Godfrey, Granger, and Morgenstern 1964) and the contemporaneous relationship between stock returns and trading volume (Epps 1975). Recently, most studies have shifted focus to looking at the dynamic relationship between the two variables. Of note is the importance that non-parametric causality tests have gained as a result of nonlinearities and structural breaks in financial variables.

Although several studies have been done on the dynamic relationship between stock returns and trading volume in emerging markets (e.g. Gebka 2012; Kamath and Wang 2006; Moosa and Al-Loughani 1995), the results reported have largely been mixed. Some of the results have reported no causal relationship between stock returns and volume, while others have reported either unidirectional or bidirectional dynamic relationships between stock returns and volume. An understanding of the return–volume relationship on the Johannesburg Stock Exchange (JSE) is important for the international investor who wants to diversify into Africa as South Africa has often been labelled as the gateway into

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the African market (Dicle and Levendis 2013). It is therefore important to explore this relationship from a South African perspective using alternative econometric models, and subsample periods that incorporate the COVID-19 period.

In South Africa, a few studies have been done to examine the dynamic relationship between volume and stock returns. Mpofu (2012) used daily data of the FTSE/JSE All Share Index for the period running from June 1988 to July 2012 and reported unidirectional causality from returns to volume using VAR-based specifications in mean. Abukari and Assogbavi (2019) use weekly data on 36 companies listed on the JSE to examine the contemporaneous and causal relationships between trading volume and stock returns between 2011 and 2017 and reported both contemporaneous and bidirectional causal relationships between the stock returns and trading volume. The results from these South African studies are not in unison, and also the use of linear Granger causality tests might have led to biased estimates if the data exhibit nonlinearities, structural breaks and regime shifts. It is therefore important to understand the dynamic relationship between the two variables using a non-parametric approach that considers tail dependence. Also, the COVID-19 pandemic has brought complexities to the dynamic relationship between trading volume and stock returns and the inclusion of a sample that covers the period of the pandemic brings new insights into the relationship in an unstable environment. This study, therefore, adds to the existing South African literature by including the COVID-19 period as well as using a different econometric model, which is more appropriate for nonlinear series.

For comparison purposes, this study utilizes the linear Granger causality test of Granger (1969) and the non-parametric Granger causality in quantile approach of Jeong, Härdle, and Song (2012) to examine the relationship between stock return and volume over a period spanning 16 years starting in 2005 to February 2021. The Granger causality tests show that under stable conditions, there is unidirectional causality between volume and returns, while during the financial crisis and the COVID-19 pandemic periods, there is bidirectional causality between the series. After testing for linearity of the return and volume series, it is confirmed that the series are nonlinear and using a linear-based model leads to model misspecification. The results of the non-parametric Granger causality test of Jeong, Härdle, and Song (2012) show that for the whole sample, returns cause volume in the middle of the distribution with no tail dependence reported at $\tau < 0.12$ and $\tau > 0.93$. The causal relation from volume to returns for the whole sample shows a weak and intermittent relationship at few quantiles near the tails of the distributions. When the sample is divided into subsamples, the results from the causality in quantiles show that there is a significant causal relationship between returns and volume in the middle quantiles during stable periods (pre-crisis and post-crisis periods), while no significant causal relationship between volume and returns is seen during the stable periods. In periods characterized by higher volatility (in-crisis period and post-COVID period), no prima facie evidence is found of a dynamic relationship between stock returns and volume.

The results from the study are important to different stakeholders who have an interest in the JSE in several ways. First, in a financial crisis or black swan event like the COVID-19 pandemic, the use of technical analysis for asset allocations is likely to be ineffective as there is no prima-facie evidence that volume can be used to predict returns in such periods. Second, the lack of a dynamic relationship between volume and returns in a crisis means that direct government intervention in the stock market during crisis periods and pandemics is likely to produce weak results. This resonates with findings from Russia (Khan and Batteau 2011) and China (Chen and Jarrett 2011) where direct intervention by the respective governments during the global financial crisis did not lift the prices of stocks. Finally, the results confirm the weak-form efficiency on the JSE as information on trading volume cannot be used to predict future returns.

The paper proceeds as follows: Section 2 explores the literature review starting with the theoretical framework as well as a review of findings from empirical studies done on the topic. Section 3 looks at the methodology used to establish the dynamic relationship between returns and trading volume. The results from the study are presented in Section 4 while Section 5 discusses the results. The paper ends with Section 6 which gives a synthesis of the paper as well as implications of the results.

2. Literature review

The literature emphasizes two theoretical explanations for the dynamic relationship between stock returns and trading volume, namely the Mixture of Distribution Hypothesis (MDH) and the Sequential Information Arrival Hypothesis (SIAH). The SIAH (Copeland 1976; Jennings, Starks, and Fellingham 1981; Smirlock and Starks 1985) presumes that the arrival of new information to traders comes in an unsystematic fashion. Thus, according to this theory, the processing of information by traders is sequential and arbitrary. Subsequently, this leads to a sequential reaction, signalling that past values of stock returns (trading volume) may help in predicting the current values of trading volume (stock returns). On the other hand, the MDH (Andersen 1996; Clark 1973; Harris 1987) does not assume sequential arrival and processing of information but rather assumes that market participants simultaneously receive new information. Consequently, utilizing this model, past values of stock returns (trading volume) cannot predict present values of trading volume (stock returns) since these variables instantaneously react to new information (Darrat, Rahman, and Zhong 2003).

