FINANCIAL MARKET RETURNS VOLATILITY IN OIL-EXPORTING COUNTRIES

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ABSTRACT

The interconnectedness amongst three financial markets namely, foreign exchange, stock, and digital currency market returns are the main focus of this study in ten oil-exporting nations. The study sampling period spans 1995 to 2023. The empirical analysis was based on the cross sectional augmented ARDL and the quantile-by-quantile (QQR) estimation methods. We employed the Breusch-Pegan LM and Pesaran CD test to analyse the dataset to see if cross-sectional dependence existed. Dynamic interaction was found in returns on digital currency stock returns, and returns on currency exchange rates in both the short-run and long-run periods. The study also established that stock market reacts differently to changes in exchange rates while exchange rate reacts differently to the stock market. Such asymmetry also applies to the digital currency market. Stock returns are dynamically sensitive in a positive direction to the effects of rate changes; returns on digital currency negatively react to the dynamic effects of exchange rates and this can be explained in terms of price determination through this market's buyer-seller interactions; while returns on stock and bitcoin markets are also dynamically sensitive in a positive direction. The implication is that both the forex and digital markets have a bearing on asset prices and vice versa. The results of the study have implications for financial market transactions.

Keyword: Bitcoin, Returns, Stock Market, Digital Currency, bitcoin market, Oil-exporting countries

JEL classification: F32, G18, E20

1. Introduction

Financial market volatility, especially in the stock and currency markets, can have a big influence in a number of ways on nations that export oil. Their export revenue and the stability of the economy as a whole may be impacted by exchange rate swings brought on by increased volatility. Long-term production and revenue may be affected, and it may also have a bearing on investment choices and raise uncertainty in the world oil market. The lack of a decisive link between digital currency trading, stock, and the forex markets is not a desirable factor for foreign investors and multinational firms that are vulnerable to exchange rate risk. The current study, which fills a gap in the literature, uses cross-sectional non-autoregressive distributed lag and QQR to evaluate the interaction between the returns associated with the financial markets of oil exporting nations. The 10 oil-exporting nations included in the study are Brazil, Canada, Japan, Kuwait, Malaysia, Mauritius, Nigeria, Saudi Arabia, Tunisia, and the United Arab Emirates. The level of volatility in individual countries could be explained on the basis of a World Bank (2025a) report where it was established that in 2024, volatility in stock prices was 39.6% in Nigeria, 33.79% in Brazil, 16.13% in Malaysia, and 17.7% in Saudi Arabia; in Tunisia, it was 38.51% and 12.87% in Canada.. In 2024, stock market volatility in the UAE was reported to be 25.6%, but in Japan it was 11.26%. These explain the degree of volatility in individual countries. It is evident from the volatility statistics that low-income countries typically experience higher levels of financial market volatility than high-income ones. This has been ascribed to a number of variables, such as inadequate economic diversification, less-developed financial markets, and increased susceptibility to external shocks (Parsons & Rabhi, 2025; UNU-WIDER, 2023; Le, 2020).

The goal of this study is to produce real empirical findings that will aid multinational corporations, investors, and policymakers. The major objective is to establish the types of interactions between stock market returns and exchange rate returns and returns on bitcoin trading between emerging markets and industrialized markets. Consequently, we hypothesized in this paper that there are no interactions between stock markets, and bitcoin trading; stock market and forex trading; and bitcoin trading and forex trading. The research findings are of significance to financial market transactions. Specifically, the findings uphold that returns on bitcoin trading are susceptible to market manipulation, just like other assets. The study provides empirical evidence to clarify the interrelationships or interconnectedness amongst the three financial markets, namely, stock, bitcoin and foreign exchange markets. The paper has five sections. Section 2 discusses the literature. The methodologies executed in the study are discussed in section 3. The analysis of the results is presented in section 4 and section 5 concludes the paper.

2. Literature Review

Financial markets typically refer to any marketplace where the trading of securities takes place, including the trading of digital currencies such as bitcoin, stocks, bonds, foreign currencies and derivatives, among others. Studies have shown that changes in one market can quickly extend to the other (Umoru et al., 2025; Umoru et al. 2024; Andriansyah & Messinis, 2019). Such interaction is crucial, particularly from the standpoint of policy, as it suggests that market volatility in the stock market or exchange rate may have considerable effects on the economy. Earlier researchers largely focused attention on developed markets, while the literature on emerging markets was relatively thin, however these markets are becoming more significant for the global economy in terms of trade and capital flow (Sui & Sun, 2016). Additionally, the findings of the few studies that have been conducted on these markets have been contradictory (Afshan et al*.,* 2018). According to Lagoarde-Segot and Lucey (2008), developing economies experience greater economic uncertainty, lesser competition, ineffective information transmission, and lower liquidity than established ones. The aforementioned issues could lower efficiency in developing markets (Oztekin et al*.,* 2016).

According to Arrondel (2021) , participation in the stock market rises monotonically with the conditional expectation of a rising stock return. In contrast, the portfolio balance theory recently re-examined by Cavusoglu et al. (2019) places a strong emphasis on how asset market volatility and capital exchanges affect exchange rates. It elucidates how changes in exchange rates reflect the supply and demand for a range of various assets priced in several currencies. Accordingly, it upholds that cash, local and foreign bonds, and other assets are distributed across people's assets within a single framework for portfolio balance. The only loans deemed perfect substitutes are non-resident and government-sponsored loans. Risk-averse stakeholders no longer care if their portfolio consists of a mix of domestic and foreign businesses because of the risk.

The monetary theory according to Msomi and Ngalawa (2024) gave much credence to the idea that changes in currency values are a consequence of financial activities. When there is an excessive supply or demand for money, the payments balance is said to be out of balance. Consequently, if one considers the nominal money stock, rising domestic nominal interest rates will result in falling demand for actual money balances, and rising domestic price levels. Thus, as the current account exemplifies, the monetary approach provides a reasonable explanation for the disintegration of the connection between financial transaction flows and the exchange rate. Nonetheless, capital transactions are the source of the correction, since they generate fluctuations in the exchange rate. It is therefore contentious whether the public's desire to keep money in circulation and the firm's imbalanced inventories are the true drivers of exchange rate volatility, rather than the flow of receipts and payments from international business over a given period of time. On the side of the empirical review, studies that have been done on a cross-country and country-specific level are included in the literature that is currently available on the relationship between the different markets.

Copious empirical research has been conducted in both advanced and emerging countries regarding the volatility transmission amongst financial markets. The following researches have examined how volatility risk in the markets for gold, cryptocurrency, and equities are dynamically related. Apostolakis's (2024) findings indicate a one-way causal association, implying that spot bitcoin market had the greatest influence on the spread of volatility spillovers. According to Harb et al. (2024), ripple is the primary shock transmitter, but there are return-volatility spillovers among bitcoin, Ethereum, and Litecoin. The study revealed that the market for bitcoin is more closely linked to the US bond market than the US stock market.

