

https://dspace.org/

Quantile dependencies between exchange rate volatility and sectorial stock returns in South Africa

Darren Mubaiwa; Ismail Fasanya

INVESTMENT ANALYSTS SOC SOUTHERN AFRICA
https://hdl.handle.net/10539/40106
WOS

Downloaded from a DSpace repository. https://dspace.org/



Investment Analysts Journal

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/riaj20

Quantile dependencies between exchange rate volatility and sectoral stock returns in South Africa

Darren Mubaiwa & Ismail Fasanya

To cite this article: Darren Mubaiwa & Ismail Fasanya (2024) Quantile dependencies between exchange rate volatility and sectoral stock returns in South Africa, Investment Analysts Journal, 53:2, 89-101, DOI: 10.1080/10293523.2023.2268372

To link to this article: https://doi.org/10.1080/10293523.2023.2268372

Published online: 24 Nov 2023.

Submit your article to this journal

Article views: 84

View related articles

View Crossmark data

Full Terms & Conditions of access and use can be found at
https://www.tandfonline.com/action/journalInformation?journalCode=riaj20

INVESTMENT ANALYSTS JOURNAL
2024, VOL. 53, NO. 2, 89–101
https://doi.org/10.1080/10293523.2023.2268372

Check for updates

Quantile dependencies between exchange rate volatility and sectoral stock returns in South Africa

Darren Mubaiwa and Ismail Fasanya

School of Economics and Finance, University of the Witwatersrand, 1 Jan Smuts Avenue, Braamfontein, 2000, South Africa

ABSTRACT

This study assesses the effect of USD-Rand exchange rate volatility on South African sectoral stock returns between 29 March 1996 and 28 July 2022. Using the quantile-on-quantile regression (QQR) technique, we uncover that, although each of the sectors exhibit important idiosyncrasies, there exists a single overarching relationship between exchange rate volatility and stock returns that persists across all sectors. We find that low levels of volatility in the exchange rate have a negative impact on stock returns. Conversely, high levels of exchange rate volatility have a positive impact on stock returns. The most important implication of the findings of this study is that investors should have a keen awareness of movements in both the exchange rate and stock markets.

ARTICLE HISTORY
Received 28 March 2023
Accepted 3 October 2023

KEYWORDS
exchange rate; sectoral stocks; quantile regression; South Africa

JEL CODES
C22; F31; G15

1. Introduction

In the period after the fall of the Bretton Woods system in 1973, many countries adopted a floating exchange rate regime. However, as a consequence of this development, it has been observed that exchange rates have experienced periods of marked volatility. The most notable examples include the Asian and Global financial crises and, most recently, the COVID-19 pandemic. In the case of South Africa, both the stock market, the JSE All Share Index, and the USD-Rand exchange deteriorated at the onset of the pandemic (Iyke & Ho, 2021). Moreover, there is evidence to suggest that, with the increase in exchange rate exposure, excepting a few export-oriented sectors, most South African stock sectors have been negatively impacted (Iyke & Ho, 2021).

Much like Iyke and Ho (2021), several studies have endeavoured to assess the relationship between exchanges rates and stock returns (see inter alia Sikhosana & Aye, 2018; Mechri et al., 2018; Tule et al., 2018; Zhu et al., 2022; Fasanya & Akinwale, 2022). Notwithstanding, no study, to the best of our knowledge, has yet examined the effect of exchange rate volatility on South African stocks at the sectoral level. This is consequential given that the effect of changes in exchange rates on a sector's returns depends on whether the sector is import/export oriented (Jorion, 1990). Considering this gap, we examine the dependency between sectoral stock returns and exchange rate volatility across each of their distributions using the quantile-on-quantile regression (QQR) approach of Sim and Zhou (2015). This technique allows us to glean more information than is possible with linear models or quantile regression (Ma & Koenker, 2006). Given the dominance of the US dollar in international transactions (see Arslanalp et al., 2022), we focus on the USD-Rand exchange rate to reveal the association between exchange rate volatility and stock returns. The focus on South Africa arises from the fact that South African financial markets have relatively

CONTACT Ismail Fasanya ismail.fasanya@wits.ac.za
© 2023 Investment Analysts Society of South Africa
Investment Analysts Journal is co-published by NISC Pty (Ltd) and Informa Limited (trading as Taylor & Francis Group)

high liquidity, and their foreign exchange turnover has been regularly ranked among that of the premier financial markets (International Monetary Fund, 2022). Because of the credibility of these markets, they are favoured with considerable foreign participation. In fact, approximately half of the traded equity securities on the Johannesburg Stock Exchange (JSE) are owned by foreign investors (International Monetary Fund, 2022).

Prior to Jorion's (1990) work, Ethier (1973) had explicitly assumed that firms have access to hedging instruments to eliminate exchange rate risk. Ethier (1973) theorised that the firm's knowledge and expectations are central to how exchange rate risk affects the firm's activities. It is however important to highlight that the use of hedging instruments is greatly correlated with financial market development (Correia et al., 2012). Despite this, a study by Correia et al. (2012) looking at derivative use among non-financial firms in Africa, at least those for which financial statements were available, found that slightly more than half of South African corporates used derivatives. Expectedly, they found that hedging exchange rate risk was the primary reason for using derivatives. Notwithstanding the development of South African financial markets, use of derivative instruments is much greater among companies which principally operate in the developed world (Correia et al., 2012). The primary objective of hedging for these companies differs slightly: instead of exchange rate risk, their foremost concern is interest rate risk. Against this background, this study analyses the impact of USD-Rand exchange rate volatility on South African sectoral stock returns across each of their distributions.

The rest of the paper is organised as follows. In Section 2, we provide a review of related works of literature while a description of the methodology is presented in Section 3. The data and preliminary analysis of the paper as well as empirical results are presented in Section 4. Finally, Section 5 presents the conclusion along with some policy implications.

