FOREIGN EXCHANGE, STOCK AND BITCOIN MARKETS: A STRATEGIC RE-VISITATION OF THE INTERRELATIONSHIP AND VOLATILITY DYNAMICS OF FINANCIAL MARKETS

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How to cite this paper: Umoru, D., Ugbaka, M. A., Atseye, A. F., Takon, S. M., Effiong, C. E., Eyo, I. E., Igbinovia, B., Asemota, G., Adie, H. I., Ojikpong, C. E., Lebo, M. P., Bassey, A. E., Akomaye, S., Inyang, L. O., Aboh, F. I., Odegha, B., Oseni, H. O., & Enaberue, E. (2025). Foreign exchange, stock and bitcoin markets: A strategic re-visitation of the interrelationship and volatility dynamics of financial markets. *Corporate & Business Strategy Review, 6*(2), 156–172. https://doi.org/10.22495/cbsrv6i2art16

ISSN Online: 2708-4965
ISSN Print: 2708-9924

Received: 24.04.2024
Revised: 04.08.2024; 24.04.2025
Accepted: 07.05.2025

JEL Classification: D28, E49, F30
DOI: 10.22495/cbsrv6i2art16

Abstract

The financial market is a decentralized market made up of global network of businesses, forex, stock investment, and digital markets. The paper evaluated the patterns and interrelationships of volatilities in return amongst foreign exchange, stock, and bitcoin markets returns in oil importing nations. The Markov-Switching and quantile regression estimation methods were executed. Results indicate stock markets of Kenya and Uganda had the most frequent depreciating returns. Bitcoin returns were negatively and significantly influenced by changes in currency values, whereas change in bitcoin trading value causes a higher change in exchange rate returns. A percentage increase in stock market returns stimulates exchange rate returns to rise also but at a higher rate. Returns on exchange rates and Bitcoin markets are significant predictors of stock market returns. Exchange rate volatility dynamics occur in the opposite direction as those in stock markets and in the floor of Bitcoin market. Volatility was significantly observed when currency devalued confirming the erratic behaviors of investors to dwindling local currency values compared to the U.S. dollar. Financial markets authorities can use the research findings to support their choice to regulate the financial markets and shield investors from information asymmetry that could result from cross-market volatility interrelationships.

Keywords: Returns on Bitcoin, Exchange Rate Returns, Stock Returns, Quintile Regression, Markov-Switching Regression

Authors' individual contribution: Conceptualization — D.U., H.O.O., and E.E.; Methodology — D.U., B.I., H.I.A., F.I.A., and H.O.O.; Software — D.U., B.I., F.I.A., H.O.O., and E.E.; Validation — A.E.B., S.A., L.O.I., and H.O.O.; Formal Analysis — D.U., M.A.U., I.E.E., H.I.A., C.E.O., M.P.L., and B.O.; Investigation — D.U., M.A.U., G.A., B.I., and E.E.; Data Curation — D.U., G.A., B.I., M.P.L., B.O., and H.O.O.; Writing — D.U., A.F.A., G.A., S.M.T., C.E.E., and B.O.; Supervision — D.U.

Declaration of conflicting interests: The Authors declare that there is no conflict of interest.

1. INTRODUCTION

The foreign exchange market, which is occasionally identified as the Forex market, is the market that permits participants to buy, sell, hedge, and speculate on the rates at which different currency pairings will be exchanged (Akhtar, 2021). The financial market is a decentralized market that is made up of a global network of businesses, commercial banks, central banks, investment companies, as well as brokers from different countries. According to Andriansyah and Messinis (2019), the link between the different financial markets has significant ramifications for the creation of portfolios, hedging tactics, and investment plans. The Forex market has been a factor in the consideration of stocks and Bitcoin trading. Recently, cryptocurrencies like Bitcoin and Ethereal, which are digital assets based on blockchain technology, were launched into the financial market. These cryptocurrencies have grown considerably on a global scale in the past few years. For traders to exchange one cryptocurrency for another or fiat money like pounds, US dollars, or euros, these exchanges maintain digital wallets. Unfortunately, the centralized financial exchange system of cryptocurrencies has left many buyers and sellers vulnerable to exchange rate risk and fraud, and this could have implications for financial markets.

Changes in the currency rate have an impact on decisions made by traders and the government. The exchange rate is a significant economic variable for every nation in the world following their participation in international trade. Hence, the choice of ten oil-importing nations (Botswana, Hong Kong, Kenya, Morocco, Rwanda, Sweden, Switzerland, Tanzania, Turkey, and Uganda) for 10 years (2013–2022) to assess the risk and return ratios from the stock, foreign exchange, and Bitcoin markets. Our objective in this paper is to ascertain the interaction between foreign exchange returns, stock market returns, and returns on Bitcoin trading in the aforementioned nations. The hypotheses tested in this research are as follows:

H0: There are no considerable interactions between returns in the stock market, the Bitcoin market, and exchange rates (Forex market).

The research gap is exposed by the fact that there are numerous studies on the interrelationship between the foreign exchange market and the stock market (Hussain et al., 2024; El-Diftar, 2023; Yuan et al., 2022; Rai & Garg, 2021; Moussa & Delhoumi, 2021; Aftab et al., 2021; Lakshmanasamy, 2021; Sheikh et al., 2020; Adeniyi & Kumeka, 2020; Mohamed & Elmahgop, 2020; Khan, 2019; Qing & Kusairi, 2019; Trabelsi, 2019; Kumar et al., 2019; Akbar et al., 2019; Mahapatra & Bhaduri, 2019). Regrettably, the scope of these studies is limited, as they make no provision for the digital currency market. Specifically, those researchers failed to empirically account for and determine the volatility patterns and associated interconnectivity across the three currency markets. Therefore, the study contributes to the literature on the relevance of not restricting the investment decision-making process of businesses to only institutional and macroeconomic fundamentals that govern the financial market system but rather the need to consider digitization of the financial market.

The study is significant because it shows that Bitcoin transactions and the returns therein favorably interconnect with stock market returns and returns on currencies. Portfolio managers and investors could utilize the research to find the most susceptible market returns to shocks and the biggest source of spillovers, as well as patterns of return dynamics. Similarly, the findings enable investors make profitable choice to spread the assets in their portfolio in oil importing nations whose currency return is volatile in value based on patterns of volatility dynamics and interactions among the three markets. This research finding equips market participants and traders with informed decisions on how to diversify their portfolios accordingly between the three markets. It also strengthens and maximizes investment behavior by putting investors in a position to know when to place their investments in alternative assets. These results are important to currency traders, hedgers, and official Forex investors aiming to direct their investments to the digital currency market. The results are also valuable to policymakers, those concerned with currency market modeling, and business and financial managers tasked with derivative pricing, asset allocation, valuation, and investment risk management. The managerial significance of the study is that the ensuing research findings are scientifically germane and suitable enough to propel the central monetary authority and policymakers to formally launch an official virtual currency that is accessible and acceptable in the threefold financial market. The positive return effect of Bitcoin constitutes a significant attraction to foreign portfolio investors because digital money is distinguishably an alternative asset that such investors can hold and transact without any cross-border limitations. This follows from the premise that cryptocurrencies are decentralized and operate independently of governments and traditional financial institutions, providing investors with more control over their investments.

The structure of this paper is as follows. Section 2 reviews the relevant literature. Section 3 provides the estimation methodologies and data description. Section 4 presents the research results. Section 5 discusses the main findings. Section 6 summarizes and concludes the study.

2. LITERATURE REVIEW

Several theories exist in the literature to explain how the exchange rate market and stocks interact. For the sake of brevity, we have chosen in this paper to center our review on the Dornbusch and Fischer (1980) theory, portfolio balance theory (PBT), and the stock-orientated postulate. According to Dornbusch and Fischer's theory, exchange rate volatility has an impact on international trade, which in turn affects firms' real revenue and production. The impact of exchange rate fluctuations is reflected in the stock price, given that a company's stock price is mostly determined by the discounted present value of its anticipated future cash flows. Consequently, the flow-orientated model postulates a positive link between stock prices and currency rates. On the contrary, the PBT due to Frankel (1983) contends that a flourishing stock market attracts foreign investment, which boosts the economy's stock market and, in turn, increases the value of the currency. The stock-orientated hypothesis (Frankel, 1992) presupposes that fluctuations in both exchange rates and stock markets are the result of a similar factor, such as interest rates (Korley & Giouvris, 2021).

In addition to estimating the value-at-risk (VaR) connected to each exchange rate and Bitcoin, Umoru et al. (2025) also assessed the dynamic impact of exchange rates and their returns on Bitcoin return. According to the research findings, there is a notable adjustment of bitcoin returns to exchange rate returns in every nation. This proves that using digital currencies like Bitcoin for investments carries a significant risk of losing money. The Standard and Poor's (S&P) 500 volatility has a significant negative impact on the Shanghai Stock Exchange (SSE) daily return, according to Zhang et al. (2024), while price fluctuations in cryptocurrencies have a positive impact on stock market price fluctuations and an inverse effect on gold market price fluctuations. The link between oil and Bitcoin suggests volatility spillover, albeit not in the same way, according to Inayah et al. (2024) dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH) model. Lee's (2024) analysis revealed that Bitcoin exchanges might be able to use market volatility as a tactical advantage. According to the study, Bitcoin holdings also improve business liquidity; this correlation is stronger in cryptocurrency exchanges. Both the Turkish and Japanese Stock Exchanges show a short-term volatility spillover from Bitcoin, according to Mishra and Dash's (2024) research on the volatility spillover effect of crude oil on all stock exchanges. The results also indicated that all stock exchanges aside from Malaysia have witnessed a spillover impact of volatility from Bitcoin; and there is no immediate link between Bitcoin's volatility and the return volatility of the stock markets in China, India, Malaysia, Pakistan, South Korea, and Singapore.