Ahlem et al. (2024) showed that there were notable market transmissions, especially during the COVID-19 pandemic, with the gold and crypto currency markets acting as the net recipients of risk. Going by the research findings, U.S. and Chinese investors could expand their holdings by combining digital currencies, gold, and stocks. During the crisis, there was a notable surge in bitcoin investments, according to Ullah et al. (2024), which increased volatility spillovers among gold, bonds, stocks, and the dollar-to-ruble exchange rate. Terraza et al. (2024) discovered evidence of a significant dynamic connection between the stock, gold, and bitcoin markets, indicating that bitcoin provided potential for a healthy diversification option to lower stock market risk. In contrast to the post-crash period, when market volatility decreased to a degree where the risk was significantly averted, Dias et al. (2023) discovered that volatile risk transfer endangered portfolio diversity in the ASEAN-5 markets. In order to identify networks of volatility spillovers, Sabri et al. (2023) evaluated quantile-VAR and revealed that both lesser and higher joint distributions had greater market spillovers. Significant shock occurrences during crisis periods were also shown by the time-varying analysis.

Karamti and Belhassine (2022) found that, with the exception of gold and digital currencies, which can be used as diversifier assets when creating U.S. portfolio strategies, concern over US market swings risk extended to international markets for financial assets. The works of Yaya et al. (2024), Sajeev and Afjal (2022) and the empirical findings of Guo et al. (2021) are also relevant in the literature search. Digital currencies backed by gold were vulnerable to volatility that was transferred from gold markets, according to Jalan et al. (2021). According to Jeribi and Ghorbel's (2021) analysis, which was based on the GO-GARCH model specification, gold and Bitcoin can be used as hedges against the volatility risks associated with developed stock markets. Using the quantile VAR approach to estimate daily data, Alqaralleh's (2024) study underscores how the transmission of volatility influenced the interconnectedness of financial markets globally.

Using the DY spillover index, Nyopa and Khumalo (2022) demonstrated that while foreign exchange markets dominated their stock markets on an individual basis, equity market shocks dominated foreign exchange markets. With the exception of China, whose market is comparatively isolated from the other BRICS economies, interrelationships between the BRICS equities and foreign exchange markets were also formed. The findings show that while the South African currency was the most integrated among BRICS, Brazil is the country that contributes the most to volatility spillovers to other BRICS markets. According to Kim et al. (2021), the commodity futures trade was the top net receiver of volatility connection shocks, whereas the bond market was the market with the highest spillover transmission. During the financial crisis when markets showed some degree of nonlinear causality reliance, ripple effects transmission grew. According to Hung (2021), there is a large degree of volatility spillover among foreign exchange markets during times of crises, but at end of a crisis, the markets become more autonomous, resulting in low volatility dynamics. Kolaiti et al. (2020) discovered that there are persisting breaks in the transmission of volatility across various financial markets and trading zones. Overall, the review shows those researches on the dynamic connectivity of stocks, digital currencies, and gold; and studies that have assessed the interconnectedness of assets in terms of volatility risk during the crisis; all reported different results, implying lack of consensus.

3. Methodology

The stationary confirmation of the variables is required by the time series component of our panel data. New methods to enhance the superiority of the results have been reported in the notion of cross-sectional independence (CSD) across units. This is exactly where the limitation of the first-generation panel unit root test techniques, including the Im, Pesaran and Shin test (2003), the Fisher tests of Maddala and Wu (1999) and Choi (2001) lies. However, in addition to addressing the problem of CSD across units, the second-generation URT approaches developed by Bai and Ng (2004), Choi (2006), Pesaran (2003; 2007), and Smith et al. (2004) also tackled the problem of structural breaks in the panel unit root test. Accordingly, we begin with the factor structure approach of Pesaran (2007) as given by Equations (1) and (2).

$$g_{it} = (1-\phi_i)\zeta_i + \delta_i g_{it-1} + \upsilon_{it} \tag{1}$$

$$\upsilon_{it} = \xi_i h_t + e_{it} \tag{2}$$

where:

g = time series variable

ζ_i = deterministic component

υ_{it} = errors across time based on one-factor structure

e_{it} = idiosyncratic shocks

Combining Equations (1) and (2) for the convenience of absence of serial correlation, we have:

$$\Delta g_{it} = \gamma_i - (1-\phi_i) g_{it-1} + \xi_i h_t + e_{it} \tag{3}$$

Similarly, the Choi test evolves according to a two-way error component model given in Equations (4) and (5):

$$g_{it} = \zeta_0 + Z_{it-1} \tag{4}$$

$$Z_{it} = \eta_i + \gamma_i + e_{it} \tag{5}$$

$$where \quad e_{it} = \sum_{j=1}^{p_i} \omega_{ij} e_{it-j} + v_{it}$$

The underlying hypothesis for the Choi test is stated as follows:

$$H_0 : \sum_{j=1}^{p_i} \omega_{ij} = 1 \;\; \forall \;\; i = 1, \ldots, N$$
$$H_1 : \sum_{j=1}^{p_i} \omega_{ij} < 1 \;\; \forall \;\; for \;\; some \;\; i$$

Pesaran's (2007) cross-sectionally augmented (CSA) panel unit root was employed in this work to account for CSD. The following regression was estimated for CSD in the series using the CS-ADF panel unit root test as:

$$g_{it} = \phi_i + d_i g_{it-1} + a_i \overline{g}_{t-1} + f_i \Delta \overline{g}_t + e_{it} \tag{6}$$

$$where \;\; \overline{g}_t = \sum_{j=1}^{N} g_{it} / N, \; \Delta \overline{g}_t = \sum_{j=1}^{N} \Delta g_{jt} / N$$

Thus, the CSA test statistic of the Pesaran ADF regression served as the foundation for the unit root test. Based on the cross section averages of the individual series' first differences and lagged levels, the augmentation was performed. The following are the specifications for Pesaran's (2007) CS-ARDL model:

$$\begin{aligned}\Delta g_{it} = \gamma_i + \phi_i (g_{it-1} - \delta_i Z_{it-1} - \alpha_{1i} \overline{g}_{t-1} - \alpha_{2i} \overline{Z}_{t-1}) \\ + \sum_{j=1}^{p-1} \varphi_{ij} \Delta g_{it-j} + \sum_{j=0}^{q-1} \xi_{ij} \Delta Z_{it-j} + \ell_{1i} \Delta \overline{g}_t + \ell_{2i} \Delta \overline{Z}_t + \upsilon_{it}\end{aligned} \tag{7}$$

Estimating the CS-ARDL was justified by the fact that it takes into consideration CSD and diversity brought about by the variations in the macroeconomic structures and GDP growth rates of oil exporting nations. In addition, we used the panel co-integration test in accordance with the guidelines established by Persyn and Westerlund (2008) and Westerlund (2007). Equation (8) governs the course of the test procedure, which is a panel co-integration strategy based on error correction.