2. Review of the literature

In pursuit of a deeper understanding of stock markets, many researchers have sought to assess, much like this study, how these markets are affected by conditions in other markets. Pertinently, several studies have focused on the association between stocks and exchange rates and came to somewhat varied conclusions. Moreover, these studies have differed in scope and in the methods employed. For example, a study by Mechri et al. (2018), looking at Turkey and Tunisia between 2003 and 2015, found that exchange rate volatility had a positive effect on stock prices. This study employed linear regressions to uncover the way currency volatility affects stock prices. Meanwhile, Iyke and Ho (2021), in a study looking at the effect of exchange rate exposure on various South African stock sectors, found that while this exposure negatively impacts most sectors, there were a few sectors (such as beverages, basic materials, consumer goods, and technology among others) which benefited from this exposure. Looking at Nigerian sectoral stock returns and exchange rate shocks, Fasanya and Akinwale (2022) found that movements in the exchange rate did not uniformly affect all stock sectors and concluded that information from one sector was not useful in forecasting returns in another sector.

Other studies such as those by Blau (2018) focused on uncovering the link between the volatility in the exchange rate of a country and that of its stock market. Specifically, the study used ADRs (negotiable certificates of foreign stocks issued by US depositary banks) and derived volatility by applying three volatility measures (standard deviation, idiosyncratic volatility and the GARCH (1,1) model). Using the volatility data, they ran panel regressions and concluded that exchange rate volatility increased volatility in stock prices. In a previous study, Blau (2017) had found that rising volatility in the exchange rate increased the probability of negative movements in the stock market. Specifically, Blau (2017) observed that higher exchange rate volatility increased the kurtosis of the stock returns distribution and was associated with negative skewness.

A study by Malik (2021) instead examined the nature of volatility transmissions between the exchange rate and stock returns using bivariate GARCH and found that volatility transmissions

were not significant between the markets. Similarly, Ghani et al. (2022) assessed the effect of that several variables, including exchange rate volatility, had on stock market volatility. They used the GARCH-MIDAS model using data on the Pakistan stock market and found that the macroeconomic variables considered possessed useful information for forecasting stock market volatility. A study by Hashmi et al. (2022) on the Pakistan economy assessed the relationships among oil prices, exchange rates and stock prices using quantile ARDL and found that exchange rates had an asymmetric effect on stock prices. However, the relationship between a country's exchange rate and its stock prices was shown to be positive across the quantiles of the exchange rate but was not significant for some of these quantiles. In their study focusing on the dependence and spillovers among China's oil, exchange rate and stock markets, Zeng et al. (2022) found that Chinese stock market returns were negatively impacted by the deterioration of the Chinese Yuan against the USD in the preceding period. Moreover, their study revealed that positive movements in the Chinese stock market in turn caused a strengthening of the Chinese Yuan against the USD. Meanwhile, Tule et al. (2018) used the multivariate GARCH on stock market returns and currency volatility and found that there were bidirectional spillovers between the two markets in Nigeria. Sikhosana and Aye (2018), while looking at South Africa, came to the same conclusion on the effect of currency volatility on the Johannesburg JSE using a similar method.

Seeking to assess the manifestation of the effect of both exchange rates and oil prices on stock returns in the BRICS group of countries, Zhu et al. (2022) used the wavelet method and the threshold quantile ARDL model and found that only China had an asymmetric exchange rate-stock returns nexus. However, the effect of exchange rates on India's stock markets was greater during normal market conditions than during extreme periods. From rolling window quantile regression, they further observed that the exchange rate had a negative association with the stock market but there was a shift where the exchange rate had a positive effect on stock returns. Moreover, among the BRICS countries, South Africa's stock markets were the least affected by exchange rates. Zhu et al. (2022) posited that this was on account of the minor international trade exposure the country had in comparison to other BRICS members. They also uncovered that the effect of the exchange rate, as well as oil prices, on stock markets was magnified by volatility in the macro financial environment. These findings were consistent with Mahapatra and Bhaduri (2019) who found a negative connection between currency variability and Indian stock market returns but based on APT two-factor arbitrage and random effects modelling. Their approach explicitly looked at whether the market prices exchange rate risk into stock prices and to what extent investors expect firms to hedge currency risk exposure. According to this same study, over its period of assessment, Indian investors expected a premium for bearing exchange rate risk. In light of the study by Correia et al. (2012), these results may be informative for the South African economy as Mahapatra and Bhaduri (2019) found that it was likely that Indian firms did not adequately hedge their currency risk exposures. These findings by Zhu et al. (2022) and Mahapatra and Bhaduri (2019) are however contrary to those of Du and Hu (2012) who found that currency volatility had no power, either across companies or across time, to explain US stock returns. Their study used regression methods developed by Fama and MacBeth (1973) and Fama and French (1996). Interestingly, Salisu and Vo (2021) sought to examine how low/high interest rate environments may affect the association between exchange rates using panel ARDL. They found that both low and high interest rates result in a negative association between exchange rate volatility and stock returns in the short run but this state of affairs was reversed in the long run. That is, in the long run, they observed a positive association between exchange rates and stock returns. However, the short run results were only significant for high interest environments while in the long run only the results for the low interest environment were significant.

Despite the great length and breadth of research on exchange rates and stock markets, no study, to the best of our knowledge, has yet assessed the nexus between exchange rate volatility and stock returns at the sectoral level in a South African context. Against this background, this study proceeds to uncover the association between currency volatility and stock returns across both of their distributions.

3. Data and methodology

3.1. Data

The study uses daily data of exchange rate movements and sectoral returns on the JSE spanning from 29 March 1996 to 28 July 2022. The period is selected on account of data availability issues for South Africa prior to 1996. The country was under the Apartheid regime prior to this time. The data are sourced from the DataStream database of Thomson Reuters. In this study the exchange rate is defined here as the numbers of units of the Rand to one US dollar. The study bases its analysis on 10 FTSE/JSE stock sectors according to the Industry Classification Benchmark (ICB). We should note that whereas the ICB uses the term "industry", we elect to use "sector" to avoid confusion with the industrials sector. Specifically, in addition to the aggregate market, the study looks at Technology, Telecommunications, Consumer Staples, Health care, Energy, Real Estate, Basic materials, Industrials, Financials, and Consumer Discretionary.