A higher connection was observed at the quantile ends of co-movements, according to our findings of Qabhobho et al. (2024), with right-tail spillovers predominating for volatility and left-tail spillovers being more noticeable for returns. Bitcoin and, to a lesser degree, gold, and oil, prove to be successful tail-ended hedges for the Nigerian naira and Egyptian pound, but not for other African currencies such as the South African rand and Algerian dinar. Therefore, in contrast to those who use South African and Algerian currencies, users of Egyptian and Nigerian currencies in global financial markets should hedge in typical digital currencies and commodities at recent 'black swan' moments.

Joseph et al. (2024) found evidence of a moderate but increasing digital currency spillover effect on the financial market in South Africa, Nigeria, and Kenya. Likewise, the study could not discover any proof of a ripple effect from the cryptocurrency market to the African financial industry. The DCC-GARCH conditional correlation finding showed a higher degree of positive integration in both markets, particularly over the long term. The COVID-19 pandemic increased volatility spillovers, which exacerbated the effect of financial contagion between markets, according to Alamaren et al.'s (2024) research. Tether and Binance Coin (BNB) are among the net volatility transmitters, whereas Bitcoin and Ethereum are among the net volatility transmitters, indicating that the pandemic's effects on the US economy increased risk transmission globally.

Impulse response functions revealed a significant inverse link between the price of Bitcoin and the Market Volatility Index, according to Köse et al. (2024). The analysis of the study further shows that the price of Bitcoin was primarily affected by its own volatility. Depending on the stock market, the conditional probability that Bitcoin can lower volatility by at least 10% given that index returns fall below the first percentile is larger, ranging from 2% to 28.4%, according to Just and Echaust (2024). Shaik et al. (2024) find that whereas bilateral intercorrelations are moderate across all other financial assets, they are robust within stock indexes. According to Attarzadeh and Balcilar (2022), the stock and clean energy markets absorb volatility shocks from Bitcoin and oil and transfer return shocks to them through the clean energy and oil markets. Additionally, the research revealed that during times of crisis, the connection between Bitcoin and other financial markets becomes significantly stronger, while during non-crisis periods, it is only weakly connected. Nadarajah et al. (2021) use a bivariate extreme value model and extreme correlation analysis to investigate the extreme connectivity between Bitcoin and eight African currencies. The document evidence finds little hedging effect.

3. ECONOMETRIC METHODOLOGY

There are numerous estimating techniques that are executable to quantify the correlations between returns on exchange rates, Bitcoin trading, and stock market performance. Among them is the variance decomposition technique, which calculates the degree to which a shock to one variable affects the variance of another; impulse response functions, which show how one or more variables behave in reaction to a shock; clustering technique for multivariate time series data based on the vector autoregressive (VAR) model; structural vector autoregressive (SVAR) models; multi-agent systems using bat neural networks; nonlinear least squares techniques; and the generalized method of moments, which seeks to minimize the distance between the theoretical moments and zero by employing a weighting matrix, among other things. Yet, the research makes use of the quantile regression estimation method and the Markov-switching regression method of analysis. Quantile regression seeks to estimate the effects of explanatory variables on different quantiles of the dependent variable. The choice for the quantile estimation method lies in the fact that quantile regressions can eliminate inconsistencies that are associated with estimation in the presence of outliers. According to Koenker and Bassett (1978), our quantile regression specification of the outcome variable Y is given by Eq. (1).

$$\mathbb{Q}_Y(\tau|X) = \beta_{0\tau} + X_\tau\beta_\tau + \upsilon_\tau, \quad \tau \in (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9) \tag{1}$$

Using the variables in our study, the quantile regression model specification becomes:

$$\mathbb{Q}_{RBTCR}\left(\tau \middle| RBTCR_{(t-1)}, REXR, RSTR,\right) = \beta_{0\tau} + RBTCR_{(t-1)_\tau}\beta_{1\tau} + REXR_\tau\beta_{2\tau} + RSTR_\tau\beta_{3\tau} + \upsilon_{1\tau} \tag{2}$$

$$\mathbb{Q}_{REXR}\left(\tau \middle| REXR_{(t-1)}, RBTCR, RSTR,\right) = \beta_{0\tau} + REXR_{(t-1)_\tau}\beta_{1\tau} + RBTCR_\tau\beta_{2\tau} + RSTR_\tau\beta_{3\tau} + \upsilon_{2\tau} \tag{3}$$

$$\mathbb{Q}_{RSTR}\left(\tau \middle| RSTR_{(t-1)}, REXR, RBTC,\right) = \beta_{0\tau} + RSTR_{(t-1)_\tau}\beta_{1\tau} + REXR_\tau\beta_{2\tau} + RBTCR_\tau\beta_{3\tau} + \upsilon_{3\tau} \tag{4}$$

where is the quantile level of interest, such that denotes 10th percentile, 20th percentile, 30th percentile, and so on. The quantile regression has the following benefits, hence the justification for its adoption in this research: the coefficients are calculated per quantile level, and it lessens bias that could result from distributional outliers. To find diverse effects of covariates at various quantiles of the outcome variables, quantile regressions were used. The three Markov-regime switching equations for returns on Bitcoin trading, exchange rate, and stock market, respectively, are here specified:

$$RBTCR_j = \partial_0 + \partial_1 REXP + \partial_2 RSTR + \partial_3 RBTCR_{t-1} + \sum R_j + \partial_2 log_j(\sigma) + \in_{it} \quad (5)$$

$$REXP_j = \partial_0 + \partial_1 RBTCR + \partial_2 RSTR + \partial_3 REXP_{t-1} + \sum R_j + \partial_2 log_j(\sigma) + \in_{it} \quad (6)$$

$$RSTR_j = \partial_0 + \partial_1 REXP + \partial_2 RBTCR + \partial_3 RSTR_{t-1} + \sum R_j + \partial_2 log_j(\sigma) + \in_{it} \quad (7)$$

where,

- *RBTCR*, *REXR*, and *RSTR* are the returns on Bitcoin trading, exchange rate, and the stock market, respectively, of individual countries *j;*
- $\sum R_j$ is the sum of non-switching regressors of the *j*th regime;
- ∂_j is the coefficient of the *j*th variable;
- σ_j is the volatility coefficient of the *j*th regime;
- $\in_{it}$ is the error term of country *i* for the *j*th regime.

After determining whether the autoregressive conditional heteroskedasticity (ARCH) effect existed, the asymmetry was measured using the Glosten-Jagannathan-Runkle (GJR) (threshold) GARCH model. The mean and variance equations of the GARCH specification are given by Eq. (8) and Eq. (9), respectively:

$$R_t = \mu_t + e_t \; where \; e_t \sim \sigma_t \in_t, \; \mathrm{E}[R_{t-1}] = \mu_t, \; \mathrm{Var}[R_{t-1}] = \sigma_t^2 \quad (8)$$

The GARCH conditional variance equation is specified as follows.

$$\sigma_t^2 = \emptyset_0 + \sum_{i=1}^{q} \emptyset_i e_{t-i}^2 + \sum_{j=1}^{p} \emptyset_j \sigma_{t-j}^2 \quad (9)$$

where,

- $\sum_{j=1}^{p} \emptyset_1 \sigma_{t-j}^2$ is the GARCH term, $\sum_{i=1}^{q} \emptyset_1 \varepsilon_{t-1}^2$ is the ARCH term,
- σ is the variance the threshold GARCH brings in the simulated variable to the GARCH model to measure asymmetry.

$$U_{t-1} = \begin{cases} 1, & e_{t-1} < 0 \\ 0, & e_{t-1} \geq 0 \end{cases}$$

$$\sigma_t^2 = \emptyset_0 + \sum_{i=1}^{q} \emptyset_i e_{t-i}^2 + \sum_{j=1}^{p} \emptyset_j \sigma_{t-j}^2 + \sum_{k=1}^{r} \pi_k e^2{}_{t-k} U_{t-k} \quad (10)$$

where,

- $\sum_{k=1}^{r} \pi_k e^2{}_{t-k} U_{t-k}$ is the asymmetric effect such that when $\pi > 0$; $\pi < 0$, it implies presence and absence of asymmetry;
- R_t stands for returns,
- σ_t^2 represents the variance of returns at time *t*.

According to Eq. (8) and Eq. (9), μ is the mean return, and the standard deviation of returns quantifies the volatility of return during the calculated time period. Therefore,

$$E(R_t) = \mu, Var(R_t) = \sigma^2 \quad (11)$$

We have weekly standardized data from 1990 to 2022 years for our sample period. We make use of extended, calculated data from the International Financial Statistics database managed by the International Monetary Fund (IMF). The following ten oil-importing countries made up our research sample: Botswana, Hong Kong, Kenya, Morocco, Rwanda, Sweden, Switzerland, Tanzania, Turkey, and Uganda. The choice and justification for choosing oil-importing countries as our research sample is based on the fact that these sets of nations have the same demand for oil, incur equivalent importing costs, and have similar risk exposure.