$$\Delta g_{it} = \lambda_i^! b_t + \phi_i (g_{i,t-1} - \gamma_i^! z_{i,t-1}) + \sum_{j=1}^{p_i} \phi_{ij} \Delta g_{i,t-j} + \sum_{j=-q_i}^{p_i} \eta_{ij} \Delta z_{i,t-j} + e_{it} \quad (8)$$
$$where \;\; t = 1,2,...,T \;\; \& \;\; i = 1,2,...,N$$

Given that errors occur separately for both *i* and *t*, Equation (8) becomes:

$$\Delta g_{it} = \lambda_i^! b_t + \phi_i g_{i,t-1} - \phi \gamma_i^! z_{i,t-1} + \sum_{j=1}^{p_i} \phi_{ij} \Delta g_{i,t-j} + \sum_{j=-q_i}^{p_i} \eta_{ij} \Delta z_{i,t-j} + e_{it} \quad (9)$$

The parameter ϕ_i controls how quickly the system returns to equilibrium following an unexpected shock. In what follows, this research conducted the Westerlund panel co-integration testing for the purpose of countering cross-sectional dependence and heterogeneity associated with individual units in our analysis. Accordingly, the corresponding null hypothesis of no co-integration and otherwise are stated as:

$$H_0 : \phi_i = 0 \;\forall\; i \quad (10)$$

$$H_1^{panel} : \phi_i < 0 \;\; for\ some\ i \quad (11)$$

$$H_1^{Panel} : \phi_i = \phi < 0 \;\; \forall\; i \quad (12)$$

Regressions using the panel test and group-mean produced the following estimated equations with least squares for each country:

$$\Delta g_{it} = \hat{\lambda}_i^! b_t + \hat{\phi}_i g_{i,t-1} + \hat{\gamma}_i^! z_{i,t-1}) + \sum_{j=1}^{p_i} \hat{\phi}_{ij} \Delta g_{i,t-j} + \sum_{j=-q_i}^{p_i} \hat{\eta}_{ij} \Delta z_{i,t-j} + e_{it} \quad (13)$$

$$\hat{g}_{it-1} = g_{i,t-1} - \hat{\lambda}_i^{!} b_t - \hat{\gamma}_i^{!} z_{i,t-1}) - \sum_{j=1}^{p_i} \hat{\phi}_{ij} \Delta g_{i,t-j} - \sum_{j=-q_i}^{p_i} \hat{\eta}_{ij} \Delta z_{i,t-j} \tag{14}$$

Accordingly, whereas the group mean regression yields the individual country error correction parameter, the panel test regression yields the common error parameter together as reported in Equations (15) and (16) respectively.

$$\phi^G = \frac{1}{N} \sum_{i=1}^{N} \frac{T\phi_i}{\hat{\phi}_i(1)} \tag{15}$$

$$\hat{\phi}^P = \left(\sum_{i=1}^{N} \sum_{t=2}^{T} \hat{g}_{i,t-1}^2 \right)^{-1} \sum_{i=1}^{N} \sum_{t=2}^{T} \frac{1}{\hat{\phi}_i(1)} \hat{y}_{i,t-1} \Delta \hat{g}_{it} \tag{16}$$

The Westerlund panel co-integration test method was found to be highly applicable considering that the panel's time-series size was significantly greater than its CS measurement (T > N).

Robustness Checks

We checked for the robustness of our estimations by conducting the Dumitrescu-Hurlin (D-H) panel causality test (Dumitrescue & Hurlin, 2012). The test equation is of the form:

$$Z_{it} = \lambda_i + \sum_{i=1}^{k} \phi_i^{(k)} Z_{i,t-k} + \sum_{i=1}^{k} \delta_i^{(k)} X_{i,t-k} + e_{i,t} \tag{17}$$

where $\phi_i^k, \delta_i^k, \delta_1^i, ..., \delta_i^k, \phi_1^i, ..., \phi_i^k$ are the slope coefficients.

We went beyond the robustness check of D-H panel causality tests which mainly ascertain the direction of causation between variables without establishing the cause-effect type of the dynamic interaction between the variables. Accordingly, the study, similar to that of Sabri et al. (2023), estimated the dynamic panel quantile regression (DPQR) model to further verify the robustness of the type of dynamic interaction effects between the returns of different financial markets. Also, DPQR discloses the heterogeneity that characterizes the interconnectedness of returns at separate quantiles. For the assets that are regularly affected by shocks and during times of significant market volatility, the DPQR approach is a suitable technique to study the interactions amongst returns that are most often influenced by economic perturbations and market volatility. The conditional quantiles of the outcome variable y hold as in Equation (15).

$$y_{it} = Z'_{it}\beta + h_t(X_{it}) + e_{it} \tag{15}$$

where:

y = outcome variable

$Z_{it} = [RETEXR_{it-1}, RSTOCK_{it-1}, RBTCOIN_{it-1})$

G = vector of regressors or independent variables that influences outcome indicator

β = parameter vector that characterizes the linear association between the response indicator and the predictors

$h_t(X_{it})$ = unknown link function that characterizes the nonlinear relationship between X and y

e_{it} = panel regression error term.

Fitting the index equation $h_t(X_{it})$ by the spline function resulted in a single indicator model as follows:

$$h_t(X_{it}) = \delta_{i1}\varpi_1(X_{it}) + \delta_{i2}\varpi_2(X_{it}) + \delta_{i3}\varpi_3(X_{it}) \tag{16}$$

The underlying conditional panel quantile function of equation (10) is thus specified as:

$$Q_\tau(y_{it} \left| Z_{it}, X_{it}\right.) = Z'_{it}\beta + h_t(X_{it}) \tag{17}$$

Accordingly, the parameter estimate of β can be obtained, by minimizing the following:

$$\sum_{i=1}^{n}\sum_{t=1}^{T}\eta_\tau(y_{it} - Q_\tau(y_{it} \left| Z_{it}, X_{it}\right.)) \tag{18}$$

An expanded form of equation (18) is given as:

$$\beta_t = min_{\beta \epsilon \aleph} k\ (\vartheta) \sum_{yt \geq xt\theta} |(y_t - Z'_t \beta)| + (1-\vartheta) \sum_{yt \geq xt\theta} |(y_t - X'_t \theta)| \quad (19)$$

$$Q\tau(RETEXR_{it}) = \propto_{\vartheta} + \theta_{1i\vartheta} RSTOCK_{it} + \theta_{2i\vartheta} RBTCOIN_{it} + e_{\vartheta i} \quad (20)$$

$$Q\tau(RSTOCK_{it}) = \propto_{\vartheta} + \theta_{1i\vartheta} RETEXR_{it} + \theta_{2i\vartheta} RBTCOIN_{it} + e_{\vartheta i} \quad (21)$$

$$Q\tau(RBTCOIN_{it}) = \propto_{\vartheta} + \theta_{1i\vartheta} RSTOCK_{it} + \theta_{2i\vartheta} RETEXR_{it} + e_{\vartheta i} \quad (22)$$

where:

RETEXR = exchange rate returns

RSTOCK = stock market returns

RBTCOIN = bitcoin returns

θ and $\propto$ are estimated parameters for different quantiles

e = error term

The study utilizes monthly data on stock returns, exchange rate returns, and bitcoin returns. The data was sourced from World Bank (2023) publications. Table 1 further elaborates on the economic sizes of the countries. Oil-exporting nations were chosen for the study because of their economic reliance on oil, the effect that changes in oil prices have on their financial markets, their unique institutional settings, and the applicability of their data to more wide-ranging research concerns. The sample period covered by the research is 1995-2023.