Several studies that support the MDH have been done using both low-frequency and high-frequency data. Granger and Morgenstern (1963) examined the return–volume relationship and reported no dynamic relationship between the two series. Using data from the Chinese stock market, Lee and Rui (2000) found no causal relationship between stock returns and trading volume. In Brazil, de Medeiros and Doornik (2008) reported results that support the MDH as they found no causal relationship between trading volume and stock returns for the Bovespa index using daily data. All these studies reinforce the MDH as information dissemination is assumed to be contemporaneous such that future returns (volume) only change when information arrives, and they evolve at a constant speed in event time (Junkus 1994), allowing immediate shifts to a new equilibrium.

Other empirical studies done on the dynamic relationship between stock returns and trading volume have reported unidirectional causality. Using data at daily frequency, Karpoff (1987); Gallant, Rossi, and Tauchen (1992) and Jones, Kaul, and Lipson (1994) reported findings that support the SIAH. These studies reported significant causal relationships between return and volume series. Other studies reporting similar results used stock prices instead of stock returns and found significant causal relationships between stock prices and volume. These studies reinforce the SIAH, which suggests that information is distributed asymmetrically as information flows sequentially from one trader to another. Other studies have also reported bidirectional causality between returns and volume, giving credence to the SIAH and rejecting the MDH (Chen, Hong, and Stein 2001). Due to the sequential nature of information flow, past values of trading volume may forecast present values of stock returns and vice versa.

While most of the studies done on the return–volume relationship assumed a linear relationship of and between the series, contemporary research is focusing more on non-parametric (data-driven) models in the presence of nonlinearities, structural breaks and regime shifts in the variables. Chuang, Kuan and Lin (2009) devise a model for testing non-causality in quantiles and use a sup-Wald test to test the hypothesis of non-causality in quantiles and found that the causal effects of volume are heterogeneous across the conditional distribution. Silvapulle and Choi (1999) use the Baek and Brock (1992) non-parametric model for testing the dynamic relationship between stock returns and volume in the Korean market and also report heterogeneous causality from returns to volume in the middle quantiles. These results strongly support nonlinear and linear bidirectional Granger causality between the series.

3. Methodology

3.1. Data

This study uses closing prices and trading volume data obtained from the JSE for the period 4 January 2005 to 26 February 2021, containing 4038 daily observations. Stock returns are computed from the daily closing prices of the FTSE/JSE All-Share Index (JALSH), which is a value-weighted index that includes the top 99% of the total pre-float market capitalization of all listed companies on the JSE. The price and trading volume data were extracted from the IRESS research domain. The sample period is carefully selected to include the global financial crisis as well as the COVID-19 pandemic. In further analysis, the sample period is split into four subperiods; the pre-crisis period, the in-crisis period, the post-crisis period, as well as the post-COVID-19 period. The crisis periods relate to the global financial crisis of 2008. The boundary dates for the four subsamples are defined in Table 1.

Though literature is not in agreement about the cut-off dates for the pre-crisis, in-crisis and post-crisis periods, this study adopts the dates proposed by Ozdemir (2020) as shown in Table 1. South Africa recorded its first COVID-19 case on 5 March 2020; and, therefore, to see the impact of the pandemic on the dynamic relationship between trading volume

Table 1. Subsample definitions.

Subsample	Start date	End date	Observations
Pre-crisis period	4 March 2005	29 September 2008	935
In-crisis period	1 October 2008	30 September 2009	250
Post-crisis period	1 October 2009	4 March 2020	2606
Post-COVID period	5 March 2020	26 February 2021	247

and stock returns, a post-COVID subsample running from 5 March 2020 to 26 February 2021 is also created.

Daily closing prices of the JALSH index are converted into log-returns using the following formula:

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

where R_t is the log return of the JALSH index at time t and P_t and P_{t-1} are the closing prices of the JALSH index at time t and $t-1$, respectively. Trading volume has been empirically used to proxy for the rate of information flow into the market in several studies. However, other studies have reported the existence of linear and nonlinear deterministic time trends in the volume data. Previous studies do not show consensus on how to deal with non-stationary trading volume. This study adopts the approach used by Chuang Kuan and Lin (2009) to detrend the volume data so as to remove the deterministic trends. The natural logarithm of the volume series is regressed on a constant (t/T) and $(t/T)^2$, where T is the total sample size and the residual of the regression is then used for further analysis. The regression equation estimated to extract the residuals for further analysis is shown below:

$$\ln(volume) = \alpha + \beta_1\left(\frac{t}{T}\right) + \beta_2\left(\frac{t}{T}\right)^2 + \epsilon \tag{2}$$