4. RESEARCH RESULTS

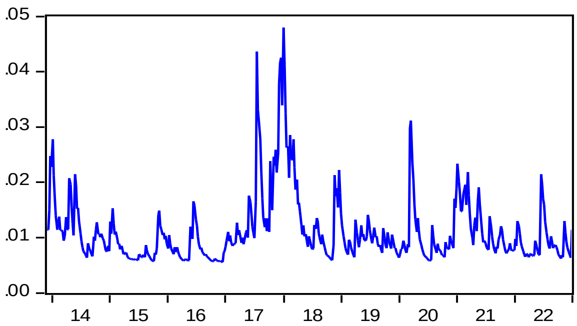
Table 1 below presents the summary statistics for *RBTCR*. According to Table 1, Bitcoin is everywhere given its blockchain status, and as a result, descriptive statistics do not have a country-level presentation. The average return of Bitcoin within the period was 1.2%, with the highest return at 43.8%. The lowest change in weekly prices showed a decline of 41.5%. The dispersion was fairly broad, as seen in the standard deviation of 0.107 compared to the mean of 0.012. The point of the 75th percentile at 0.061, which is much lower than the maximum value, confirms the inherent spread in the dataset. The dataset does not follow a normal distribution with a kurtosis value above 3, and all concluded items were 4.730 in total. The oil-importing countries in the study show very sparse or no oil reserves and import all their crude oil needs.

Table 1. Summary statistics for *RBTCR*

Statistic	*Value*
Mean	0.012
Max	0.438
Min	-0.415
Quantile*	0.061
Std. dev.	0.107
Kurtosis	4.569
Observations	4730

*Note: * Quantiles computed for p = 0.75.*
Source: Authors' elaboration using EViews 13.

Figure 1. Bitcoin returns



Source: Authors' elaboration using EViews 13.

Figure 1 is a representation of the volatility behavior of Bitcoin estimated using the transaction prices in USD. Noticeably, the transaction prices exhibit volatility clustering estimates are shown by the blue line.

Table 2. Summary statistics of exchange rate returns

Metric	*Botswana*	*Hong Kong*	*Kenya*	*Morocco*	*Rwanda*	*Sweden*	*Switzerland*	*Tanzania*	*Turkey*	*Uganda*	*All*
Mean	0.0009	0.0000	0.0008	0.0005	0.0011	0.0011	0.0002	0.0008	0.0053	0.0009	0.0011
Max	0.0499	0.0037	0.0302	0.0398	0.0965	0.0693	0.0458	0.0741	0.2649	0.0401	0.2649
Min	-0.0301	-0.0047	-0.0243	-0.0237	-0.0722	-0.0484	-0.1545	-0.0647	-0.3513	-0.0553	-0.3513
Quantile (Q1)*	0.0084	0.0003	0.0023	0.0049	0.0021	0.0101	0.0077	0.0009	0.0132	0.0044	0.0043
Std. dev.	0.0123	0.0008	0.0045	0.0078	0.0141	0.0142	0.0136	0.0079	0.0329	0.0088	0.0144
Kurtosis	3.70	10.21	11.53	5.31	18.10	4.52	37.72	36.86	47.62	10.63	137.36
Observations	4730	4730	4730	4730	4730	4730	4730	4730	4730	4730	47300

*Note: * Quantiles computed for p = 0.75.*
Source: Authors' elaboration using EViews 13.

For sampled oil-importing countries, according to Table 2, average returns on weekly currency values ranged from 0.0002 (0.02%) in Switzerland to 0.0053 (0.53%) in Turkey. Turkey also had the highest weekly exchange rate rise in the period, at 26.49%. Rwanda, Tanzania, and Sweden followed consecutively on maximum values at 9.65%, 7.41%, and 6.93%, respectively. Turkey had the lowest value of -35.13%, showing the Turkish dinar as the most volatile of the currencies in the pool.

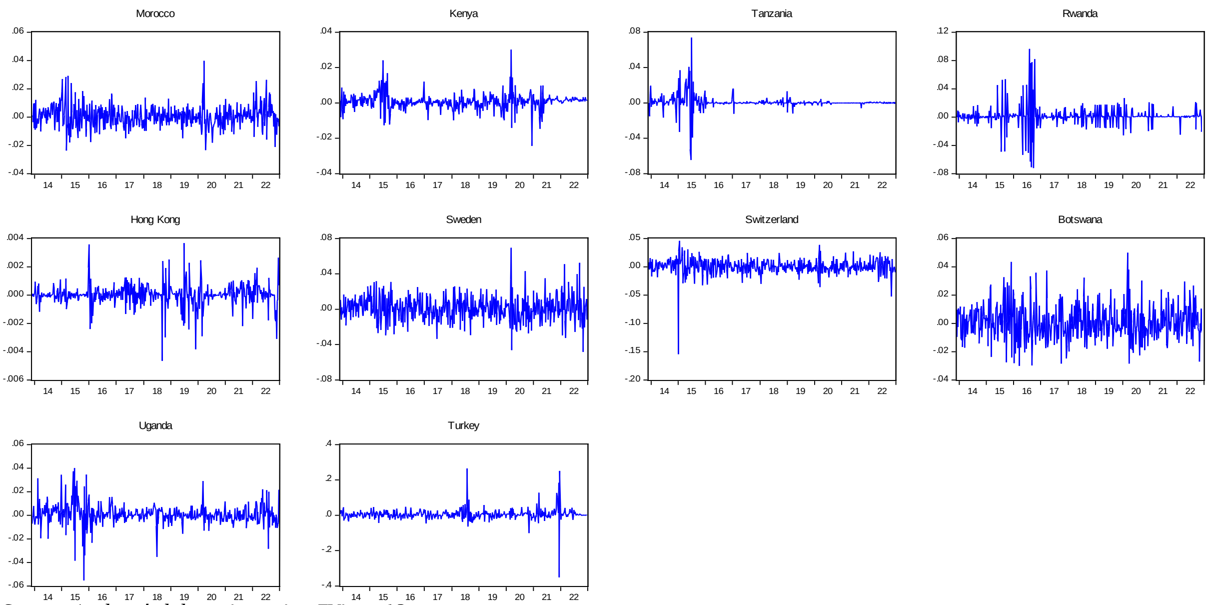
Table 3. Stock market returns

Metric	*Botswana*	*Hong Kong*	*Kenya*	*Morocco*	*Rwanda*	*Sweden*	*Switzerland*	*Tanzania*	*Turkey*	*Uganda*	*All*
Mean	0.0003	0.0001	-0.0021	0.0004	0.0001	0.0014	0.0008	0.0004	0.0050	-0.0002	0.0006
Max	0.0305	0.1193	0.0979	0.0798	0.1155	0.0682	0.0705	0.3239	0.1091	0.1264	0.3239
Min	-0.0367	-0.0829	-0.1149	-0.0869	-0.0397	-0.1605	-0.1387	-0.2538	-0.1424	-0.1081	-0.2538
Quantile (Q1)*	0.0019	0.0150	0.0077	0.0087	0.0003	0.0163	0.0130	0.0116	0.0251	0.0135	0.0102
Std. dev.	0.0056	0.0253	0.0186	0.0156	0.0078	0.0250	0.0209	0.0278	0.0319	0.0253	0.0220
Kurtosis	10.52	4.70	8.07	8.71	115.43	7.16	11.88	55.05	4.85	6.63	21.09
Observations	4730	4730	4730	4730	4730	4730	4730	4730	4730	4730	47300

*Note: *Quantiles computed for p = 0.75.*
Source: Authors' elaboration using EViews 13.

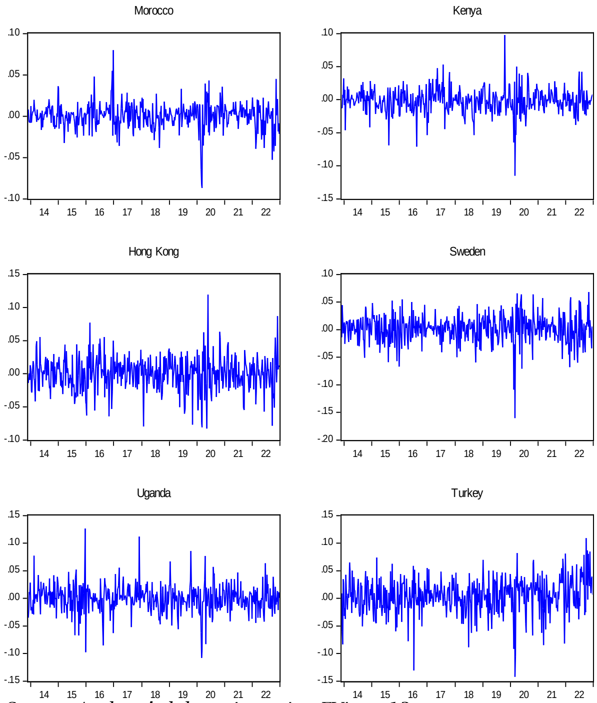
According to Table 3, stock market descriptions for oil-importing countries reveal that Kenya and Uganda had the most frequent depreciating returns, as depicted by a negative average value (0.21%). The country with the highest average value was Turkey at 0.5%. Tanzania had the highest weekly stock market returns of 32.39%, while Botswana's highest returns for the period were 3.05%, the least among the maximum value distributions. Tanzania also maintained the highest drop value of -25.38%, suggesting a very volatile stock market, given the adjoining maximum value of 32.39%. The country-level distribution had the normality characteristic absent in all cases (k > 3).

Figure 2. Exchange rate returns



Source: Authors' elaboration using EViews 13.