Table 1: Economic Sizes of Countries

Larger Economies (GDP over $1 Trillion)		**Smaller Economies (GDP under $1 Trillion)**	
Country	GDP	Country	GDP
Saudi Arabia	$1.108 trillion	Kuwait	$185 billion
Brazil	$1.920 trillion	Malaysia	$406 billion
Canada	$2.140 trillion	Nigeria	$477 billion
Japan	$4.231 trillion	UAE	$508 billion
Smaller Economies (GDP under $1 Trillion)			
Tunisia	$46.66 billion	Mauritius	$12.90 billion

Source: World Bank (2023). *GDP by country*. World Bank data compiled by Worldometer. Retrieved from https://www.worldometers.info/gdp/gdp-by-country/

4. Results

This section provides a layout of outputs from different tests and discussions about the findings. First is a presentation of data, followed by descriptive statistics, pre-diagnostic tests, hypotheses testing, post-diagnostic tests, and the relevance of results for policy and comparison with past works for validation. There was volatile concentration in the time series plots of the majority of the countries, although at varying degrees. As shown in Figure 1, Saudi Arabia appears to have the highest variations in returns across the study period. This may be attributed to the propensity of Saudi investors' to closely monitor sharp increases in stock prices. This is in line with the findings of Alshammari and Shingo (2022), who observed that the quick price increases of high MAX stocks draw significant investor interest and transactions in Saudi Arabia.

While realistic conditions show that many countries import and export at the same time, the study's selected oil-exporting countries that have considerably large quantities of crude oil reserves and export, regardless of whether they import simultaneously. The country-level statistics for the sampled oil-exporting countries in Table 2 show that exchange rate fluctuations were fairly uniform across these countries, from no fluctuation at all in the United Arab Emirates, Saudi Arabia, and Kuwait to a 0.2% average change in weekly currency rates during the period. Nigeria had the all-time highest change of 41.6%, despite its weak volatility in the charts. Apart from the UAE, other countries fell in some weeks, with the lowest drop of 8.7% in Nigeria. Panel data did not satisfy normality conditions (kurtosis > 3).

Table 3 shows that the average stock return for each country ranged from a negative -0.562% to a positive 0.441%. Japan had the highest change in returns recorded in any week throughout the years, while Kuwait had a week in which stock prices declined by 100%. The study's data distribution can be viewed as a time series for different countries, making them subject to high variation across periods. To avoid spurious results, a test for stationarity was conducted for each variable.

According to Table 4, the variables all exhibit cross sectional dependence with low level of multicollinearity as indicated by the correlation coefficient for all samples.

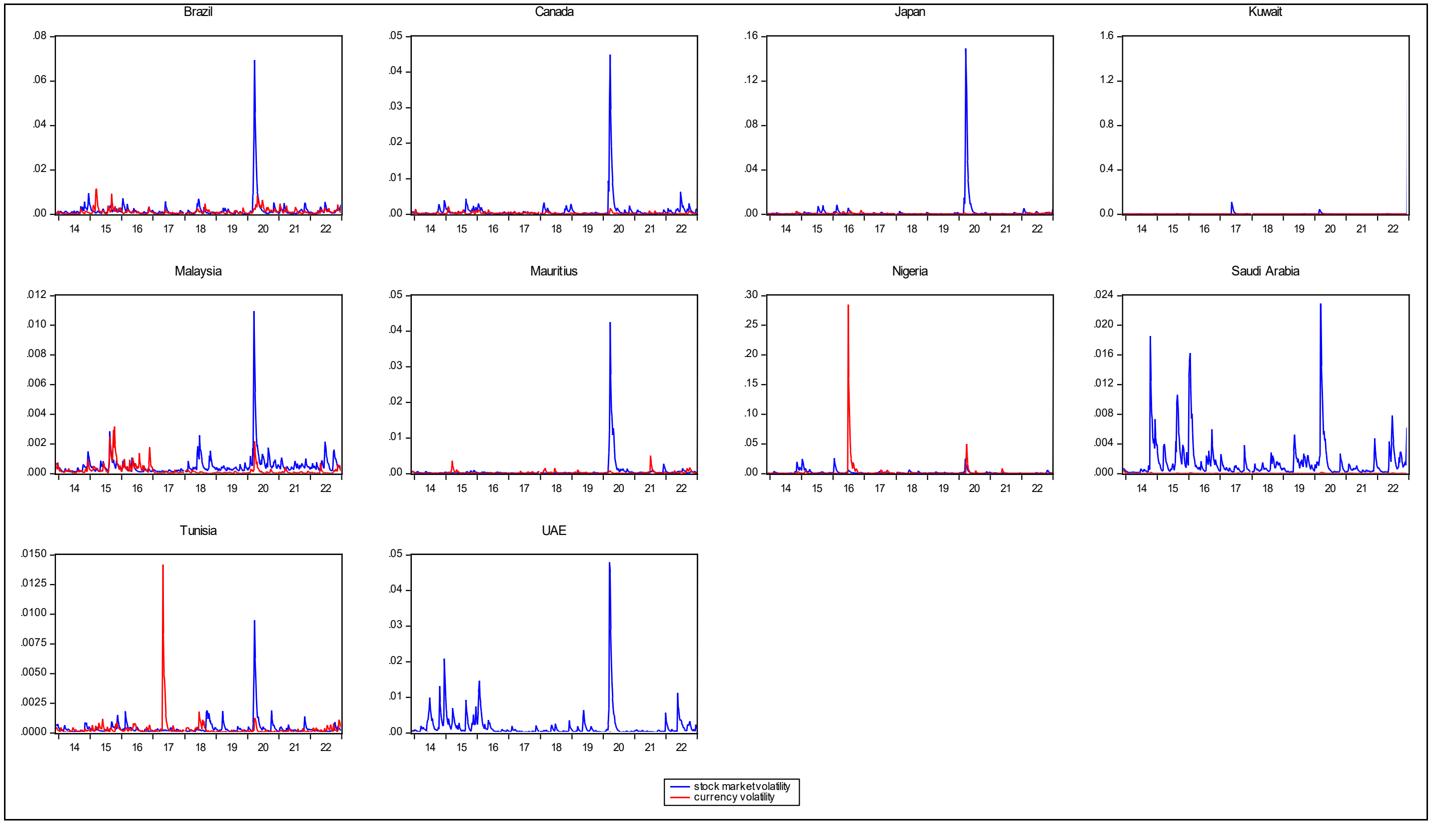

Figure 1: Dynamic interaction of stock market and exchange rate returns of sampled countries

Source: Authors' (2024) estimation results

Table 2: Exchange Rate Returns' Statistics

Country	Mean	Maximum	Minimum	Quantile	Standard Deviation	Kurtosis
Brazil	0.002	0.078	-0.071	1.139	0.022	6.752
Canada	0.001	0.040	-0.029	2.287	0.010	3.545
Japan	0.001	0.043	-0.053	1.104	0.012	5.898
Kuwait	0.006	0.010	-0.012	0.354	0.002	8.508
Malaysia	0.001	0.042	-0.062	2.154	0.009	9.798
Mauritius	0.001	0.053	-0.042	3.208	0.009	9.598
Nigeria	0.002	0.416	-0.087	1.245	0.024	79.362
Saudi Arabia	0.017	0.033	-0.052	2.389	0.091	20.581
Tunisia	0.001	0.091	-0.031	1.281	0.810	15.572
UAE	0.059	0.014	0.001	3.421	0.067	10.307

Source: Authors' (2024) estimation results.