3.2. Testing causality in mean

To test for the dynamic relationship between stock returns and trading volume in mean, a bivariate VAR model was used with the optimal number of lags decided using the minimum Akaike Information Criterion (AIC) value. The following VAR was used:

$$R_t = \alpha_R + \sum_{i=1}^{p} \beta_i R_{t-1} + \sum_{i=1}^{p} \gamma_i V_{t-1} + \mu \tag{3}$$

$$V_t = \alpha_V + \sum_{i=1}^{p} \beta_i V_{t-1} + \sum_{i=1}^{p} \gamma_i R + \epsilon \tag{4}$$

where R_t represents the daily continuous returns of the FTSE/JSE All Share Index, V_t is the detrended volume as described in Section 3.1, β_i and γ_i are parameters, μ and ϵ are the error terms. The null hypotheses that return (volume) does not Granger cause volume (return) imply that the values of γ_i ($i = 1, 2, \ldots, p$) are not significantly different from zero. Statistical significance was tested at the 5% level of significance in line with other studies done on the topic.

3.3. Testing causality in quantiles

While causality in mean has been used widely in empirical studies in the broad area of finance, some of the stylized facts of financial returns like fat tails and non-elliptical distributions may result in biased estimates emanating from a misspecified model. This is especially so as some studies have shown that causality relationships at the centre of a distribution may not be the same as at the tails (Wang, Ho, and Li 2020). Research has also shown that correlations among financial variables tend to increase under extreme market conditions and this often translates into contagion and volatility spillovers during market turmoil. Several studies have been done to test the relationship between returns and volume across distributions of variables instead of the mean only (Balcilar et al. 2017; Chuang, Kuan and Lin 2009). For the purpose of this study, a non-parametric Granger causality test in quantile developed by Jeong, Härdle, and Song (2012) based on the kernel density method is used to test the causal relationship between stock returns and trading volume. According to Jeong, Härdle, and Song (2012) Granger causality in quantile is defined as follows:

$$x_t \textit{ does not cause } y_t \textit{ in the } \theta - \textit{quantile with respect to } \{y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots x_{t-p}\}\ Q_\theta \textit{ if } (y_t|y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p}) = Q_\theta(y_t|y_{t-1},\ldots,y_{t-p}) \tag{5}$$

x_t is a prima facie cause of y_t in the θ-quantile with respect to $\{y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots x_{t-p}\}$ if

$$Q_\theta(y_t|y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p}) \neq Q_\theta(y_t|y_{t-1},\ldots,y_{t-p}) \tag{6}$$

where $Q_\theta(y_t|.)$ is the θth conditional quantile of y_t which depends on t and $0<\theta<1$. Let $Y_{t-1}\equiv(y_{t-1},\ldots,y_{t-p})$, $Z_{t-1}\equiv(y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p})$, $V_t\equiv(X_t,Z_t)$, and $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ are the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1} respectively. The conditional distribution $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is assumed to be completely continuous in y_t for almost all V_{t-1}.

Denoting $Q_\theta(Z_{t-1})\equiv Q_\theta(y_t|y_{t-1})$ and $Q_\theta(Y_{t-1})\equiv Q_\theta(y_t|Y_{t-1})$, we have

$$F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta w.p.1$$

The hypotheses to be tested based on the definitions in Equations (5) and (6) therefore become:

$$H_0 = P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1a.s \tag{7}$$

$$H_1 = P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1a.s \tag{8}$$

Jeong, Härdle, and Song (2012) utilize the work done by Zheng (1998) to ameliorate the complexities of testing quantile restriction by using the measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1})f_z(Z_{t-1})\}$, where ε_t is the regression error term and $f_z(Z_{t-1})$ is the marginal density function of Z_{t-1}. This necessitates the testing of the quantile restriction as testing a particular type of mean restriction. The regression error ε_t emanates from the fact that the null hypothesis in Equation (5) can only be true if and only if:

$E[1\{y_t \leq Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$ or equivalent $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{.\}$ is the indicator function. The distance function is then specified as:

$$J = E[\{F_{yt|Z_t}\{Q_\theta(Y_{t-1})|Z_{t-1}\} - \theta\}^2 f_Z(Z_{t-1}) \tag{9}$$

where $J \geq 0$ and the equality holds if and only if the null hypothesis in Equation (5) is true, while $J \geq 0$ holds under the alternative hypothesis in Equation (6). Fan and Li (1999) report that a feasible test based on the distance measure J in Equation (6) has the leading term that follows a second-order degenerate U-statistic. Jeong, Härdle, and Song (2012) prove that under the $\beta - mixing$ process, the asymptotic distribution of the statistic is asymptotically normal. Also, Jeong, Härdle, and Song (2012) prove that the feasible kernel-based test statistic based on J has the following form:

$$\hat{J}_T = \frac{1}{(T-1)h^{2p}} \sum_{t=1}^{T} \sum_{s \neq t}^{T} K\left(\frac{Z_{t-1} - Z_s}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{10}$$

where K(.) is the kernel function with bandwidth h and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is estimated from:

$$\hat{\varepsilon}_t = \mathbf{1}\left\{y_t \leq \hat{Q}_\theta(Y_{t-1}) - \theta\right\} \tag{11}$$

where $\hat{Q}_\theta(Y_{t-1})$ is the estimate of the θth conditional quantile of y_t given Y_{t-1}. $\hat{Q}_\theta(Y_{t-1})$ can be estimated by the nonparametric kernel method as:

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(\theta|Y_{t-1}) \tag{12}$$

where:

$\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ is the Nadarya–Watson kernel estimator and is given by the following equation:

$$\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s \neq t} L\left(\frac{Y_{t-1} - Y_s}{h}\right) \mathbf{1}(Y_s \leq Y_{t-1})}{\sum_{s \neq t} L\left(\frac{Y_{t-1} - Y_s}{h}\right)} \tag{13}$$

with the kernel function $L(.)$ and bandwidth h.