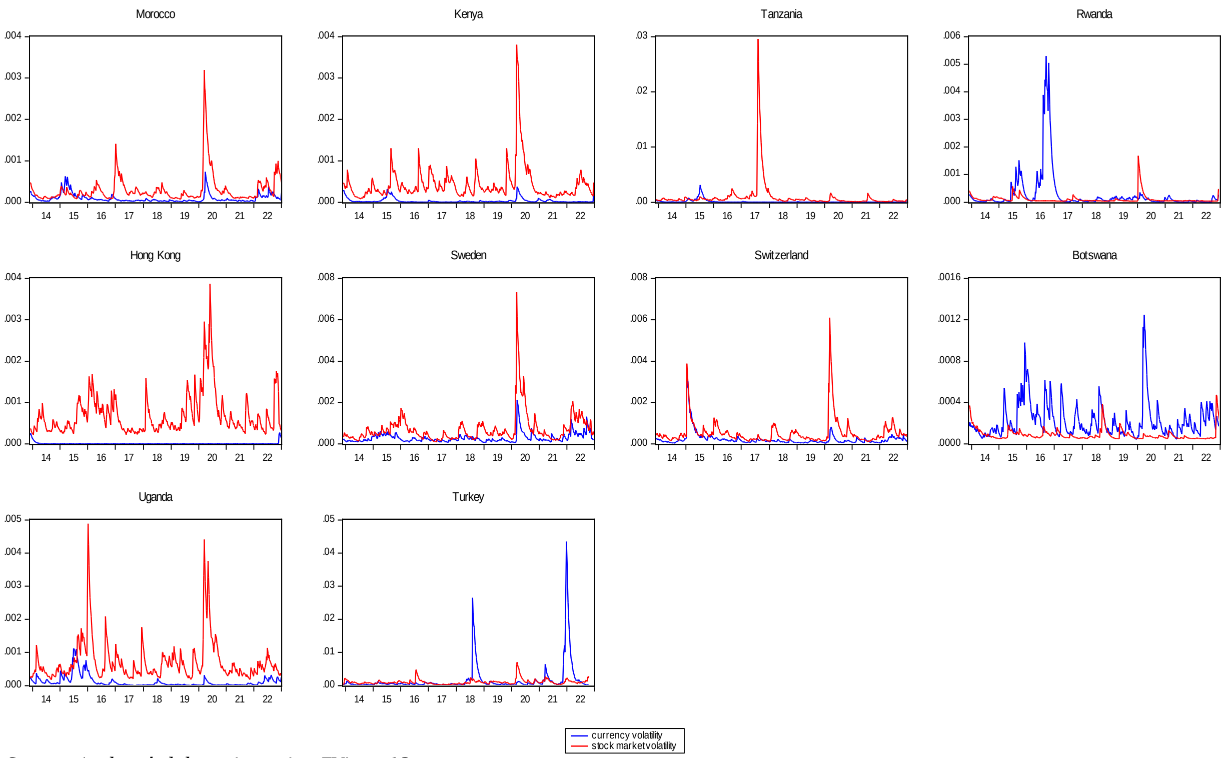
Figure 3. Stock market returns



Source: Authors' elaboration using EViews 13.

Figure 2 and Figure 3 are graphical presentations of variations in exchange rates and stock market returns for sampled countries that do not have oil and thus have to import the same into their local economies. The study finds volatility clustering in exchange rates and in all the stock markets though at different degrees as revealed in the cross-sectional chart labeled in Figures 2 and 3 above.

Figure 4. Conditional variance (volatility) of stock market returns and exchange rate returns



Source: Authors' elaboration using EViews 13.

Figure 4 shows that stock market return spikes denoting volatility typically last for an extended period before returning to their equilibrium level. The stock markets of Morocco, Kenya, Tanzania, Hong Kong, Sweden, Rwanda, Switzerland, and Uganda, in that order, exhibit this behavior. While exchange rate and stock return volatility are quite persistent, it has been discovered that stock market return fluctuations influence exchange rate return variation.

Table 4. Unit root test results

Test method	*REXR*	*RSTR*	*RBTCR*
Levin, Lin and Chu t*	-107.536***	-110.726***	-129.71***
Breitung t-stat.	-37.171***	-44.342***	-30.4083***
Im, Pesaran and Shin W-stat.	-70.255***	-72.227***	-81.47***
ADF — Fisher Chi-square	1839.71***	1857.92***	2172.4***
PP — Fisher Chi-square	2002.85***	2022.96***	2175.7***

*Note: *** Significant at 1%; ** significant at 5%; * significant at 10%.*
Source: Authors' elaboration using EViews 13.

Table 4 shows that the unit root was absent in all data sets at a level. Alternate hypotheses of stationarity of data were accepted in all without first-difference ($p < 0.01$). Stationarity at a certain level usually implies that co-integration tests are exempt from econometric analysis. However, for confirmation, the study carries out a panel co-integration test to confirm the long-term relationship status of the variables for the respective groups.

Table 5. Unrestricted co-integration rank test (trace and maximum eigenvalue)

Fisher stat. (trace test)	*None*	*At most 1*	*At most 2*
Hypothesized No. of CE(s)	184.2***	2634***	2404***
Fisher stat. (max-eigen test)	184.2***	184.2***	2404***

*Note: *** Significant at 1%; ** significant at 5%; * significant at 10%.*
Source: Authors' elaboration using EViews 13.

Table 5 shows very evidently that all statistics were significant ($p < 0.01$) and confirm the long-term relationship among Bitcoin return, stock return, and currency return. As occurrences in the financial markets, long-term association is expected. Given that GARCH analysis was carried out in the study, the ARCH effects were tested for significance. Table 6 shows clearly the presence of heteroscedasticity (variance in residuals) in data sets.

Table 6. Test for ARCH effects

Variable	*F-stat.*	*p-value (F-stat.)*	*Obs. * R-squared*	*p-value (Obs. * R-squared)*
REXR	868.79**	0.00	733.76**	0.00
RSTR	766.47**	0.00	659.44**	0.00
RBTCR	154.09**	0.00	149.27**	0.00

*Note: *** Significant at 1%; ** significant at 5%; * significant at 10%.*
Source: Authors' elaboration using EViews 13.

After the test results for ARCH effects, where the presence of the heteroscedasticity element within the panel series was pre-diagnostically identified as shown in Table 6; we proceeded to carry out GARCH estimations. The results of threshold GARCH estimations are presented in Table 7 below.

Table 7. Threshold-GARCH results

s	*Parameter*	*REXR*	*RBTCR*	*RSTR*
Mean equation	Constant	0.00006	0.00924*	0.00004
	AR(1)	-0.061*	0.02794	0.0975*
	REXR	-	-0.42068*	0.0279*
	RBTCR	-0.0004	-	0.0049*
	RSTR	-0.00264*	0.3575*	-
Variance equation	Constant	5.60E-08*	0.0016*	7.25E-06*
	ARCH	0.124768*	0.1461*	0.214719*
	TARCH/LEVERAGE	0.219782*	0.0139	-0.09056*
	GARCH	0.822649*	0.702788*	0.839623*
	Persistence	0.947	0.849	1.054
Likelihood		16649.61	4103.915	12253.17
Wald statistic		28.39	78.35	47.22

*Note: *** Significant at 1%; ** significant at 5%; * significant at 10%.*
Source: Authors' elaboration using EViews 13.

Table 8. Quantile regressions (dependence variable is *RBTCR*)

Metrics	*REXR*	*RSTR*	*C*
Ordinary least squares (OLS)	-0.3884 (0.00)	0.3480 (0.00)	0.0120 (0.00)
Quantiles			
Q0.1	-0.3510 (0.16)	0.5130*** (0.00)	-0.1168 (0.00)
Q0.2	-0.3336 (0.05)	0.3546*** (0.01)	-0.057 (0.00)
Q0.3	-0.1593 (0.00)	0.1280** (0.00)	-0.027*** (0.00)
Q0.4	-0.2895 (0.00)	0.1948*** (0.00)	-0.009*** (0.00)
Q0.5	-0.0328** (0.03)	0.1486 (0.02)	0.0063*** (0.00)
Q0.6	-0.1426*** (0.00)	0.1296 (0.12)	0.0262*** (0.00)
Q0.7	-0.1392*** (0.00)	0.2139** (0.02)	0.0492*** (0.00)
Q0.8	-0.4632** (0.01)	0.2357 (0.06)	0.0820** (0.02)
Q0.9	-0.7695*** (0.00)	0.2739 (0.21)	0.1427*** (0.00)
Quantile slope equality test, Wald test = 63.45, stability test = Ramsey test Quandt likelihood ratio-test (QLR) = 1.00682 (0.93).			

*Note: *** Significant at 1%; ** significant at 5%; * significant at 10%.*
Source: Authors' elaboration using EViews 13.

Table 9. Quantile regressions (dependence variable is *REXR*)

Metrics	*RBTCR*	*RSTR*	*C*
Ordinary least squares (OLS)	-0.0069 (0.00)	-0.0169*** (0.07)	0.0012*** (0.00)
Quantiles			
Q0.1	-0.0035 (0.24)	-0.0536*** (0.00)	-0.0097*** (0.00)
Q0.2	-0.0054** (0.00)	-0.025** (0.03)	-0.0042** (0.01)
Q0.3	0.0031*** (0.00)	-0.0135*** (0.00)	-0.0013*** (0.00)
Q0.4	-0.0008*** (0.11)	-0.0054 (0.03)	-0.0001*** (0.06)
Q0.5	-0.0011** (0.03)	-0.0064*** (0.00)	0.0003*** (0.00)
Q0.6	-0.0026*** (0.00)	-0.0090** (0.03)	0.0011*** (0.00)
Q0.7	-0.0046 (0.00)	-0.0181** (0.04)	0.0028*** (0.00)
Q0.8	-0.0091** (0.02)	-0.0325 (0.09)	0.0065*** (0.00)
Q0.9	-0.0119*** (0.00)	-0.0446*** (0.00)	0.0127*** (0.00)
Quantile slope equality test, Wald test = 63.45, stability test = Ramsey test QLR = 1.00682 (0.93).			