Table 3: Stock Market Returns Statistics

Country	Mean	Maximum	Minimum	Quantile	S. Deviation	Kurtosis
Brazil	0.135	0.165	-0.189	0.023	0.032	7.507
Canada	0.024	0.095	-0.156	0.012	0.020	15.738
Japan	0.091	0.346	-0.283	0.010	0.030	59.749
Kuwait	-0.562	0.077	-1.000	0.012	0.052	282.762
Malaysia	0.042	0.056	-0.093	0.007	0.015	7.143
Mauritius	0.019	0.161	-0.247	0.006	0.016	51.030
Nigeria	0.441	0.169	-0.165	0.013	0.029	9.640
Saudi Arabia	0.021	0.077	-0.129	0.015	0.026	5.741
Tunisia	0.031	0.064	-0.073	0.007	0.012	9.309
UAE	0.011	0.105	-0.178	0.016	0.028	7.853

Source: Authors' (2024) estimation results

Table 4: Bitcoin Returns' Statistics

Country	Mean	Maximum	Minimum	Quantile	Standard Deviation	Kurtosis
RBTCOIN	1.0279	2.1983	0.1568	3.2892	0.00187	5.2893

Source: Authors' (2024) estimation results

Table 5: Results of Cross-Sectional Dependence (CD)

Samples	Breusch-Pegan LM Test			Pesaran CD			Correlation Coefficient		
	RETEXR	RSTOCK	RBTCOIN	RBTCOIN	RSTOCK	RETEXR	RETEXR	RBTCOIN	RBTCOIN
Full Panel	29.367***	23.4809***	19.273***	14.289***	17.289***	30.178***	0.014	0.211	0.189
Sub-panel 1	25.389***	38.467***	34.289***	40.198***	18.156***	20.310***	0.028	0.003	0.001
Sub-panel 2	33.218***	10.3487***	18.289***	22.1801***	60.138***	13.219***	0.015	0.014	0.193

Note: *** at 1% significance level

Source: Authors' (2024) estimation results

Table 6 presents stationarity test results based on the Pesaran test and Choi test statistics which revealed that all variables were, at most, found to be stationary at first differencing.

Table 6: Results of Second-Generation Panel Unit Root Tests

Samples	Variables	Pesaran test (level)	Pesaran test (1st difference)	Choi test (level)	Choi test (1st difference)
Full Panel	RETEXR	-3.1194**	-7.297***	-1.372	6.189***
	RSTOCK	-1.8434	-6.5309***	-2.180	10.022***
	RBTCOIN	-1.5371	-9.7387***	-1.329	14.187***
Sub-panel 1	RETEXR	-0.3487	-16.161***	-3.289	-5.034***
	RSTOCK	-1.156	-11.354***	-4.102	-7.419***
	RBTCOIN	-2.3014	-21.197***	-1.289	-9.389***
Sub-panel 2	RETEXR	-1.0289	-8.1194***	-1.006	-77.297***
	RSTOCK	-1.3520	-3.8434**	-1.309	-64.5309***
	RBTCOIN	-2.4879	-4.5371**	-1.093	-21.7387***

Note: *** (**) at 1% (5%) significance level
Source: Authors' (2024) estimation results

Aside the returns on bitcoin, dates of structural breaks were determined by the ZA test findings as seen in 2016, 2020, 2022 and 2023. These breaks correspond to a health crisis as manifested in COVID-19 (2020-present) and the Russia-Ukraine war (2022 – present). All significantly disrupted economic activities, increased uncertainties and influenced stock returns and the returns on the exchange rates of countries in our samples. Nevertheless, in line with the results of Abugu et al. (2024), low-income economies with fragile financial markets, that have been susceptible to international economic shifts, can benefit from circumnavigating the intricacies of integrating into regions.

Table 8 presents co-integration test results of the variables in our study based on the Westerlund test. In line with critical statistics, *** denotes significance of a co-integrating relation at the 0.01 level. The panel co-integration test signifies the presence of a significant relationship among panel variables.

Table 7: Results of Zivot & Andrew Structural Break Test

Full panel			Sub-panel 1			Sub-panel 2		
RETEXR	RSTOCK	RBTCOIN	RBTCOIN	RSTOCK	RETEXR	RETEXR	RBTCOIN	RSTOCK
-10.287**	-18.1045***	-2.3891	-1.1034	-9.2047***	-1.1093	-1.1357	-1.1021	- 7.8791***

Note: *** (**) at 1% (5%) significance level

Source: Authors' (2024) estimation results

Table 8: Westerlund Test Results

Samples	Variance Ratio	F-statistics	T-statistics	Remarks
Full panel sample	5.648***	123.059***	-3.256**	Co-integrated
Sub-panel sample 1	4.589**	10.387***	-15.255***	Co-integrated
Sub-panel sample 2	4.480***	11.129***	-15.289***	Co-integrated

Note: *** (**) at 1% (5%) significance level
Source: Authors' (2024) estimation results