4. Results and discussions

4.1. Summary statistics

Table 2 shows the summary statistics for the variables used in the study for the whole period sampled. At a glance, it can be seen that the series are not normally distributed as seen by the negative skewness for log returns, kurtosis values that deviate from 3, as well as the Jarque–Bera statistics, which are statistically significant at the lowest significance level thereby signifying that the variables are not normally distributed. The variables are also visualized in Figure 1.

As shown in Figure 1 above, the natural logarithm of the volume series in Panel A exhibits a deterministic trend. The detrended volume series in Panel B shows that the

Table 2. Descriptive statistics.

	Closing price	Volume	ln (volume)	Volume (detrended)	Log returns
Mean	39313.08	218345675	19.1209	1.19e-17	0.0004
Median	39117.28	201851876	19.1230	0.0012	0.0008
Minimum	12467.3	22244576	16.9176	−2.2641	−0.1022
Maximum	67483.76	1352997022	21.0255	1.6862	0.0726
SD	14255.3	100028729	0.3983	0.3394	−0.4060
Skewness	−0.1218633	3.362119	−0.1560	−0.5153	−0.4060
Kurtosis	−1.372276	23.44437	2.9784	4.8335	5.6248
Jarque–Bera	326.47***	100193***	1511.9***	4116.1***	5442.3***

SD stands for standard deviation. For the Jarque–Bera test, the null hypothesis is that the series is normally distributed.
*** represents statistical significance at the 0.01% level

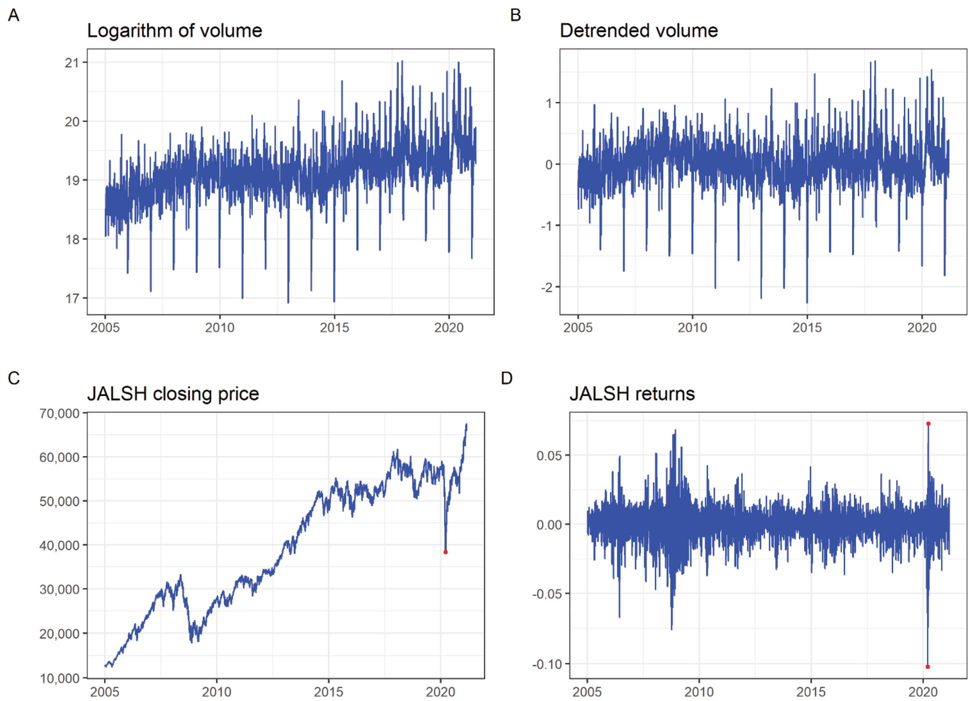

Figure 1. Visualization of the raw series and the transformed series.

deterministic trend has been removed and the series visually appears to be stationary. Panel D of Figure 1 demonstrates the stylized fact of volatility clustering. Also, it can be seen that return returns were more volatile around the time of the global financial crisis of 2008 as well as the COVID-19 pandemic. Panel D shows that the maximum and minimum returns over the whole sample (points highlighted in red) occurred on 6 March 2020 and 24 March 2020, respectively. The minimum return of the JALSH for the whole sample occurs a day after the announcement of the first COVID-19 case in South Africa. The maximum return of the JALSH index for the full sample occurs on 24 March 2020, a day after the announcement of the first COVID-induced national lockdown in South Africa. Before the Granger causality in mean and in quantiles is conducted on the series, the variables are first tested for the presence of unit roots using the Augmented Dicky-Fuller (ADF) test and for stationarity using the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test and the results are reported in Table 3 below:

Following other studies, the criteria for rejecting the null hypotheses of the ADF and the KPSS tests in Table 3 are set at 5%. As shown in Table 3, using the ADF, the null hypothesis that the return and detrended volume series contain unit roots can be rejected at the 1% significance level showing that the series are stationary. Using the KPSS test, the null hypothesis that the return and detrended volume series are stationary at the 5% significance level can be rejected as the series are only marginally significant at the 10% significance level. Thus, the requirement for conducting Granger causality in mean and in quantiles is met.