3.2. Methodology

The QQR employed in this study was proposed by Sim and Zhou (2015) as a generalisation of the quantile regression. This method allows one to analyse the effect of the quantiles of one variable (in our case, exchange rate volatility) across the conditional quantiles of another variable (sectoral stock returns).

We develop the QQR approach that is employed, with quantile regression (QR) as our starting point. The QR model is given by the following equation:

$$SR_t^i = \beta^\theta(EXRV_t) + \mu_t^\theta \tag{1}$$

where SR denotes sectoral stock returns at time t, EXRV represents exchange rate volatility at time t. θ denotes the θth quantile of the conditional distribution of sectoral stock returns. The quantile error term (μ_t^θ) has a conditional distribution of zero. From Equation (1), we can see that the QR approach allows us to regress different quantiles of sectoral returns on exchange rate volatility.

To examine the relationship between the θth quantile of sectoral returns and the τth quantile of exchange rate volatility denoted by $EXRV^\tau$, we let $\beta^\theta(\cdot)$ be an unknown function of a standard quantile regression, and the first Taylor expansion around a quantile $EXRV^\tau$ is given by:

$$\beta^\theta(EXRV_t) \approx \beta^\theta(EXRV^\tau) + \beta^{\theta'}(EXRV^\tau)(EXRV_t - EXRV^\tau) \tag{2}$$

$\beta^{\theta'}$ represents a partial derivative of $\beta^\theta(EXRV^\tau)$. It is noted that $\beta^\theta(EXRV^\tau)$ and $\beta^{\theta'}(EXRV^\tau)$ are renamed $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$ respectively.

$$\beta^\theta(\theta, \tau) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(EXRV_t - EXRV^\tau) \tag{3}$$

Given that parameters of Equation (3) are indexed with both θ and τ, the equation can capture the dependence between the quantiles of exchange rate volatility and stock returns.

We then substitute Equation (3) into Equation (1) to derive Equation (4).

$$SR_t^i = \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(EXRV_t - EXRV^\tau) + \mu_t^\theta \tag{4}$$

The QQR approach decomposes the estimates of the QR regression model and regresses the θth quantile of sectoral stock returns on the τth quantile of exchange rate volatility. This means that the QQR approach possesses more disaggregated results and can more fully express the relationship between exchange rate volatility and the returns of each sector of the stock market (e.g., Financials). This relation (or dependence) is primarily expressed by terms $\beta_0(\theta, \tau)$ *and* $\beta_1(\theta, \tau)$.

To estimate Equation (4), we replace $EXRV_t$ *and* $EXRV^\tau$ with their empirical versions $\widehat{EXRV}_t$ *and* $\widehat{EXRV}^\tau$. We then obtain the local linear regression estimates of the parameters b_0

and b_1 by the solving the following minimisation problem:

$$\min_{b0,b1} \sum_{k=0}^{n} \rho_\theta \left[SR_t^i - b_0 - b_1 \left(\widehat{SR}_t - \widehat{EXRV}^\tau\right)\right] K\left(\frac{F_n(\widehat{EXRV}_t - \tau)}{h}\right) \tag{5}$$

ρ_θ is the quantile loss function. We make use of the local linear regression to avoid the problem of dimensionality (Stone, 1977; Cleveland, 1979). In addition, we use the gaussian kernel $K(\cdot)$ to weight the observations in proximity of $\widehat{EXRV}^\tau$ based on bandwidth h as we seek to assess the effect exerted locally by the τth quantile of exchange rate volatility. Selection of the bandwidth is important because it affects the bias and variance of the estimates. We follow Sim and Zhou (2015) and select a bandwidth of h = 0.05.

4. Empirical results

4.1. Preliminary analysis

We derive stock returns series (r_t) by taking the first difference of the natural logarithm of the price level of each of the stock sector indices (P_t).

$$r_t = (\Delta lnP_t) \times 100$$

Further, we obtain the exchange rate volatility by estimating a GARCH (1,1) model from USD-Rand exchange rate data. The GARCH (1,1) is given by:

$$\delta_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \delta_{t-1}^2$$

which says that the conditional variance (δ_t^2) depends on the previous period's squared error term (ε_t^2) and the previous period's conditional variance (δ_{t-1}^2) (Gujarati & Porter, 2017). From the descriptive statistics in Table 1 we can observe that all sectoral stocks and the aggregate stock market had a marginally positive average return. An assessment of the standard deviation, the minimum and maximum values shows that the returns are closely clustered around the average values. This initial assessment is corroborated by a graphical analysis of the stock returns series over the selected period in Figure 1. From Figure 1, it is evident that the returns straddle the average returns roughly evenly. Moreover, given that the average returns are not much greater than zero, values lower than the average returns are almost entirely negative. Put into context, returns lower (higher) than the average returns (or zero) entail bearish (bullish) market conditions.

The results of the Jacque-Bera test show that the variables are not normally distributed. This entails heavy left or right tails and/or excess kurtosis. Moreover, non-normality suggests that the associations between the variables are non-linear. We are therefore justified in pursuing quantile-based approaches as they are more robust in the presence of non-linearity (Arain et al., 2019; Mishra et al., 2019; Troster et al., 2018).

We perform unit root tests on all the variables using the Augmented Dickey-Fuller and the Phillips-Perron tests. The results presented in Table 1 show that all the series are stationary at levels.