*Note: *** Significant at 1%; ** significant at 5%; * significant at 10%.*
Source: Authors' elaboration using EViews 13.

Table 10. Quantile regressions (dependence variable is *RSTR*)

Metrics	*REXR*	*RBTCR*	*C*
Ordinary least squares (OLS)	-0.0087 (0.62)	-0.0027 (0.08)	0.0002 (0.2200)
Quantiles			
Q0.1	-0.0812 (0.30)	0.017*** (0.00)	-0.0228*** (0.00)
Q0.2	-0.0891 (0.14)	0.0124*** (0.00)	-0.0117** (0.0015)
Q0.3	-0.0172 (0.18)	0.0063** (0.03)	-0.0051*** (0.00)
Q0.4	-0.0165 (0.37)	0.0039** (0.011)	-0.0013*** (0.00)
Q0.5	-0.0087 (0.62)	0.0027 (0.09)	1.0002 (0.2400)
Q0.6	-0.0095 (0.71)	0.0078*** (0.00)	0.0026*** (0.00)
Q0.7	-0.0581*** (0.00)	1.0119*** (0.00)	0.0073*** (0.00)
Q0.8	-0.0513 (0.49)	0.0126** (0.03)	0.013*** (0.00)
Q0.9	-0.0626** (0.01)	0.0142** (0.02)	0.0235** (0.0002)
Quantile slope equality test, Wald test = 63.45, stability test = Ramsey test QLR = 1.00682 (0.93).			

*Note: *** Significant at 1%; ** significant at 5%; * significant at 10%.*
Source: Authors' elaboration using EViews 13.

5. DISCUSSION

Table 7 clearly demonstrates that the stock market returns had no volatility persistence (persistence = 1.054 > 1). The leverage effect was also absent; hence reactions are symmetrical. Bitcoin returns also had an insignificant threshold autoregressive conditional heteroskedasticity (TARCH) term, weakening the hypothesis of the presence of asymmetry. Nevertheless, exchange rate returns had a TARCH term greater than 0 (0.2197), which is also significant, confirming that currency volatility in oil-exporting countries possesses leverage effects. Investors or players within the exchange rate market react more to bad news (depreciation of currency rates) than they do to good news (currency appreciation). The ordinary least squares (OLS) quantile estimations in Table 8 showed that exchange rate return had a negative impact (-0.3884) on BTC (Bitcoin) returns, while stock return was a direct predictor of Bitcoin returns of a significant magnitude of 0.348. On the tenth percentile of Bitcoin returns, exchange rate returns had a coefficient of -0.3510, indicating that a unit increase in exchange rates would bring about a decrease in the tenth percentile of Bitcoin returns. However, this is not at a significant level ($p = 0.16 > 0.05$).

Stock returns in the equation had a positive and significant coefficient of 0.5153 ($p = 0.00 < 0.05$). The positive coefficient for stock returns suggests that a 1% increase in Bitcoin growth is associated with a 0.515% increase in growth in the tenth percentile of Bitcoin returns. In the same vein, the 30th, 40th, 50th, 60th, 70th, 80th, and 90th percentiles of Bitcoin returns were inversely and significantly associated with exchange rate returns, with coefficients of -0.3593, -0.2895, -0.2328, -0.2842, -0.3992, -0.4632, and -0.7695, respectively ($p < 0.05$). The coefficients for each of these equations showed that stock returns in oil-importing countries are strong predictors of movements in Bitcoin values. The coefficients in order of earlier mention are 0.1280, 0.1948, 0.1486, 0.1296, 0.2139, 0.2357, and 0.2739, with p-values of each except the last two percentiles, which are less than 5%. In addition, when the stock markets of countries that import oil face a 1% rise in returns, Bitcoin returns fall by 0.128%, 0.195%, 0.148%, 0.129%, and 0.214% for significant coefficients. Comparing all significant equations for Bitcoin returns, exchange rate returns have a higher effect on the 90th percentile value of Bitcoin returns. Comparing equations in which stock returns had a significant effect on Bitcoin returns, the effect of stock returns was strongest in the 10th percentile of Bitcoin returns.

Quantile regression estimates generally show the same forms of relationship (negative for exchange rates and positive for stock returns) but at varying levels and significance of impacts. The significance of exchange rate returns is found from the third quantile equation up to the ninth quantile equation, while significance is observed for stock returns from the first quantile equation to the eighth, with an exemption of the sixth equation. Therefore, higher stock fluctuations would result in higher fluctuations in Bitcoin, while a percentage rise in exchange rates would be accompanied by a decline in Bitcoin prices by a lesser rate (-0.35%, -0.23%, -0.28%, -0.39%, -0.46%, and -0.76%).

Figure 5a. Quantile process estimates: *RSTR*

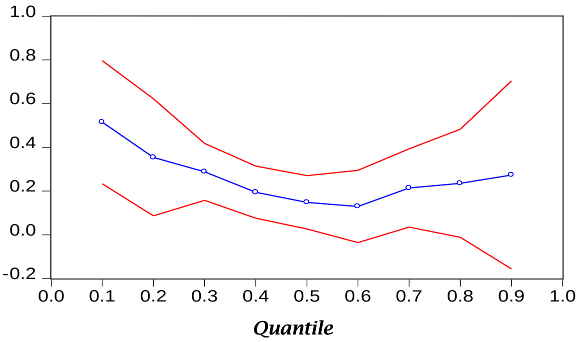


Figure 5b. Quantile process estimates: *REXR*

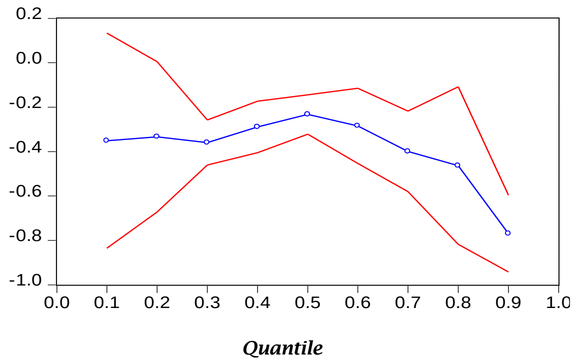
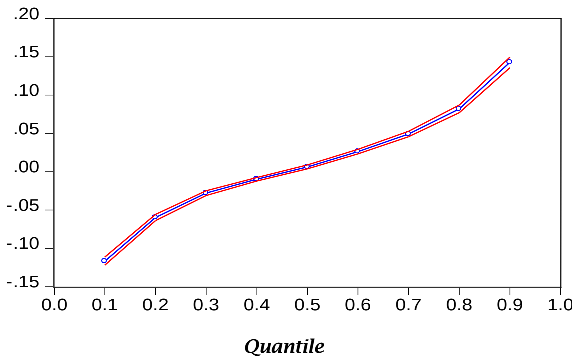


Figure 5c. Quantile process estimates: *C*



Source: Authors' elaboration using EViews 13.

The quantile process estimates for the dependent Bitcoin returns in Figures 5a, 5b, and 5c showed that stock returns had declining effects on Bitcoin returns as the quantiles progressed. The effect of exchange rate adjustments on Bitcoin was not as uniform, as the chart shows undulating effects on Bitcoin returns. The quantile estimations in Table 9 showed that exchange rates change without interference from Bitcoin, and stock returns are 0.12% (constant = 0.0012; $p < 0.05$). The independent variables, Bitcoin returns, and stock returns were indirect predictors of currency returns, although stock returns were found to be insignificant in the model. Every unit increase in Bitcoin returns caused exchange rate returns to drop by 0.007%. On the 10th percentile of exchange rate returns, stock returns had a significant coefficient of -0.0536, indicating that a unit increase in exchange rates brings about a decrease in the tenth percentile of stock returns ($p < 0.05$). Bitcoin returns in the equation also had a negative coefficient of -0.0035 ($p = 0.24 > 0.05$), but this was insignificant in the model. For the 20th, 50th, 60th, 70th, and 90th percentiles of exchange rate returns, Bitcoin returns were inversely and significantly associated with exchange rate returns, with coefficients of -0.0054, -0.0011, -0.0026, -0.0046, and -0.0119, respectively ($p > 0.05$, -0.005%, -0.001%, -0.003%, -0.005%, and -0.012%, respectively. With coefficients in order of earlier mention for stock returns as an independent variable in the model, -0.025, -0.0064, -0.009, -0.0181, and 0.0446, and p-values of each less than 5%, values of exchange rate return at these percentiles reflect similar movements in Bitcoin markets, with a 1% rise in Bitcoin returns matched with 0.05%, 0.006%, 0.009%, 0.018%, and 0.045% changes in each percentile value. The 30th percentile conditional equation, Q0.3, had the coefficient of Bitcoin returns switch from the nature of the coefficients in other equations to a positive coefficient of 0.0031, significant at 5%. This indicates that a 1% rise in Bitcoin returns is associated with a 0.003% increase in the 30th percentile value of exchange rate returns, ceteris paribus. Comparing all significant equations for stock returns and Bitcoin returns both had the largest magnitude on the 90th percentile of exchange rate returns.