Table 9: Cross-Sectional (CS) Augmented ARDL Results

Samples	**Short-run Elasticities**								
	RBTCOIN			RETEXR			RSTOCK		
	RETEXR	RSTOCK	C	RBTCOIN	RSTOCK	C	RETEXR	RBTCOIN	C
Full Panel	-0.3762***	0.1422**	0.0184**	-0.2369***	0.0261**	5.0127**	0.0733***	0.1437**	-0.0091***
Sub-panel 1	-0.1037***	1.0187***	3.1092***	-0.0173***	0.1873**	1.3892**	1.2093***	0.1092**	-0.0177***
Sub-panel 2	-0.1035**	0.4192***	1.2094**	-1.0226***	0.0931**	2.1039**	1.3790***	1.0433***	3.2791***
Brazil	0.0937***	0.1802**	0.0024***	0.0418***	-0.0038**	0.0002**	-0.0255**	0.1249***	0.0037***
Canada	-1.4016**	0.0136***	-0.186**	-0.0031**	-0.1136**	0.0124***	0.0254***	-0.1240**	0.0173**
Japan	-0.7839***	-0.2785***	-0.0104**	0.0162**	0.0048**	0.0218**	-0.0023**	0.0195**	0.0067***
Kuwait	-0.1022**	1.0489***	0.0142**	-0.0189**	1.0245**	-0.1871***	0.0321***	0.0732***	1.0375**
Malaysia	-0.0293**	0.2311***	0.5130***	-0.0216**	1.0217***	-0.1937**	-0.0079**	0.1173***	1.0184***
Mauritius	-0.0611**	0.0187**	0.1092***	0.0278**	1.0873***	-0.3621***	-0.0197**	0.1273***	0.1174***
Nigeria	-0.0269***	1.0245***	0.3879***	-1.0369**	0.3871**	-1.2487***	-0.0481**	0.1893***	0.1879***
Saudi Arabia	0.0485**	0.3872***	0.1724**	0.2873***	0.1573***	-1.0395***	0.1345***	1.0211**	0.2356***
Tunisia	0.0297***	0.1908**	1.0231***	0.5091***	0.1809**	-0.1134**	0.1456***	0.1734***	0.7892***
UAE	0.4890**	0.5971**	0.1671**	0.0489***	1.8791***	0.1872***	0.0172***	0.1673***	0.0381***
ecm	-0.850***	-0.5602***	-0.5891***	0.6734**	-0.3674**	0.5876***	-0.1794***	-0.465***	-0.583**

Samples	Long-run Elasticities								
	RBTCOIN			RETEXR			RSTOCK		
	RETEXR	RSTOCK	C	RBTCOIN	RSTOCK	C	RETEXR	RBTCOIN	C
Full Panel	-1.124***	0.1374***	0.1514**	-0.2134**	-0.0192**	0.426***	0.3587**	-1.0435**	-0.1392**
Sub-panel 1	-0.2566***	0.0561***	1.0524**	-0.0169***	-0.1352**	0.3791**	1.0179***	-0.1283**	0.1127**
Sub-panel 2	-0.1036**	0.0143***	0.1823**	-0.0345***	-0.0465***	0.1372**	1.0289***	-0.0287***	1.2489***
Brazil	0.0521***	0.0146**	0.1725**	0.6921***	-0.1931**	0.197***	0.1892***	1.2093***	0.1863***
Canada	-0.2874**	0.1763***	-0.281**	-0.8794**	-0.1209***	1.3089***	0.1379***	-0.0871**	1.2893**
Japan	-0.1873**	-0.328**	-0.279**	0.0275***	0.1387**	1.0328***	0.3891**	0.1761***	0.1893**
Kuwait	-1.3890***	1.2093***	0.1809**	-0.0283**	0.2803**	-0.0183**	1.2335**	0.0873**	0.0941***
Malaysia	-0.1878**	0.3871**	0.1905***	-0.0961**	0.5672***	-0.1028***	1.2048***	0.5672***	0.02973***
Mauritius	-0.4390**	0.0132**	1.2340**	0.0872***	0.1924**	-0.0163***	1.0638**	0.9721**	0.4322***
Nigeria	-0.1937***	0.3401**	-1.0287**	-0.389**	1.3809**	-1.099**	0.1925**	1.0195**	1.0229**
Saudi Arabia	0.37512**	1.2083***	0.1739**	0.5463***	0.1092***	-0.8711***	1.0287***	0.0792***	0.0937***
Tunisia	1.2309***	1.0935***	1.3287***	0.2791**	1.0387**	-0.9742**	0.1456	0.1734	0.1032***
UAE	1.1873***	0.6941***	1.0289**	0.1187**	0.0371**	-1.2256**	0.0172	0.1673	0.1983***
Breusch Godfrey	0.256 (0.572)***	0.667 (0.334)***	0.678 (0.255)**	0.349 (0.387)***	0.893 (0.526)**	0.487 (0.299)**	0.561 (0.246)**	0.354 (0.862)**	0.3912*** (0.789)**
Breusch-Pegan Godfrey	0.682 (0.661)***	0.562 (0.894)***	0.654 (0.289)**	0.672 (0.871)***	0.524 (0.356)**	0.298 (0.669)**	0.897 (0.684)**	0.389 (0.445)**	0.226 (0.335)**
Residual Normality	0.293 (0.653)**	0.654 (0.289)***	0.268 (0.285)**	0.956 (0.489) ***	0.457 (0.298) ***	0.365 (0.682) ***	0.789 (0.267) ***	0.756 (0.568) ***	0.532 (0.223) ***

Note: *** (**) at 1% (5%) significance level

Source: Authors' (2024) estimation results

According to the Dumitrescu-Hurlin test results reported in Table 10, the alternative hypothesis which supports that the panel data has no fewer than one Granger causal link is appropriate. By implication, the existence of homogenous Granger causality between every unit of cross-section is validated for all series of returns of the 3 financial markets.

Table 10: Results of Panel Causality Tests

Hypothesis	Z-statistic	W-statistic	p-value	Results
Full Panel sample				
RETEXR $\rightarrow$ RSTOCK	6.932***	2.922**	0.000	RETEXR causes RSTOCK
RBTCOIN $\rightarrow$ RSTOCK	8.209***	2.987***	0.000	RBTCOIN causes RSTOCK
RETEXR $\rightarrow$ RRBTCOIN	10.139***	1.992**	0.000	RETEXR causes RRBTCOIN
RSTOCK $\rightarrow$ RRBTCOIN	9.139***	2.6293**	0.000	RSTOCK causes RRBTCOIN
RSTOCK $\rightarrow$ RETEXR	5.129**	1.789**	0.000	RSTOCK causes RETEXR
RBTCOIN $\rightarrow$ RETEXR	9.216***	2.334**	0.000	RBTCOIN causes RETEXR
Sub-panel sample 1	Brazil, Canada, Japan, and Saudi Arabia			
RETEXR $\rightarrow$ RSTOCK	4.566***	2.561**	0.000	RETEXR causes RSTOCK
RBTCOIN $\rightarrow$ RSTOCK	5.311***	2.398**	0.000	RBTCOIN causes RSTOCK
RETEXR $\rightarrow$ RRBTCOIN	5.321***	1.890**	0.000	RETEXR causes RRBTCOIN
RSTOCK $\rightarrow$ RRBTCOIN	12.350***	2.487**	0.000	RSTOCK causes RRBTCOIN
RSTOCK $\rightarrow$ RETEXR	9.108***	2.297**	0.000	RSTOCK causes RETEXR
RBTCOIN $\rightarrow$ RETEXR	6.384***	1.885**	0.000	RBTCOIN causes RETEXR
Sub-panel sample 2	Kuwait, Malaysia, Mauritius, Nigeria, Tunisia, and UAE			
RETEXR $\rightarrow$ RSTOCK	7.556***	2.264**	0.000	RETEXR causes RSTOCK
RBTCOIN $\rightarrow$ RSTOCK	4.256***	1.762**	0.000	RBTCOIN causes RSTOCK
RETEXR $\rightarrow$ RRBTCOIN	5.225***	1.937**	0.000	RETEXR causes RRBTCOIN
RSTOCK $\rightarrow$ RRBTCOIN	4.228***	2.409**	0.000	RSTOCK causes RRBTCOIN
RSTOCK $\rightarrow$ RETEXR	6.559***	2.129**	0.000	RSTOCK causes RETEXR
RBTCOIN $\rightarrow$ RETEXR	3.986**	1.579**	0.000	RBTCOIN causes RETEXR