4.2. Discussion of results

Analysing the quantile relationship between exchange rate volatility and stock returns, Figure 2 shows the graphical representation of the quantile-on-quantile slope coefficients, $\beta_1(\theta, \tau)$. Recalling that this slope coefficient is doubly indexed by both θ and τ, it therefore quantifies the effect of the τth quantile of exchange rate volatility on the θth quantile of the stock returns series. One of the salient observations from the descriptive analysis is that the lower and upper values of the different stock returns series convey different states of the market. That is, negative (positive) stock returns entail bearish (bullish) market conditions. Describing the association between the

Table 1. Descriptive statistics and unit root tests.

								Augmented Dickey Fuller (ADF)		Philips-Perron (PP)	
Series	Mean	Std. Dev	Min.	Max.	Skewness	Kurtosis	Jacque-Bera	Level	I(d)	level	I(d)
Technology	0.0666	2.3995	−16.8573	20.5303	−0.0088	8.6451	9121***	−70.317***	I(0)	−70.279***	I(0)
Telecoms	0.0518	2.2049	−20.7649	21.7113	−0.1246	12.3144	24849***	−68.529***	I(0)	−68.450***	I(0)
Health	0.0308	1.4243	−17.8400	8.6795	−0.6034	12.3979	25695***	−71.789***	I(0)	−71.762***	I(0)
Financials	0.0286	1.4746	−14.5811	8.4916	−0.4763	10.7948	17649***	−70.078***	I(0)	−70.026***	I(0)
Real Estate	0.0182	1.5366	−21.2532	12.1458	−0.8166	21.4935	98650***	−74.042***	I(0)	−74.091***	I(0)
Cons. Disc.	0.0281	1.4444	−17.0770	12.5125	−0.5271	11.2007	19566***	−70.012***	I(0)	−70.003***	I(0)
Cons. Staples	0.0232	1.6683	−37.0966	19.1438	−1.7641	47.6374	573831***	−65.916***	I(0)	−66.098***	I(0)
Industrials	0.0233	1.4610	−26.0383	9.1958	−1.0796	23.7118	124112***	−73.945***	I(0)	−73.961***	I(0)
Basic Mat.	0.0252	2.0523	−20.2173	21.3192	−0.0364	12.9673	28436***	−71.633***	I(0)	−71.638***	I(0)
Energy	0.0305	2.3330	−43.0945	21.9742	−0.9593	26.1253	154112***	−70.250***	I(0)	−70.261***	I(0)
Aggr. market	0.0284	1.2244	−14.6071	8.2956	−0.6793	11.3543	20504***	−72.253***	I(0)	−72.253***	I(0)
Exch. Vol.	0.0135	0.0228	0.0001	0.3537	7.1544	77.8034	1660089***	−9.094***	I(0)	−9.877***	I(0)

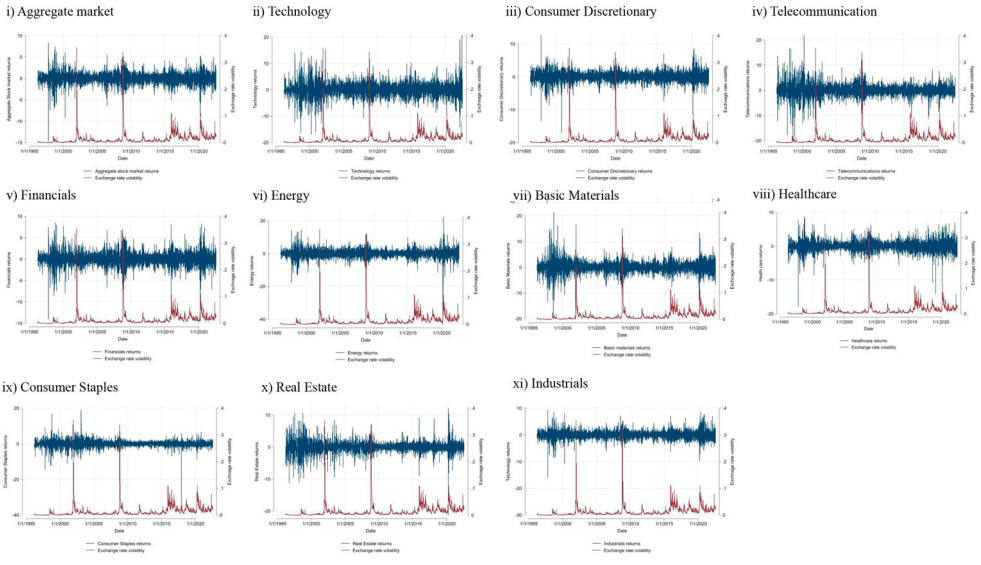

Figure 1. Exchange rate volatility and sectoral stock returns. Source: Author's own compilation

dependent and independent variables in this manner makes the insights of the QQR analysis more apparent. For example, lower (higher) exchange rate volatility has a negative (positive) effect on the Aggregate stock market's returns. This relationship is however inverted where the aggregate stock market is extremely bullish. In this state the effects of lower and higher currency volatility are inverted: lower (higher) exchange rate volatility has a positive (negative) effect on the aggregate stock's returns. The results obtained for the aggregate market are consistent with those of Mechri et al. (2018). Beyond this, these findings add another dimension to the period-focused observations of Zhu et al. (2022) and those of Iyke and Ho (2021). From a theoretical perspective, the results seem to be consistent with the theoretical work of De Grauwe (1988) which posits that the marginal utility of trade increases as risk in the exchange rate rises.