Table 3. Results of the ADF and KPPS tests for unit roots and stationarity.

	Test statistic		Decision	
Variable	ADF	KPSS	Unit root	Stationary
Full sample period				
Return	−15.952***	0.1480*	NO	YES
Detrended volume	−11.211***	0.1776*	NO	YES
Pre-crisis period				
Return	−9.9539***	0.5689*	NO	YES
Detrended volume	−7.1417***	0.4129*	NO	
In-crisis period				
Return	−6.5047***	0.1160*	NO	YES
Detrended volume	−4.2215***	0.1944 *	NO	YES
Post-crisis period				
Return	−14.972***	0.2269*	NO	YES
Detrended volume	−10.605***	0.2558*	NO	YES
Post-COVID period				
Return	−6.3223***	0.0882**	NO	YES
Detrended volume	−4.1954***	0.3137*	NO	YES

Note: The null hypothesis of the ADF test is that the series has a unit root. The null hypothesis of the KPSS test is that the series is stationary. ***, ** and * denote statistical significance at the 1%, 5% and 10%, respectively.

4.2. Causality in the mean

Before resorting to the causality in quantiles tests, the results from the causality in mean are presented first before linearity tests and structural break tests are conducted. Using Akaike Information Criterion (AIC), the linear Granger causality tests were based on VAR (p) models with p ranging from 1 to 12 for the different subsamples as shown in Table 4. The results on the linear dynamic relationship between stock returns and trading volume for the full sample, as well as the different subsamples, are presented in Table 4 below:

The linear Granger causality test results show causality from volume to return, while there is no causal relationship between return and volume for the full sample, pre-crisis and post-crisis periods. The other subsamples, namely in-crisis and post-COVID periods, show bidirectional causality.

4.3. Causality in quantiles

The results on the dynamic relationship between trading volume and trading volume using Granger causality in the mean reported in the previous section are unbiased provided that the variables are non-linear, do not have structural breaks and do not have regime shifts. The return and detrended volume series are examined in order to establish whether linear Granger causality can be relied on compared to the non-parametric quantile causality approach. The variables are examined to see if there are any structural breaks using the Bai and Perron (2003) tests for multiple structural breaks and linearity using the BDS test (Broock et al. 1996).

The null hypothesis for the BDS test is that the return and volume series are independently and identically distributed. The epsilon values are chosen following recommendations from Brock et al. (1991). The optimal embedding dimension (m) used is 6 in line with other empirical studies testing the dependence between returns and volume. As shown in Table 5, the null hypothesis that the return and volume series are independently and

Table 4. Granger causality in mean results.

Hypothesis	*F*	*p-value*	Lags	Conclusion
Full sample				
Return $\nRightarrow$ volume	2.78	0.0019	10	No causality
Volume $\nRightarrow$ return	0.262	0.9890	10	Causality
Pre-crisis period				
Return $\nRightarrow$ volume	2.4741	0.0034	12	No causality
Volume $\nRightarrow$ return	1.0088	0.4383	12	Causality
In-crisis period				
Return $\nRightarrow$ volume	1.4472	0.1875	7	Causality
Volume $\nRightarrow$ return	0.6338	0.7277	7	Causality
Post-crisis period				
Return $\nRightarrow$ volume	3.0491	0.0007	10	No causality
Volume $\nRightarrow$ return	0.6181	0.7996	10	Causality
Post-COVID period				
Return $\nRightarrow$ volume	0.1477	0.7011	1	Causality
Volume $\nRightarrow$ return	2.4868	0.1161	1	Causality

Table 5. BDS test results.

		m				
Variable	Epsilon	2	3	4	5	6
Return	0.5σ	13.3495***	17.6771***	21.4801***	25.2801***	30.3450***
	1.0σ	14.4234***	19.3505***	23.0004***	26.0756***	29.0842***
	1.5σ	15.1736***	20.8215***	24.1411***	26.5490***	28.5535***
	2.0σ	15.3964***	21.4095***	24.3547***	26.1884***	27.4705***
Volume	0.5σ	44.6877***	46.4247***	48.0703***	52.9778***	60.7488***
	1.0σ	41.2030***	41.6696***	41.7792***	43.7260***	46.8838***
	1.5σ	38.9975***	38.5568***	37.8056***	37.9868***	38.7385***
	2.0σ	37.3744***	36.6556***	35.5879***	34.8955***	34.5534***

Notes: *** represent statistical significance at the 1% level

identically distributed can be rejected at the 1% significance level, signifying that the transformed variables are nonlinear and therefore the use of linear models leads to biased estimates emanating from misspecifications.