Quantile regression for the nine quantiles confirmed the negative impacts of the independent variables on exchange rate returns. The negative coefficients confirm that the fluctuations in exchange rates go in the opposite direction of fluctuations that occur in stock markets and Bitcoin floors in the economies of countries that import fossil oil. The coefficient values of Bitcoin return show that a 1% rise in Bitcoin returns will cause a corresponding 0.4% fall in the tenth quantile of the exchange rate, though not significant; an insignificant effect of Bitcoin returns was also found on the fourth quantile. Stock returns in quantile analysis influenced exchange rate returns negatively, such that a unit change in stock returns impacted exchange rate returns at the 10th quantile by 0.054%. Other quantiles had an alternate effect in intensity, with a lesser fall in the 20th and 30th quantiles (-0.025% and -0.0135%; $p < 0.05$) before a 0.0054% negative change in the fourth quantile equation. Stock market returns for oil-importing countries had more magnifying influence as the quantiles heightened till the 40th quantile, where stability was reached up to the 60th quantile, before losing effect magnitude on exchange rate returns in subsequent quantiles. Bitcoin had a more fluctuating outlook through the exchange rate quantiles. Post-estimation tests confirm asymmetry in the model (Wald test; $p < 0.05$) and stability of coefficients.

Figure 6a. Quantile process estimates: *RSTR*

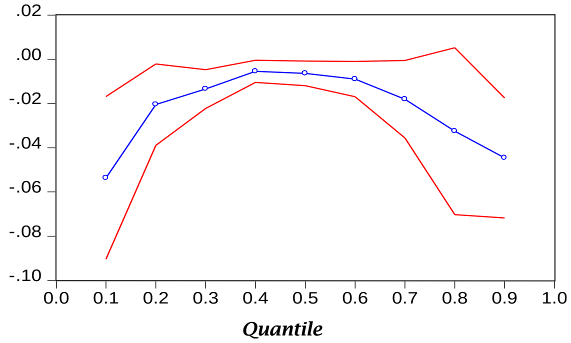


Figure 6b. Quantile process estimates: *RBTCR*

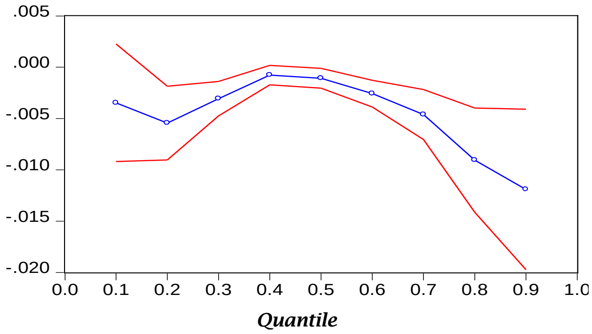
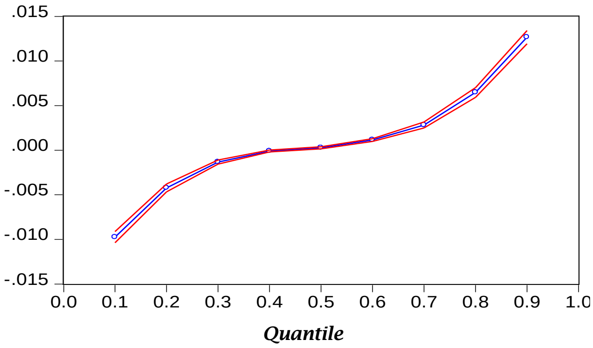


Figure 6c. Quantile process estimates: *C*



Source: Authors' elaboration using EViews 13.

Figures 6a, 6b, and 6c displays the quantile process results reached for stock market returns. The blue line indicates the quantile process coefficients of stock market returns. The 95% confidence interval is represented by the two orange lines. The conditional distribution of the return on exchange rates' quantiles is shown on the X-axis, while the size of the stock return coefficients is displayed on the Y-axis. The charts indicated that stock returns were having declining effects on exchange rate returns as the quantiles proceeded. The graphics illustrate how different stock market movements have an impact on exchange rate returns, indicating that the influence is not homogeneous.

For the quantile regressions in Table 10, OLS estimates revealed that stock returns were independent of exchange rate and Bitcoin fluctuations, although the coefficients of both variables (-0.0087 and -0.0027) are negative. On the 10th percentile of stock returns, exchange rate returns had a coefficient of -0.0812, indicating that a unit increase in exchange rates would bring about a decrease in the tenth percentile of stock returns. Nonetheless, this is not at a significant level ($p = 0.3 > 0.05$). Bitcoin returns in the equation had a positive and significant coefficient of 0.0119 ($p = 0.00 < 0.05$). The positive coefficient for Bitcoin returns suggests that a 1% increase in Bitcoin growth is associated with a 0.017% increase in growth in the 10th percentile of stock returns. In the same vein, the 20th, 30th, 40th, 60th, and 80th percentiles of stock returns were inversely but insignificantly associated with exchange rate returns, with coefficients of -0.0891, -0.0172, -0.0165, -0.0095, and -0.0513, respectively ($p > 0.05$). Our results corroborate those of Kao et al. (2024), Udom and Nnamini (2023), and Corbet et al. (2020). Kao et al. (2024) found that negative market news had a significant short-term impact on Bitcoin returns. Udom and Nnamini (2023) have established that Bitcoin cannot be regarded as a protection for South African stocks.

Additionally, Corbet et al. (2020) discovered that a decrease in Bitcoin returns was caused by an increase in good news that followed stock market announcements. Bitcoin returns for each of these equations showed that Bitcoin returns were strong predictors of movements in stock prices in oil-importing countries. With coefficients in order of earlier mention at 0.0124, 0.0063, 0.0039, 0.0027, and 0.0078 and p-values of each less than 5%, the values of stock returns at these percentiles reflect similar movements in Bitcoin markets, with a 1% rise in Bitcoin returns matched with 0.012%, 0.006%, 0.004%, 0.003%, and 0.008% changes in each percentile value.

The median conditional equation, Q0.5, also showed that exchange rate returns are an insignificant predictor of the median of stock returns (-0.0087; $p > 0.05$). Bitcoin returns' parameter was 0.0027 for the median equation, but this was found to be insignificant in the equation at a p-value of 0.09, indicating that Bitcoin returns were non-impactful only on stock returns' median. The 70th percentile parameters show that exchange rate returns had a significant, negative coefficient of -0.0581 on stock returns ($p < 0.05$). Therefore, a 1% rise in exchange rate returns is associated with a 0.000581 decrease in the 70th percentile value of stock returns, ceteris paribus. Our result supports those of Hussain et al. (2024) and El-Diftar (2023). The findings by Hussain et al. (2024) uphold that stock return volatility during pandemic-induced crises is negatively correlated with changes in the exchange rate. El-Diftar's (2023) results also show that exchange rates have a significant negative effect on stock returns in Indonesia, but in the seven emerging economies that perform the best, the relationship between exchange rates and stock market returns is significantly positive over the long term.

Bitcoin returns in the equation had a positive and significant coefficient of 0.0119 ($p = 0.00 < 0.05$). The positive coefficient for Bitcoin returns suggests that a 1% increase in Bitcoin growth is associated with a 0.012% increase in growth in the 70th percentile of stock returns. The study finds an adverse effect on the 90th percentile equation for exchange rate returns with a coefficient of -0.0626 significant at the 5% significance level ($p < 0.05$). A 1% rise in exchange rate returns is associated with a 0.000626% decrease in the 90th percentile value of stock returns, ceteris paribus. Bitcoin returns were also a significant direct predictor of stock returns (0.0142; $p < 0.05$). Comparing both significant equations for exchange rate returns, exchange rate returns have a higher effect on the 90th percentile value of stock returns than on the 70th percentile value of stock returns. Comparing equations that were significant for Bitcoin, the effect of Bitcoin returns on stock returns was strongest in the 10th and 90th percentiles of stock returns. However, by grouping values based on quantiles, the study finds that returns in the exchange rates and Bitcoin markets are significant predictors of stock market returns in their 70th and 90th quantiles. Bitcoin returns also go further to affect stock market returns in all other quantiles except the median equation (Q0.5; 0.0027 with $p > 0.05$). Bitcoin returns' estimate for OLS was negative, but this switched in quantile regressions to all positive coefficients, depicting a direct impact on stock market fluctuations in countries that import oil.

Figure 7a. Quantile process estimates: *RBCTR*

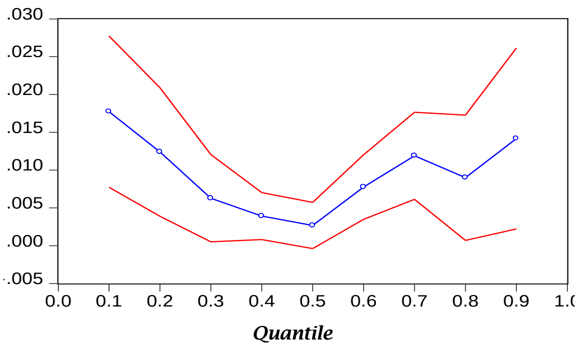


Figure 7b. Quantile process estimates: *REXR*

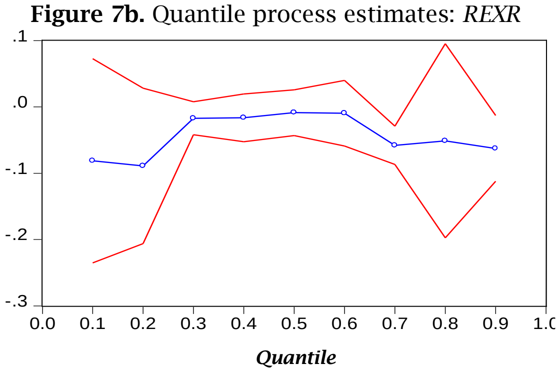
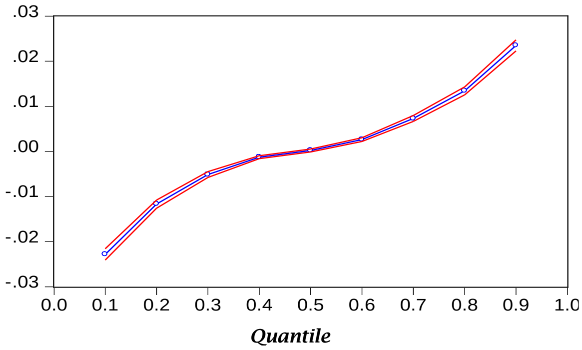


Figure 7c. Quantile process estimates: *C*



Source: Authors' elaboration using EViews 13.