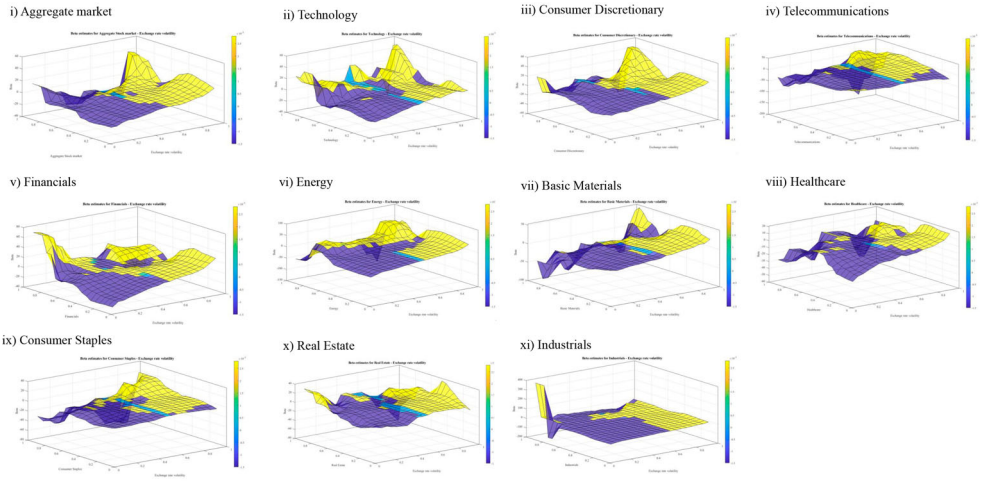

Figure 2. Relationship between exchange rate volatility and stock returns. Source: Authors' compilation

Note: The graphs show the slope coefficients, $\beta_1(\theta, \tau)$.

Although the effects of exchange rate volatility on the different sectoral stock returns and the Aggregate stock market are similar, the sectoral stock returns series exhibit special characteristics. The existence of these idiosyncrasies implies that there may be material portfolio diversification opportunities available to investors among the sectors. The differences in the nexus between stock market returns and currency volatility for the sectors can be observed in Figure 2 (ii) where it can be seen that a bullish technology sector will not benefit from high levels of volatility in the exchange rate to the same extent as the aggregate market. As previously alluded to, there are similarities. For example, like the aggregate market, exchange rate volatility's low and median quantiles (0.05–0.60) have a negative effect on the Technology sector's own low and median quantiles. Conversely, the upper quantiles of exchange rate volatility have a positive impact on Technology sector returns. Noticeably, there is an inversion of this association when the sector is bullish (0.80–0.95). In this region, low (high) exchange rate volatility has a positive (negative) effect on technology sector returns. Overall, a thorough assessment of Figure 2 (i) to (xi) shows that there is some variation between how someone invested in the overall market may expect their position to be affected by currency volatility as opposed to a position in any of the stock sectors. However, among the sectors, consumer discretionary shows the most similarity with the aggregate market. Specifically, the core nature of the effect of exchange rate volatility on Consumer Discretionary sector returns is almost identical to the aggregate market and Technology sector. Conversely, unlike the aggregate market and the aforementioned sectors, low and average levels of volatility have a broadly negative effect across all the quantiles of Telecommunication stock returns. On the other hand, exchange rate volatility's upper quantiles (0.60–0.95) exert a positive impact on all the quantiles of the sector's stock returns except for the uppermost quantiles (0.80–0.95) when the sector is bullish. The result is that, unlike the inversion observed for the aggregate stock market and the technology sector, Telecommunications only experiences a partial inversion in its upper most quantiles. Noticeably, very high exchange rate volatility has a negative effect on Telecommunications when the market is bearish.

Although both Financials and Energy show the same general effects as other stock series, they possess a shared characteristic different from other sectors and the aggregate market. When these two sectors experience normal conditions (0.45–0.65), all levels of volatility in the exchange rate exert a negative effect on their returns. The results of the Basic materials in Figure 2 (vii) show that the sector is greatly negatively affected by the lower quantiles of exchange rate volatility. As with other sectoral stock returns series, the uppermost quantiles of exchange rate volatility exert a positive effect on basic materials sector returns when it is bullish. Basic materials show a similar effect to that of Financials and Energy, but this effect is over its upper quantiles (0.60–0.80) instead of its median quantiles. Over these quantiles, the effect of low and high exchange rate volatility on returns is negative. However, low exchange rate volatility does not have a positive effect on the uppermost quantiles of Basic material. That is, when the Basic materials sector is bullish, it only experiences a partial inversion.

As with Telecommunications and Basic materials, the partial inversion is observed for Healthcare and Consumer staples. The beta coefficients in Figure 2 (viii) show that only very high exchange rate volatility has a positive effect across the quantiles of Healthcare sector returns. Similar to Telecommunications, very high exchange rate volatility has a negative effect on Consumer staples sector returns when the sector is bearish (low θ-quantiles). Apart from these differences, low (high) exchange rate volatility has a generally negative (positive) effect on the two sectors. From Figure 2 (x), $\beta_1(\theta, \tau)$ shows that the upper τ-quantiles (0.05–0.60) have a negative effect on the low and median θ-quantiles. This suggests that low and average exchange rate volatility has a negative effect on the Real Estate sector when it is experiencing bearish and normal market conditions. Higher exchange rate volatility has a positive effect across the spectrum of Real Estate returns. Much like the Technology sector and the aggregate market, low (high) exchange rate volatility has a positive (negative) effect on Real Estate sector returns when the sector is bullish. Excepting the uppermost θ-quantiles of Industrial stock returns, low (high) currency volatility has a negative

(positive) effect on Industrials sector returns. There is an inversion of this effect when the sector is performing very well. However, the positive effect of low exchange rate volatility on industrials in this bullish state is more pronounced than in all other series as shown in Figure 2 (xi). The differences observed in the stock sectors in terms of both the nature and magnitude of how currency volatility impacts stock returns will likely have material consequences for any investor seeking to create portfolios. However, knowing where the markets are in relation to their quantiles may prove difficult and it would be remiss not to caution any practitioner intending to implement the analysis of this study.

Overall, these findings suggest that exchange rate volatility does not have an exacerbating relationship with the different stock series: it does not magnify whatever state is prevailing in the market or sector. Instead, it has a decreasing or increasing effect depending on whether exchange rate volatility is low or high. Moreover, there are regions where this general relationship is not observed. The more prominent of these aberrations is the inversion (or partial inversion) when the stock sectors and the aggregate market are bullish.