Table 6 also shows that the return and volume series for the whole sample and the different subsamples have structural breaks, which gives further justification against using Granger causality in mean to examine the relationship between the series. The results for the Granger causality in quantiles proposed by Jeong, Härdle, and Song (2012), which is more effective at the tails, are shown for the whole sample in Figure 2. In the results presented in Figure 2, the lag order of 10 was determined using the Schwarz Information Criterion (SIC) under a VAR comprising detrended volume and log of returns. The SIC has been used in other studies employing the Jeong, Härdle, and Song (2012) causality in quantiles approach and has been noted as parsimonious compared to other approaches.

The vertical axis presents the test statistics corresponding to the null hypothesis that the return series (volume series) does not Granger cause the volume series (return series). The horizontal axis measures the different quantiles, and the red dotted line represents the 5% critical value (1.96). From Figure 2, it can be seen that for the relationship visualized in the top panel, the test statistic is consistently greater than the critical value of 1.96 for the quantiles between 0.12 and 0.9. It can therefore be concluded that returns do not cause trading volume in $\tau < 0.12$ or $\tau > 0.9$, whereas it is prima facie cause in the $0.12 \leq \tau \leq 0.8$ quantiles. Thus, there is no tail dependency between the return series and the volume series as causality in the middle quantiles only. Contrary to the return-volume

Table 6. Structural break dates.

Sample period	Variable	Break dates
Full sample	Returns	11 October 2007
Full sample	Volume	6 June 2007
Pre-crisis period	Returns	6 March 2008
Pre-crisis period	Volume	6 February 2007
In-crisis period	Returns	3 March 2009
In-crisis period	Volume	19 December 2008
Post-crisis period	Returns	4 July 2014
Post-crisis period	Volume	19 December 2011
Post-COVID period	Returns	30 October 2020
Post-COVID period	Volume	1 July 2020

dynamic relationship, the volume-return dynamic relationship shows different characteristics across the quantile distribution. The bottom panel of Figure 2 shows that there is no causality from trading volume to returns in the middle quantile (between 0.2 and 0.76) while there is prima facie evidence that volume intermittently causes returns between 0.13 and 0.19 as well as between 0.77 and 0.93 return quantiles. Again, there is no tail dependence from volume to returns in the quantiles less than 0.13 and quantiles greater than 0.93. The findings corroborate Chuang, Kuan and Lin (2009) who report that the causal relationship between volume and returns is heterogeneous across quantiles and is complicated to be understood solely in the lens of least-squares models.

4.4. Robustness

As the sample extends a fairly long time (16 years), we check the robustness of our results by evaluating the causal relations between return and volume in different sub-samples as explained in section 3.2. The lag orders of 12, 7, 10 and 1 for the pre-crisis, in-crisis, post-crisis and post-COVID periods were determined using the Schwarz Information Criterion (SIC) under a VAR comprising detrended volume and log of returns. Several trends can be seen in the dynamic relationship between trading volume and stock returns using different non-overlapping subsamples as shown in Figure 3:

The vertical axis presents the test statistics corresponding to the null hypothesis that the return series (volume series) does not Granger cause the volume series (return series). The horizontal axis measures the different quantiles, and the red dotted line represents the 5% critical value (1.96). First, during the in-crisis period, the return-volume dynamic relationship is intermittent at a few middle quantiles. In the post-COVID period, there is no prima facie evidence that returns Granger causes the trading volume across all the quantiles. On the other hand, the stable periods (pre-crisis period and post-crisis periods) are characterized by significant causal relationships between returns and trading volume in the middle quantiles, with the tail quantiles showing no prima facie evidence of dependence. Across all the non-overlapping subsamples, Figure 3 shows that the causal relationship between volume and returns is not significant across all the quantile distributions. It can therefore be concluded that there is no prima facie evidence that volume causes returns on the JSE and that the causal relationship between returns volume is heterogeneous during stable periods, while during crises and pandemics, the relationship dissipates.