Note: *** (**) at 1% (5%) significance level
Source: Authors' (2024) estimation results

5. Discussion

According to Table 8, the CS-augmented ARDL findings for the 3 samples, namely full panel, sub-panel 1 and sub-panel 2 suggest that currency returns negatively impacted returns on digital currency while stock returns had positive prominent effects on bitcoin returns. Whilst the dynamic interaction between currency exchange rate and market returns was significantly positive over the short-term horizon, the influence of returns on exchange rates on stock returns turned negative over the long-term horizon at the 5% level of significance. Stock markets in oil-exporting countries positively impacted the digital currency market. Currency returns in a like-contradictory manner as stock market returns positively influenced returns on digital currency with an effect size given by 0.1374. Only one autoregressive term was significant in the model predicting digital currency returns in oil-exporting countries, revealing that the immediate past weekly returns from digital currency trading significantly influenced its current value.

In the stock returns CS-ARDL regressions, the estimates of exchange rate returns and returns of digital currency predicted stock price variations significantly for the 3 samples. Returns on digital currency were significant in all samples. The exchange rate also had an impact on stock market reduction in the second regime, from 0.0733 to 0.00325, and both were equally significant. Hence, a 1% rise in exchange rate returns and bitcoin returns would cause stock market returns to rise by 0.07% and dwindle by up to 0.34%, respectively. As economic conditions change in the positive direction, , the effects reduce to a rise of 0.003% and dwindle by 0.32%, respectively. Uncertainties or shifts in macroeconomic dynamics contribute to volatility in currency markets as investors adjust their positions based on perceived risks. Political events and geopolitical factors, conflicts, or international trade disputes can significantly impact currency values without influence from stock market dynamics. Still, oil-producing countries have a higher possibility of opening their borders to foreign portfolio investment within the oil and gas industry, given the proximity to crude oil as a raw material for refineries or in pursuance of an operating mining lease which in turn increases capital flows and impacts the supply and demand for local currencies.

The QQR results for digital currency returns as reported in Table 11 show that a 1% increase in exchange returns would cause a reduction in bitcoin returns by 0.18% at the 25th percentile. Stock market returns were found to significantly influence returns on digital currency in the first, second, and third quintiles, after which no significance was recorded. A 1% change in currency rate returns is associated with -0.246%, -0.257%, and -0.639% changes in the 50th, 75th, and 90th percentile values of digital currency returns. The corresponding coefficients of stock returns have respective coefficients of 0.1877, 0.0515, and 0.1673. These coefficients predicting the 50th, through to the 90th percentile of digital currency returns are significant, indicating that a 1% increase in stock returns would cause a corresponding 0.1807%, 0.052% and 0.167% rise in bitcoin returns. The conditional median equation and other conditional equations for the 50th, 75th, and 90th percentiles had coefficients of both returns on exchange rates and stock market prices that were insignificant, with all having corresponding p values greater than 5%.

Table 11: Panel Quantile Regressions for RBTCOIN

Variable	*OLS*	$\tau = 10\%$	$\tau = 25\%$	$\tau = 50\%$	$\tau = 75\%$	$\tau = 90\%$
RETEXR	-0.3497***	-0.4828	-0.1807***	-0.2463***	-0.2573***	-0.6391***
p-value	0.0000	0.1420	0.0000	0.0000	0.0000	0.0000
RSTOCK	0.0067**	0.3274***	0.2907**	0.1877**	0.0515	0.1673
p-value	0.0100	0.0000	0.0200	0.0124	0.1300	0.3000
C	-0.0572***	-0.1166***	-0.0612***	-0.0290***	-0.1540***	-0.0285***
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
DW	2.109	2.0183	2.0146	2.0309	2.0584	2.0032
F-statistics	188.389	189.389	182.340	178.392	198.267	181597

Note: *** (**) at 1% (5%) significance level.

Source: Authors' (2024) estimation results.

Relating stock returns that had a significant effect on returns of digital currency, the effect of stock returns was strongest in the 10th percentile of digital currency returns. This is juxtaposed with panel estimates (mean) that showed that stock market returns influence digital currency returns absolutely. The findings for the complete panel markets sample suggest that exchange rate returns have negative effects on stock returns, across the various quantiles while stock returns tend to affect positively the returns on digital currency.

Stock returns and returns on digital currency had the largest magnitude on the 10th percentile of exchange rate returns. Even after controlling for various percentiles of the dependent variable, the dynamic interactive effect between returns remains robust. In all the panel quantile estimations, Durbin Watson's statistics confirm the absence of autocorrelation in the models, as each statistic is in the region of 2. The F-statistics are significant for all the models, confirming the efficiency and hence reliability of the estimated coefficients.

For QQR estimates of Table 12, bitcoin returns did have a significant influence on exchange returns throughout the quantile of the distribution. Values at the 50th to 90th percentile also showed that returns on digital currency had an indirect effect on the corresponding quantile of exchange rate returns. Stock returns also had negative and significant effects on exchange returns as seen in -0.0986, -0.0141, -0.0141, -0.0434, and -0.0796 declines in exchange rate returns for the 10th, 25th, 50th, 75th, and 90th percentiles.

Table 12: Quantile Regressions for RETEXR

Variable	OLS	$\tau = 10\%$	$\tau = 25\%$	$\tau = 50\%$	$\tau = 75\%$	$\tau = 90\%$
RBTCOIN	-0.3497***	-0.1945***	-0.019***	-0.0112***	-0.0238***	-0.251***
p-value	0.0000	0.0000	0.0000	0.5433	0.0000	0.0000
RSTOCK	0.0067**	-0.0986***	-0.0141***	-0.0141	-0.0434***	-0.0796***
p-value	0.0100	0.0000	0.0000	0.3870	0.0000	0.0000
C	-0.0316***	-0.082***	-0.0197***	0.1426***	0.1689***	0.0253***
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
DW	2.2931	2.0145	2.1089	2.1032	2.0134	2.0153
F-statistics	190.362	291.328	189.136	187.367	190.287	189.272

Note: *** (**) at 1% (5%) significance level

Source: Authors' (2024) estimation results

The first three coefficients of stock returns show ascending effects of stock returns on exchange rate returns before non-significance in the 40th and median equations. The results depict that a percentage rise in returns on the returns on digital currency will cause the respective percentile values of currency fluctuations in oil-exporting countries to dwindle. This confirms the dependence on oil revenue for economic stability in oil-exporting countries.

Post-diagnostic tests for symmetry of the regression estimates using the Wald test confirm evidence of asymmetry across quantiles.