In the pursuit to uncover how the COVID-19 pandemic may have affected the nexus between currency volatility and stock returns, we selected a sub-sample period beginning 1 January 2020 to 28 July 2022. Although the COVID-19 sample period still exhibits the same general relationship between exchange rate volatility and stock returns across the sectors, there are differences of note. As Figure 3 shows, sectors such as Telecommunications benefited during the pandemic. During this period, only the lowest levels of currency volatility negatively impacted the Technology stock returns. These results seem to corroborate those of Iyke and Ho (2021) who found that the Technology sector benefited from the exposure to exchange rates. However, the good fortunes of the Technology sector were not experienced by all sectors. The Industrials sector was particularly negatively affected as its nexus with currency volatility had a much wider range over which volatility in the exchange rate negatively affects the sector's returns. Overall, the association between currency volatility and stock returns during this period shows a much more uniform distribution with fewer irregularities.

4.3.1. Comparing OLS, QR and QQR

To demonstrate the superiority of the QQR approach in modelling the association between exchange rate volatility and stock returns, we compare its results to those of OLS and QR. In

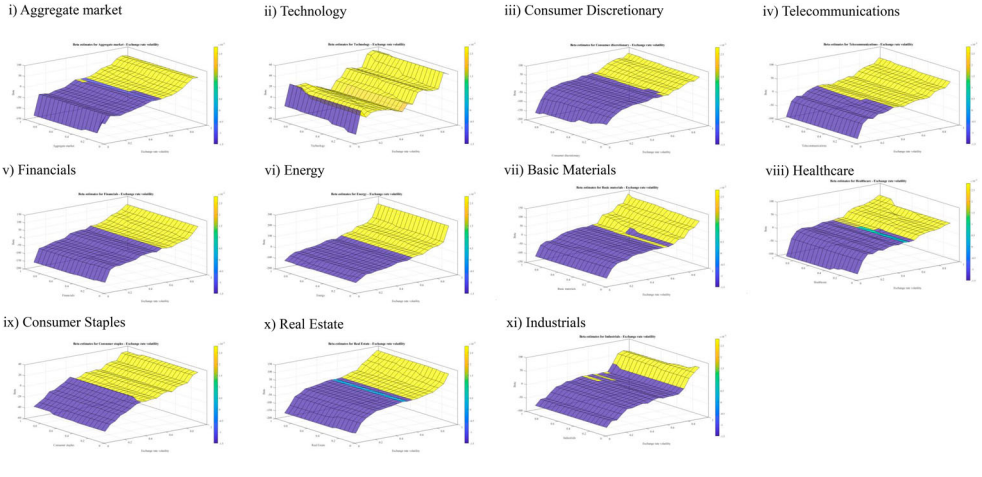

Figure 3. Relationship between exchange rate volatility and stock returns (COVID-19 sub-sample period). Source: Authors' compilation.
Note: The graphs show the slope coefficients, $\beta_1(\theta, \tau)$.