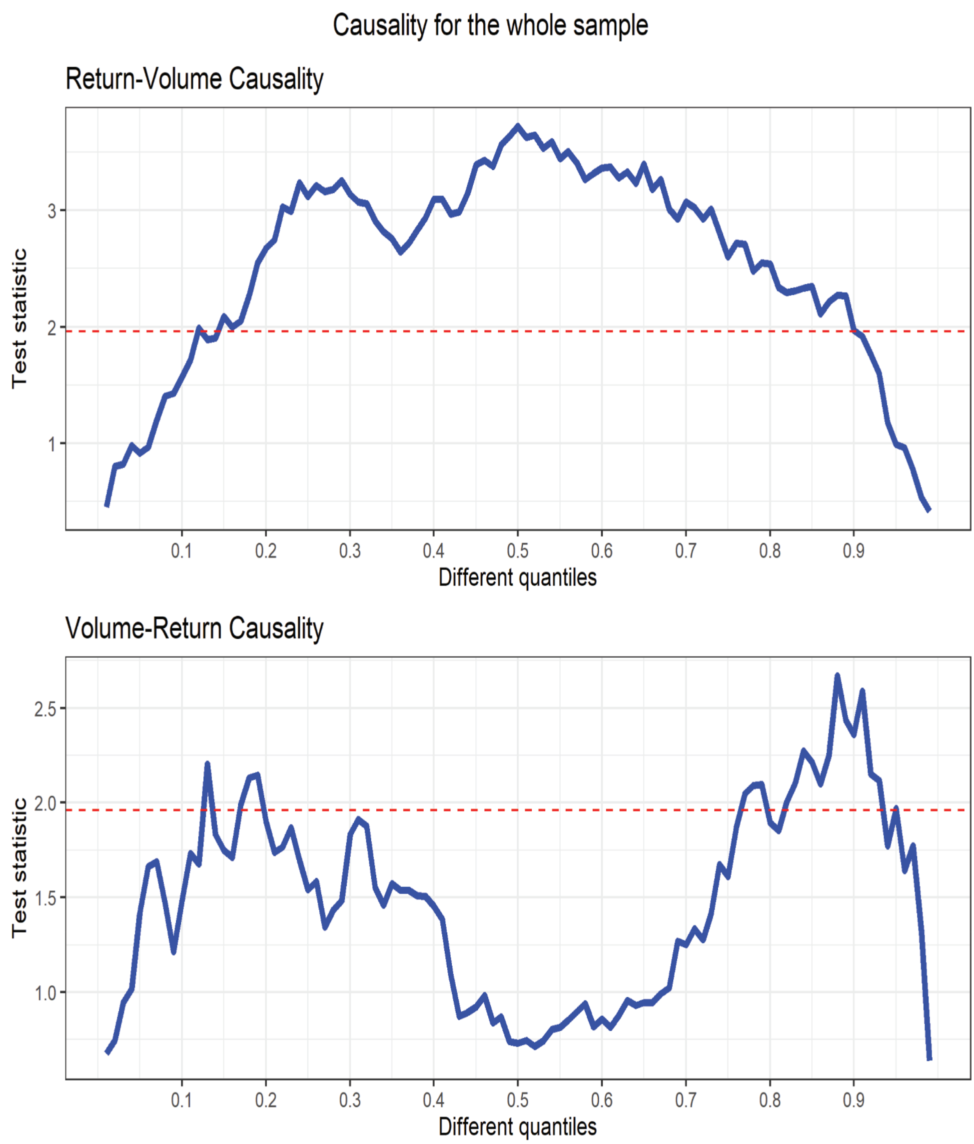

Figure 2. Non-parametric causality in quantiles: Whole sample.

5. Discussion

The results from linear Granger causality support the MDH as there is evidence of unidirectional and bidirectional causality from volume (returns) to returns (volume). This shows that there is a sequential reaction to information arriving into the market by traders. However, the results from the Granger causality in quantiles, which is more appropriate for modelling the dynamic relationship between trading volume and stock returns of the FTSE/JSE index in the presence of nonlinearities and structural breaks, support the MDH in relatively stable periods, while high volatility periods (in-crisis and post-COVID periods) support the SIAH. The findings from the study show that