The quantile plots of coefficients in Figures 7a, 7b, and 7c show the pattern of effects of each predictor variable across solved quantiles of stock market returns. Bitcoin returns fall in their level of impact, with the lowest at the median point before the effects become significant again. Exchange rate returns had negative coefficients found to be stable within the third and seventh equations. Post-estimation tests confirm asymmetry in explanatory models and the stability of coefficients. The outputs in the Microsoft Linear (M-S) regressions section as reported in Table 11 below examine mutual effects in different regimes within the study period or in the presence of structural breaks. The equation specification comprised two regimes with switching mean regressors and four accounts receivable (AR) terms identified as non-switching.

Table 11a. Markov-switching regression results

Dependent variables	*Explanatory variables*	*Regimes*		*AR*				*LOG(SIGMA)*
		Regime 1	*Regime 2*	*AR(1)*	*AR(2)*	*AR(3)*	*AR(4)*	
RBTCR	*REXR*	-0.3107** (0.0956)	-1.4916 (0.7839)	-0.0049	0.0531**	0.0421*	0.0269	-2.4177**
	RSTR	0.3198* (0.0679)	0.3360 (0.2785)	0.8007	0.0020	0.0148	0.1458	0.0000
	C	-0.0025 (0.0019)	0.2274 (0.0104)	-	-	-	-	-
REXR	*RBTCR*	-1.2350** (0.0770)	-0.0052** (0.0016)	-0.1293**	-0.0146	-0.0102	0.1574**	-4.4444**
	RSTR	2.1108** (0.0886)	-0.0453** (0.0078)	0.0000	0.3341	0.4934	0.0000	0.0000
	C	0.1032 (0.0045)	0.0011*** (0.0002)	-	-	-	-	-

*Note: *** Significant at 1%; ** significant at 5%; * significant at 10%.*
Source: Authors' elaboration using EViews 13.

Table 11b. Markov-switching regression results

Variables		*Regime 1 coefficient (std. error)*	*Regime 2 coefficient (std. error)*	*AR(1)*	*AR(2)*	*AR(3)*	*AR(4)*	*LOG(SIGMA)*	*S.E. of regression*	*Durbin-Watson stat.*
RSTR	*REXR*	0.0616* (0.0279)	-1.8041** (0.2145)	-0.0076***	0.0186	-0.0192	0.0481**	-3.8905**	0.1059	2.1131
	RBTCR	0.0031 (0.0033)	0.1925** (0.0538)	0.0000	0.6276	0.1245	0.0000	0.0000	0.0140	2.1230
	C	0.0007 (0.0005)	0.0001 (0.0111)	-	-	-	-	-	0.0218	1.9866
	Transition parameters									
	P11-C	2.9315** (0.1325)		-0.7998 (0.5537)					3.7292*** (0.2517)	
	P21-C	0.9458** (0.2049)		-5.9736** (0.3385)					-0.1738 (0.5623)	

*Note: *** Significant at 1%; ** significant at 5%; * significant at 10%.*
Source: Authors' elaboration using EViews 13.

According to Table 11a and Table 11b, Bitcoin returns were found to be negatively and significantly influenced by changes in the currency and stock markets in oil-importing economies, as revealed by the significant coefficient of -0.3107. A percentage change in currency fluctuations would reflect in Bitcoin markets as a reduction in Bitcoin fluctuations by 0.31%. In the same model and within the same state of the economy, stock market returns directly affect Bitcoin returns by a corresponding 0.31% rise in returns. The effects are compared with observations in a different economic state of high fluctuations and reveal that when fluctuations in stock market prices and currency values are high, Bitcoin fluctuations become independent of such fluctuations. Autoregressive terms for the model have AR(2) and AR(3) terms that are significant in the model. The first and last autoregressive terms had coefficients of -0.0049 and 0.0269, respectively, which were non-significant, confirming that the immediate past weekly returns from Bitcoin do not significantly influence its present value. AR(2) term of 0.0531 confirms that the fluctuation of Bitcoin from two weeks ago significantly influences the current returns directly, such that a unit change in returns in the present week can help Bitcoin dealers predict that a similar direction of returns would occur in a fortnight with 5% of the same magnitude.

Returns from the currency market in the first regime were negatively affected by Bitcoin returns (-1.235) and directly influenced by stock market returns (2.1108). Therefore, a percentage change in Bitcoin causes a higher change in exchange rate returns by 1.235% in the opposite direction, while a percentage increase in stock market returns caused exchange rate returns to also increase, but at a higher rate of 2.11%. When the state of the economy changes, these two predictors still exert significant influence on exchange rate returns, but to a lesser degree. These findings are in line with previous studies, such as the work of Sosa et al. (2018). Bitcoin's alterations will have a significant effect, resulting in a 0.0005% change in exchange rates as opposed to the 1.235% in the first regime. Stock returns also begin to have currency returns move in the opposite direction (-0.0453), as confirmed by the sign change from positive to negative. Autoregressive terms in the equation confirm that only the immediate past weekly return (-0.12) and return of about a month ago (0.15) were significant predictors of present currency fluctuations.

Moving to the last M-S model for oil-importing countries that specifies predictive variables for stock market returns, the estimates of the first regime show that only exchange rate returns predicted returns for stock markets significantly. Bitcoin was not a significant predictor until the second regime when the coefficient up-scaled from 0.003 to 0.1925 and became significant at a 5% significance level. The exchange rate, however, becomes an indirect predictor, such that a 1% rise in the variable influences stock market returns to dwindle by up to 1.804% in a change of economic conditions. Only the stock market returns of the last four weeks can predict the outcomes of the current *RSTR* significantly, as depicted by the significant coefficient of AR(4) as a non-switching regressor in the model.

The Durbin-Watson statistics confirm the absence of serial correlation, as each statistic is approximately 2. Inverse roots of AR/MA (autoregressive moving-average model) polynomials show that roots lie within the circle and confirm the stability of AR coefficients. Transition probabilities are significant for the model explaining Bitcoin returns and confirm the reliability of the model. In oil-exporting countries, regime 1 is more likely to persist given the higher coefficient in the transition parameter for Bitcoin returns. However, the model for exchange rates shows that transition probability is only significant for regime 2, implying that the occurrences for regime 2 in this model are more likely to exist and continue for a longer period than those of the first regime. The last model estimating stock returns had regime 1 as the regime most likely to persist. This is confirmed by the transition probabilities graphs below in Appendix (Figures A.1, A.2, and A.3, respectively). The graphical plots of Appendix (Figure A.1) demonstrate the presence of constant Markov transition from one state to the other state with respect to the distribution of return of exchange rate. Appendix (Figure A.2) also demonstrates the incidence of constant Markov transition for stock market return from one state to the other state with respect to the distribution of return of exchange rate. The occurrence of a constant Markov transition for Bitcoin returns from one state to another with regard to the distribution is also depicted in Appendix (Figure A.3). Appendix (Figure A.4) illustrates how the volatility and returns of Bitcoin, exchange rate returns, and stock market returns all exhibit clustering tendencies across all countries. These results reinforce the theory that speculators with a high-risk tolerance are drawn to financial market swings. Appendix (Figure A.5) investigates the graphical depiction of inverse functions and shows that there is located and found outside of the circle. It shows that there is a co-integrated equation in the system and that the estimation process of the Markov model is stable. By extension, the distribution of each error term is standardized.

6. CONCLUSION

In this research, our attempt was to estimate the types of interactions that connect returns in the stock market, returns on the Bitcoin market/trading, and foreign exchange returns. The estimation techniques deployed included the quantile and Markov-switching methods of estimation. The estimation period covers 1990–2022 years. The pertinent research findings include the following: In oil-importing economies, the influence of Bitcoin on stock market fluctuations is significantly pronounced during specific market circumstances, and this is not always consistent. Exchange rate movements are affected by stock market indices and Bitcoin exchange values as investment in them reduces the purchasing power of the citizens and may require more demand for foreign currency, causing demand for currencies to fluctuate. The impact exists regardless of the state of the economy at a given time. Volatility is observed more when currency is devalued, confirming the erratic behaviors of investors towards dwindling currency value in the US dollars. Importing oil often leads to a negative impact on the current account balance of a country. Higher oil prices can lead to increased import costs, creating a trade deficit. This deficit can put downward pressure on the country's currency as it requires more foreign currency to pay for the imports.

The asymmetrical investor behavior in the exchange rate market can stem from concerns about the current account deficit and its impact on the overall economy. Oil imports can contribute to inflationary pressures in a country. Investor behavior in the exchange rate market can be influenced by expectations of changes in monetary policy and the impact on the country's currency. Countries that are profoundly reliant on oil exports are vulnerable to fluctuations in oil prices. When oil prices are high, these countries experience increased revenue, which can strengthen their currencies. Conversely, when oil prices decline, it can lead to reduced revenue and weaker currencies. This relationship, therefore, causes investors to target investments in cryptocurrency (Bitcoin, which transcends the economic situations of individual countries.