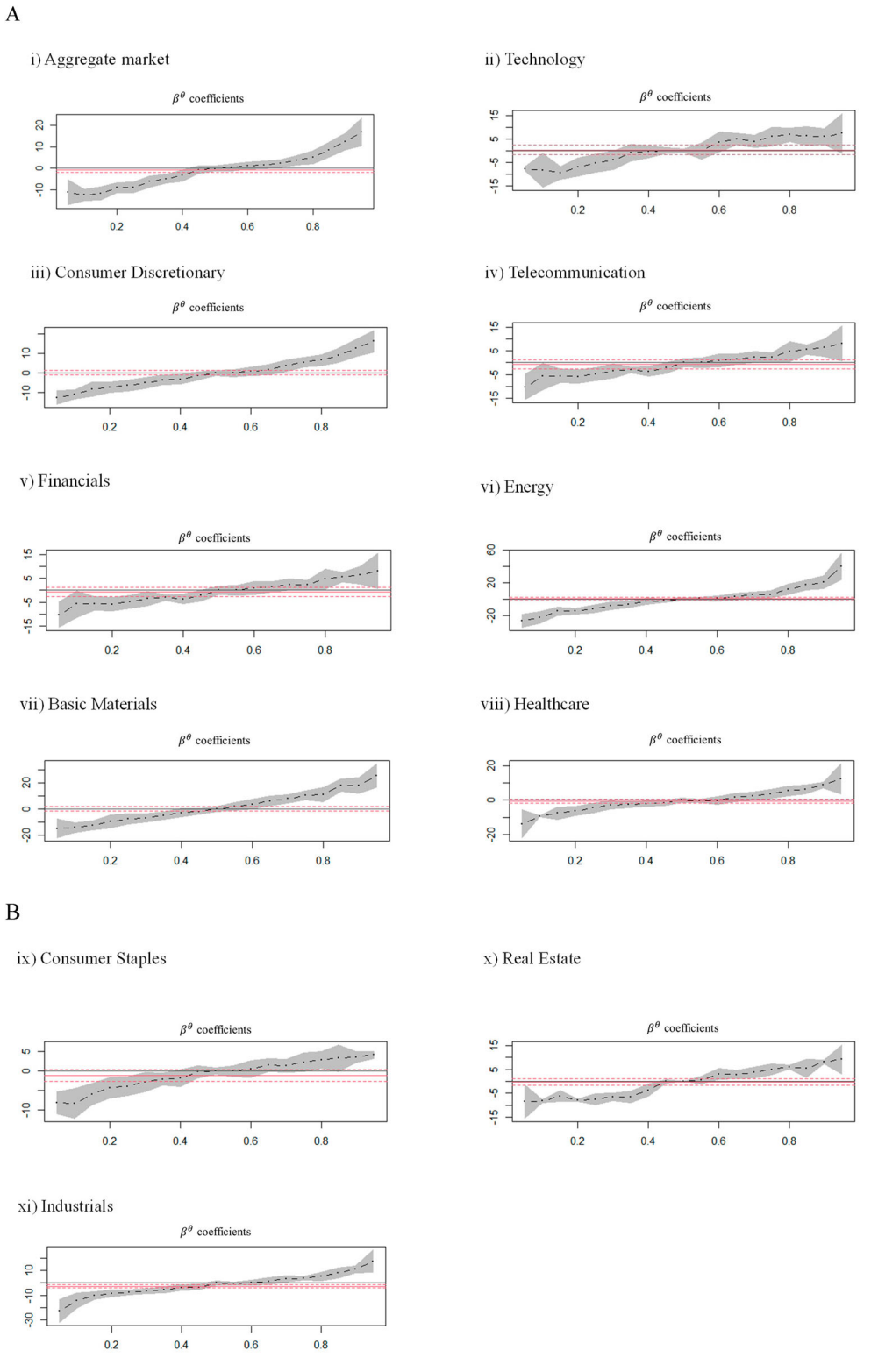

Figure 4. (A): Graphs of quantile regression; (B): Graphs of quantile regression. Source: Authors' own compilation.
Note: β^θ refers to the slope coefficients at the different quantiles.

Figure 4, where OLS only measures a weak linear association between the response and explanatory variables, quantile regression shows that the relationships among variables are heterogeneous across the distribution of the response variable. Notwithstanding, we are still not able to see for instance that there is generally an inversion of the relationship between exchange rate volatility and sectoral stock returns when the stock market is highly bullish. From assessing the QR plots, it would seem that exchange rate volatility has an exacerbating effect on aggregate market and stock sector returns. From the results of the QQR, however, we know this is not the case. Therefore, the QQR results show that the aggregation of the effects of currency volatility quantiles obfuscates a great amount of detail and may potentially lead to erroneous conclusions.

For illustrative purposes we provide the OLS regression equation of the Technology sector:

$$SR_t^{Tech} = 0.06242 + 0.30893\ (EXRV_t)$$

The coefficients of the OLS equation suggest that exchange rate volatility only has a weak relationship with stock returns. Moreover, the beta coefficient of the independent variable is not significant at an alpha of 10%. Based on this analysis, it is tempting to conclude that exchange rate volatility has no relationship with stock returns. However, the study has demonstrated that such a conclusion would be incorrect.

5. Conclusion and Implication for policy

The study sought to reassess the association between exchange rate volatility and stock market returns by employing the relatively new quantile-on-quantile methodology. The specific objectives of the study were to assess the quantile dependency between exchange rate volatility and stock returns as well as to examine the nature of this dependency at a sectoral level. The empirical results of the study show that the effect of exchange rate volatility is generally similar across the aggregate market and stock sectors. There are however certain deviations in the general relationship between currency volatility and stock returns. That is, in general we observe that low (high) exchange rate volatility has a negative (positive) effect on stock returns across the quantiles of the aggregate market and all stock sectors. When the aggregate market and stock sectors are extremely bullish, there is an inversion of the aforementioned general relationship. In the highest quantiles of the stock returns series, low (high) currency volatility has a positive (negative) effect on stock returns. The study also uncovers that, during the COVID-19 pandemic, the Technology and Industrials sectors' nexus with exchange rate volatility changed significantly. Understanding why this is the case presents a potentially fruitful area of study. Furthermore, the study also demonstrates the superiority of the QQR approach in modelling the nexus between currency volatility and sectoral stock returns by juxtaposing the method with OLS and quantile regression. The study demonstrates that the quantile-on-quantile regression (QQR) is better able to model the heterogeneous nature of the exchange rate volatility and stock returns nexus.

By taking the findings of this study into consideration, policymakers will have a better understanding of how their actions (those relating to currency volatility) may likely affect the stock market. Moreover, the value of the analysis in this study for investors and practitioners is summarised in three statements. First, the relationship between exchange rate volatility and stock returns changes depending on the state prevailing in either market. Second, knowing whether exchange rate volatility is above or below average is the crucial factor in discerning the likely effect on stock returns. Third, for every state prevailing in either market, some sectors are less (more) sensitive to exchange rate volatility than others. The third point refers to the observed idiosyncrasies of the stock sectors in their response to exchange rate volatility. The aforementioned sensitivity concerns both a decreasing and increasing effect on stock returns. These findings mean that, in addition to being cognisant of changes in the conditions prevailing in the stock market, investors should also have an awareness of changes in the exchange rate volatility.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID iD

Ismail Fasanya http://orcid.org/0000-0001-5816-4815

References

Arain, H., Han, L., Sharif, A., & Meo, M. S. (2019). Investigating the effect of inbound tourism on FDI: The importance of quantile estimations. *Tourism Economics*, *26*(4), 682–703. https://doi.org/10.1177/1354816619859695

Arslanalp, S., Eichengreen, B., & Simpson-Bell, C. (2022). The stealth erosion of dollar dominance and the rise of nontraditional reserve currencies. *Journal of International Economics*, *138*, 103656. https://doi.org/10.1016/j.jinteco.2022.103656

Blau, B. M. (2017). The volatility of exchange rates and the non-normality of stock returns. *Journal of Economics and Business*, *91*, 41–52. https://doi.org/10.1016/j.jeconbus.2017.03.002

Blau, B. M. (2018). Exchange rate volatility and the stability of stock prices. *International Review of Economics & Finance*, *58*, 299–311. https://doi.org/10.1016/j.iref.2018.04.002

Cleveland, W. S. (1979). Robust locally weighted regression and smoothing scatterplots. *Journal of the American Statistical Association*, *74*(368), 829–836. https://doi.org/10.1080/01621459.1979.10481038