In Table 13, equations predicting stock returns had exchange rate returns as a significant variable. From the 25th percentile to the 90th percentile, each of the coefficients of exchange rate returns (-0.4515, -0.2497, -0.4109, and -0.3149) were substantially different from zero. These confirm the change that will occur in the stock market returns of oil-exporting countries for a percentage change in currency returns. The coefficients of digital currency returns explaining variations in stock returns were significant for the 25th percentile value of stock returns up to the 75th percentile value of stock returns.

Table 13: Quantile Regressions for RSTOCK

Variable	*OLS*	$\tau = 10\%$	$\tau = 25\%$	$\tau = 50\%$	$\tau = 75\%$	$\tau = 90\%$
RETEXR	-0.3497**	-0.6005**	-0.4515***	-0.2497**	-0.4109**	-0.3149***
p-value	0.0050	0.0050	0.0000	0.0034	0.0163	0.0001
RBTCOIN	0.0067**	0.0222***	0.0104***	0.0067***	0.0015***	0.0081
p-value	0.0100	0.0000	0.0000	0.0001	0.0001	0.1900
C	-0.1098***	-0.1166***	-0.0112***	-0.1807***	0.0127***	0.1453***
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
DW	2.1038	2.1573	2.1098	2.0319	2.1893	2.3591
F-statistics	173.382	189.367	199.367	168.173	176.267	198.273

Note: *** (**) at 1% (5%) significance level
Source: Authors' 2024 estimation results

Making juxtapositions of the empirical results of the different methods, volatility persistence was found in bitcoin returns (persistence= 0.847 <1) which is the summation of the ARCH and GARCH terms (not reported). The results of QQR for the explanation of bitcoin returns' shifts show that a percentage increase in exchange rate returns would cause a reduction in bitcoin returns by 0.18% at the 25th quantile. Stock market returns were found to significantly influence bitcoin returns in the first, second, and third quintiles, after which no significance is recorded. The outcomes support the finding of Adegboyo and Sarwar (2025) who reported negative shocks with greater influence on stock prices than positive ones.

The interpretations of CS-ARDL regressions have the following policy implications: The decentralized nature of digital currency and its potential as a store of value or hedge against traditional financial systems can contribute to price fluctuations independent of currency movements. Digital currency value can be influenced by its level of adoption and awareness. Positive news, such as increased acceptance by merchants or financial institutions, regulatory developments that support digital currencies can drive digital currency prices upward. Conversely, negative news or events, such as supervisory restrictions or security breaches, can cause downward price movements. Digital currency like other investments is also susceptible to market manipulation. Activities such as coordinated trading efforts can artificially influence the price of digital currency. These manipulations can occur independently of currency variations and can cause significant short-term price swings. The negative effect of exchange rate returns on the returns on digital currency can be explained in terms of price determination by the interaction of buyers and sellers in this market. In the short term, digital currency prices would fluctuate with local currencies given that investors value digital currency first with the equivalent US dollar value and with local currencies of the country the investors or dealers are domiciled. Lower returns recorded in currency markets from exchange rate depreciation could cause digital currency demand to increase as investors try to store their wealth in more sustainable investments. If there is a shift in market sentiment, changes in demand or supply dynamics specific to digital currency, together with the interaction of other variables can lead to price fluctuations of the crypto instrument that are independent of currency movements.

Stock returns were also found to be influenced significantly by returns arising from currency volatility. In other words, exchange rate fluctuations can influence the competitiveness of a country's exports and imports. Devaluation or depreciation in the domestic currency can make exports more attractive and competitive, potentially benefiting companies that rely heavily on foreign sales. As a result, the stock prices of exporting firms may increase during a period of currency depreciation. Conversely, a currency appreciation can make imports relatively cheaper, impacting companies that rely on imported goods or raw materials and creating a change in company stock value. Exchange rate fluctuations can influence investor sentiment and risk perception. Sharp or unexpected currency movements can create uncertainty and volatility in financial markets. This increased uncertainty may lead to risk aversion among investors, resulting in stock market sell-offs or increased volatility. Exchange rate fluctuations can also serve as an indicator of economic instability, which can affect investor confidence and sentiment in the stock market. Correlation between stock markets and currency fluctuation in oil-exporting countries suggests that the currencies of these countries are largely affected by global economic trends and external shocks from imports and fixed oil prices by the OPEC cartel, and not necessarily the investments in their stock markets.

6. Conclusion

This study evaluates the interactions between returns on the stock market, digital currency trading, and exchange rates in ten oil-exporting nations (Brazil, Canada, Japan, Kuwait, Malaysia, Mauritius, Nigeria, Saudi Arabia, Tunisia, and UAE). The methodology of the study is the CS-augmented ARDL. Regarding the research findings, below are points to note: Returns on digital currency react negatively to the dynamic effects of exchange rates over a range of time horizons, while stock and digital currency market returns are also spontaneously sensitive in an upward trajectory only during short-term periods, while the dynamic effects of exchange rate changes on stock markets are negative over the long-term horizon. Essentially, it implies that asset prices are influenced by both the digital financial market and the currency exchange market, and vice versa. The volatility in stock markets of oil-exporting countries can be explained by oil-price fluctuations. Countries that import or export oil often has companies operating in the energy sector, which can be sensitive to oil price movements. The stock prices of energy companies, including oil exploration and production companies can be directly influenced by changes in oil prices. If oil prices are volatile, it can result in significant fluctuations in the stock prices of energy companies, impacting the overall stock market volatility. Oil price fluctuations can impact investor sentiment, as investors in oil-importing countries may interpret higher oil prices as a potential risk to the overall economy and corporate profitability. This can lead to heightened uncertainty and increased selling pressure in the stock market, contributing to volatility. In contrast, investors in oil-exporting firms could interpret higher oil prices as a boost in investment income and economic prosperity, increasing the purchase of securities, which reflects on stock prices and overall volatility. Quantile results confirm that returns on exchange rates, digital currency trading, and stock market assets are dynamically interactive as varied parts of the broad financial market. The significance of the research findings is that trading price of digital currency can is influenced by the volatility patterns of other market trading activities. These dynamic interconnectivities, which can happen independently of changes in currencies, have the potential to lead to huge short-term price movements. The study also found that there is an uneven relationship between the three markets, the FX, stock, and crypto currency markets. As a result, the stock market responds differently to fluctuations in exchange rates, and the exchange rate responds differently to various stock markets. The same is true for trading digital currency in underdeveloped nations. Additionally, the study demonstrated empirically that the interaction between buyers and sellers in this market can account for the negative impact of exchange rate returns on digital currency returns in terms of price determination. Given that investors initially value bitcoin using the comparable US dollar value and local currencies of the countries in which they invest, short-term fluctuations in bitcoin values would occur. The limitations of the study include the fact that the study focuses solely on oil-producing countries, failing to account for distinctions between emerging markets and advanced economies, which may have different macroeconomic situations and market systems. Hence, additional research is needed to confirm the findings and explore the interconnectivity in greater depth. The paper recommends the need to base effective regulations by monetary authorities in different countries on market mechanisms, exchange rate controls, and stock market investors who frequently study the behaviour of market variables.

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