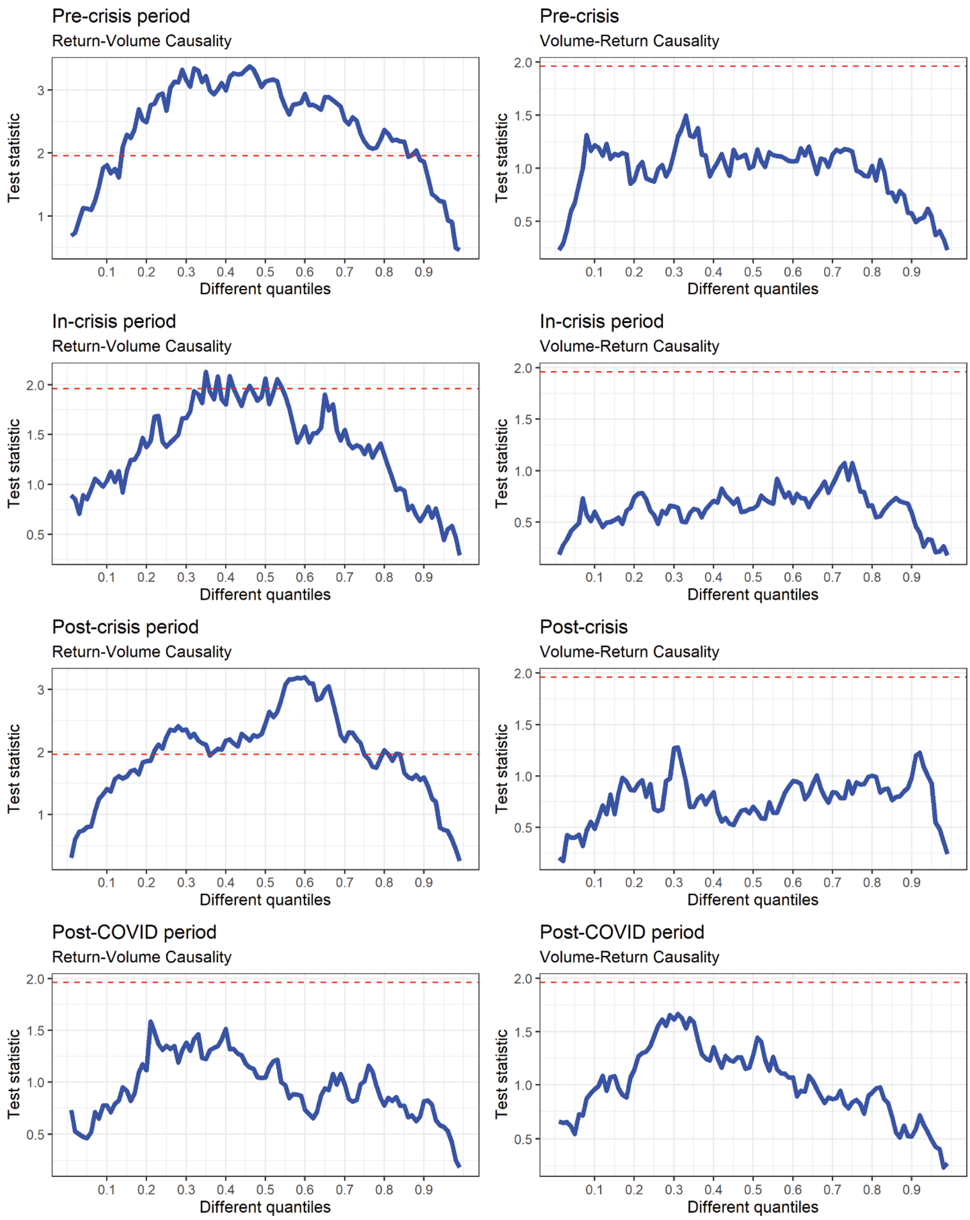

Figure 3. Causality in quantile by subperiods.

nonlinearities matter in efforts to model the relationship between trading volume and stock returns. This is corroborated by several recent studies that have also reported the importance of incorporating nonlinear dynamics in modelling techniques. Several studies have emphasized the importance of modelling nonlinear dynamics between trading volume and stock returns using different methodologies like Shannon entropy (Behrendt and Schmidt 2021), sup-Wald test (Chuang, Kuan, and Lin 2009), the smooth transition autoregressive model (Chuang, Ou-Yang, and Lo 2009) as well as ARCH-type models (Silvapulle and Choi 1999).

The results providence evidence of the dynamic nature of market efficiency on the JSE as seen by the in-crisis period and the post-crisis period in which trading volume does not Granger cause returns at all quantiles of returns, while the periods outside the financial crisis and the COVID-19 pandemic are characterized by a unidirectional causality from returns to trading volume in the middle quantiles. The evidence of weak-form efficiency on the JSE during the in-crisis period corroborates the findings of Chen and Jarrett (2011), who report that the Chinese stock market was not efficient in the pre-crisis period but exhibited some form of weak-form efficiency during the crisis. While it is expected that in a crisis or black swan event like COVID-19, overreaction by investors should lead to the predictability of stock returns and hence an inefficient market, the JSE is dominated by institutional investors, and the impact from retail investors may be negligible in a crisis or pandemic.

6. Conclusion

The study aimed to empirically investigate the dynamic relationship between stock returns and trading volume using the FTSE/JSE All Share Index for the period 2005 to 2021. Continuous stock returns and detrended trading volume were used, first, using Granger causality tests in the mean. The results from the linear Granger causality tests revealed that in the stable periods (pre-crisis and post-crisis periods) and the full sample, there is unidirectional causality from volume to returns. The in-crisis and post-COVID periods were marked by bidirectional causality between the two series. After conducting the BDS tests for independence and the structural change tests on the time series, it was discovered that both series exhibit nonlinearity and have structural breaks across all the subsamples used in the study. A non-parametric quantile causality approach based on the non-parametric kernel was, therefore, used to test causality between the series in the presence of nonlinearity and structural breaks.

First, the results show that there is prima facie evidence of causality from returns to trading volume in the middle quantiles of the conditional distributions during stable periods (pre-crisis and post-crisis) as well as the full sample and this causal relationship disappears during the in-crisis and the post-COVID periods. Second, it is observed that the highest impact occurs in the middle of the conditional distribution but not necessarily the median. Third, across all the samples used in the study, no evidence is found of causality from trading volume to return. The findings from the study highlight the importance of going beyond the traditional Granger causality tests, which are solely based on conditional means. Model specifications using linear Granger causality might be misspecified because of the presence of nonlinearity and structural breaks often found in financial time series. From a policy perspective, the findings signal to governments and statutory authorities that direct intervention in the stock market during high-volatility periods is likely to be ineffective. The JSE is dominated by institutional investors and using interventionist policies that are normally targeted at retail investors to spur the stock market in a South African context is likely to produce disappointing results. The implication for forecasting is that practitioners should incorporate nonlinear dynamics in their modelling techniques. The use of linear models will probably lead to misspecified forecasts and thereby negatively affecting asset allocation. Future studies could expand this study further by exploring the dynamic relationship between trading volume and stock returns at the firm level.

Disclosure statement

No potential conflict of interest was reported by the author.

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