Correia, C., Holman, G., & Jahreskog, A. (2012). The corporate use of derivatives: A survey of South Africa's large listed non-financial firms. *South African Journal of Accounting Research*, *26*(1), 67–94. https://doi.org/10.1080/10291954.2012.11435164

De Grauwe, P. (1988). Exchange rate variability and the slowdown in growth of international trade. *Staff Papers – International Monetary Fund*, *35*(1), 63–84. https://doi.org/10.2307/3867277

Du, D., & Hu, O. (2012). Foreign exchange volatility and stock returns. *Journal of International Financial Markets, Institutions and Money*, *22*(5), 1202–1216. https://doi.org/10.1016/j.intfin.2012.07.001

Ethier, W. (1973). International trade and the forward exchange market. *The American Economic Review*, *63*(3), 494–503. http://www.jstor.org/stable/1914383

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, *51*(1), 55–84. https://doi.org/10.1111/j.1540-6261.1996.tb05202.x

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, *81*(3), 607–636. https://doi.org/10.1086/260061

Fasanya, I. O., & Akinwale, O. A. (2022). Exchange rate shocks and sectoral stock returns in Nigeria: Do asymmetry and structural breaks matter? *Cogent Economics & Finance*, *10*(1), 2045719. https://doi.org/10.1080/23322039.2022.2045719

Ghani, M., Guo, Q., Ma, F., & Li, T. (2022). Forecasting Pakistan stock market volatility: Evidence from economic variables and the uncertainty index. *International Review of Economics & Finance*, *80*, 1180–1189. https://doi.org/10.1016/j.iref.2022.04.003

Gujarati, D. N., & Porter, D. C. (2017). Basic econometrics. New York: McGraw-Hill/Irwin.

Hashmi, S. M., Chang, B. H., Huang, L., & Uche, E. (2022). Revisiting the relationship between oil prices, exchange rate, and stock prices: An application of quantile ARDL model. *Resources Policy*, *75*, 102543. https://doi.org/10.1016/j.resourpol.2021.102543

International Monetary Fund. (2022). South Africa: Financial sector assessment program-technical note on systemic liquidity management. *IMF Staff Country Reports*, 2022(183), 1–35. https://doi.org/10.5089/9798400214523.002

Iyke, B. N., & Ho, S.-Y. (2021). Exchange rate exposure in the South African stock market before and during the COVID-19 pandemic. *Finance Research Letters*, *43*, 102000. https://doi.org/10.1016/j.frl.2021.102000

Jorion, P. (1990). The exchange-rate exposure of U.S. multinationals. *The Journal of Business*, *63*(3), 331–345. https://doi.org/10.1086/296510

Ma, L., & Koenker, R. (2006). Quantile regression methods for recursive structural equation models. *Journal of Econometrics*, *134*(2), 471–506. https://doi.org/10.1016/j.jeconom.2005.07.003

Mahapatra, S., & Bhaduri, S. N. (2019). Dynamics of the impact of currency fluctuations on stock markets in India: Assessing the pricing of exchange rate risks. *Borsa Istanbul Review*, *19*(1), 15–23. https://doi.org/10.1016/j.bir.2018.04.004

Malik, F. (2021). Volatility spillover between exchange rate and stock returns under volatility shifts. *The Quarterly Review of Economics and Finance*, *80*, 605–613. https://doi.org/10.1016/j.qref.2021.04.011

Mechri, N., Ben Hamad, S., de Peretti, C., & Charfi, S. (2018). The impact of the exchange rate volatilities on stock markets dynamics: Evidence from Tunisia and Turkey. Available at SSRN: https://ssrn.com/abstract=3304040 or https://doi.org/10.2139/ssrn.3304040

Mishra, S., Sharif, A., Khuntia, S., Meo, M. S., & Rehman Khan, S. A. (2019). Does oil prices impede Islamic stock indices? fresh insights from wavelet-based quantile-on-quantile approach. *Resources Policy*, *62*, 292–304. https://doi.org/10.1016/j.resourpol.2019.04.005

Salisu, A. A., & Vo, X. V. (2021). The behavior of exchange rate and stock returns in high and low interest rate environments. *International Review of Economics & Finance*, *74*, 138–149. https://doi.org/10.1016/j.iref.2021.02.008

Sikhosana, A., & Aye, G. C. (2018). Asymmetric volatility transmission between the real exchange rate and stock returns in South Africa. *Economic Analysis and Policy*, *60*, 1–8. https://doi.org/10.1016/j.eap.2018.08.002

Sim, N., & Zhou, H. (2015). Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking & Finance*, *55*, 1–8. https://doi.org/10.1016/j.jbankfin.2015.01.013

Stone, C. J. (1977). Consistent nonparametric regression. *Annals of Statistics*, *5*(4), 595–620. https://doi.org/10.1214/aos/1176343886

Troster, V., Shahbaz, M., & Uddin, G. S. (2018). Renewable energy, oil prices, and economic activity: A Granger-causality in quantiles analysis. *Energy Economics*, *70*, 440–452. https://doi.org/10.1016/j.eneco.2018.01.029

Tule, M., Dogo, M., & Uzonwanne, G. (2018). Volatility of stock market returns and the naira exchange rate. *Global Finance Journal*, *35*, 97–105. https://doi.org/10.1016/j.gfj.2017.08.001

Zeng, H., Ahmed, A. D., Lu, R., & Dai, N. (2022). Dependence and spillover among oil market, China's stock market and exchange rate: New evidence from the vine-copula-covar and Var-Bekk-Garch Frameworks. *Heliyon*, *8*(11), e11737. Advance online publication. https://doi.org/10.1016/j.heliyon.2022.e11737

Zhu, H., Yu, D., Hau, L., Wu, H., & Ye, F. (2022). Time-frequency effect of crude oil and exchange rates on stock markets in BRICS countries: Evidence from wavelet quantile regression analysis. *The North American Journal of Economics and Finance*, *61*, 101708. https://doi.org/10.1016/j.najef.2022.101708