Stock returns were found to be positively correlated with Bitcoin trading returns. Cryptocurrency markets, which Bitcoin falls under, are known for their speculative nature. Investors and traders actively monitor both stock markets and cryptocurrency markets for opportunities to profit from short-term price movements, causing stock market fluctuations to influence trading strategies and trigger correlated trading actions in the Bitcoin market. Investors who participate in both stock markets and cryptocurrency markets may exhibit similar behavior patterns. For example, if there is a significant downturn in the stock market, some investors may decide to liquidate their holdings to reduce risk or cover losses. This selling pressure can spill over into the cryptocurrency market, causing similar downward pressure on Bitcoin prices and vice versa. Exchange rate returns were found to occur without significant interference with movements in the Bitcoin market. Bitcoin operates outside the traditional financial system and thus does not have a direct link to any local currency.

Currency fluctuations in traditional fiat currencies are influenced by a broader range of factors, such as geopolitical events and trade dynamics, rather than the Bitcoin markets, which are influenced by demand and supply dynamics as well as certain international news of large purchases by recognized individuals. The overall market size and trading volume of Bitcoin are relatively small compared to the global Forex market. The Forex market involves the massive exchange of currencies between countries, financial institutions, and corporations. Bitcoin's market, while growing, is still relatively niche in comparison. Therefore, the influence of Bitcoin on currency fluctuations is limited.

Returns on Bitcoin trading were not found to be a significant predictor of stock market returns. This is evidence that both markets operate on different principles and exhibit distinct market dynamics. The stock market represents ownership in publicly traded companies, while Bitcoin operates as a decentralized digital currency. The factors that drive stock market fluctuations, such as company earnings, economic indicators, and corporate news, are fundamentally different from those influencing Bitcoin, such as supply and demand dynamics, investor sentiment, and regulatory developments. The common characteristics of participants in each market differ. Participants in the stock market include institutional investors, individual investors, and fund managers who consider various factors such as company fundamentals, valuation metrics, and industry trends. In contrast, the Bitcoin market often attracts a diverse range of participants, from retail investors to crypto enthusiasts, speculators, and early adopters. The different participant profiles and investment approaches can contribute to the absence of a strong correlation between Bitcoin and stock market fluctuations. However, in a different state of the economy, stock market returns are observed to adjust to alterations in Bitcoin values, confirming instances of short-term correlations between Bitcoin and stock markets. In times of extreme volatility, institutional investors and hedge funds may resort to arbitrage opportunities or trading strategies that involve both Bitcoin and stocks. Changes in Bitcoin's price or market sentiment can influence these trading activities and potentially impact stock market fluctuations. Conclusively, the study's exclusive focus on 10 non-oil-exporting nations may limit how broadly the conclusions of this present study could be applied to other kinds of economies. Therefore, we suggest that this study be replicated in more countries and that the results be subjected to sensitivity analysis for alternative model specifications or daily data periods. Additionally, adding geopolitical events and legislative changes to the analysis could shed more light on how broadly applicable the results are. This can strengthen the robustness of the conclusions.

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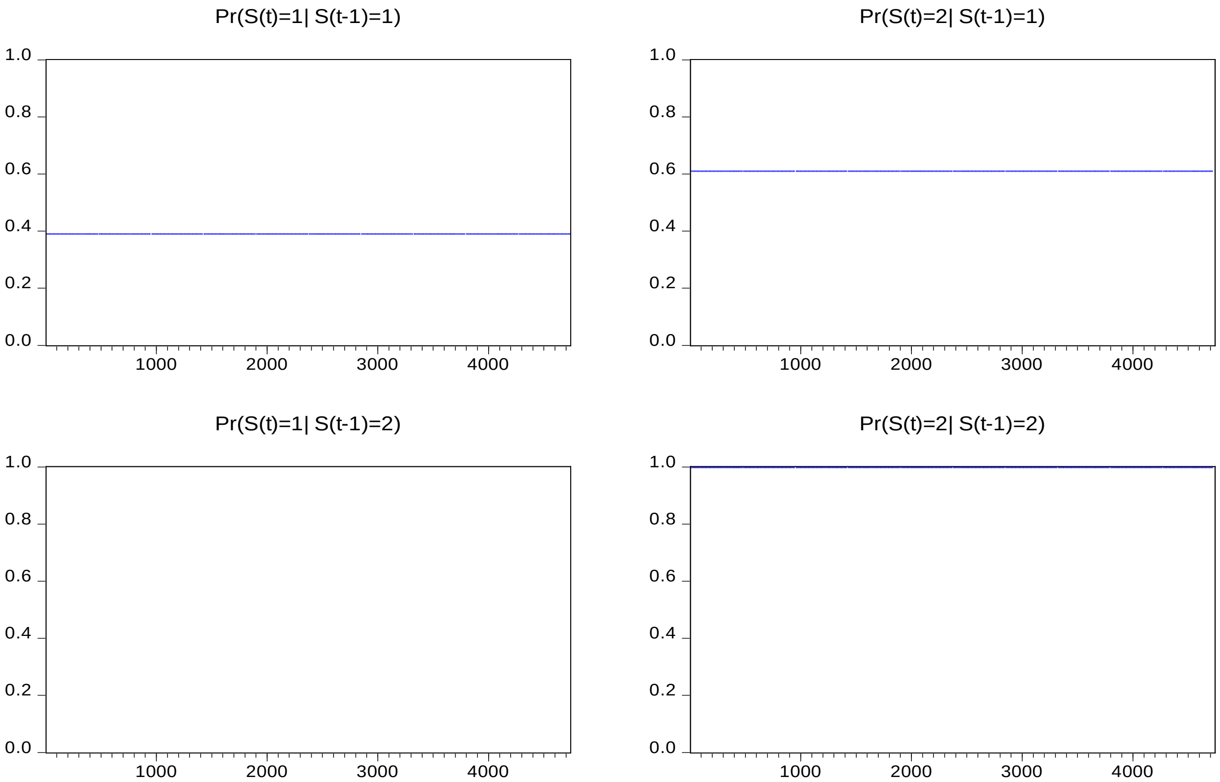
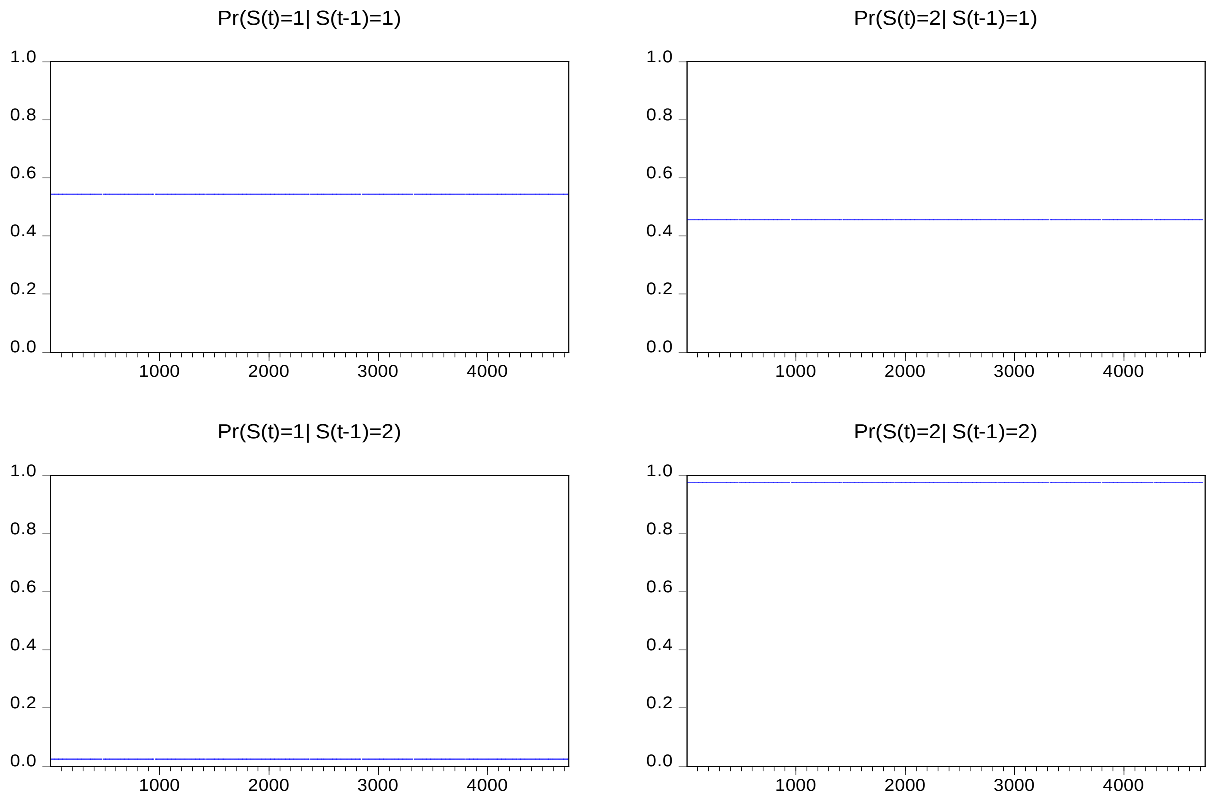
APPENDIX

Figure A.1. Transition probabilities of exchange rate returns



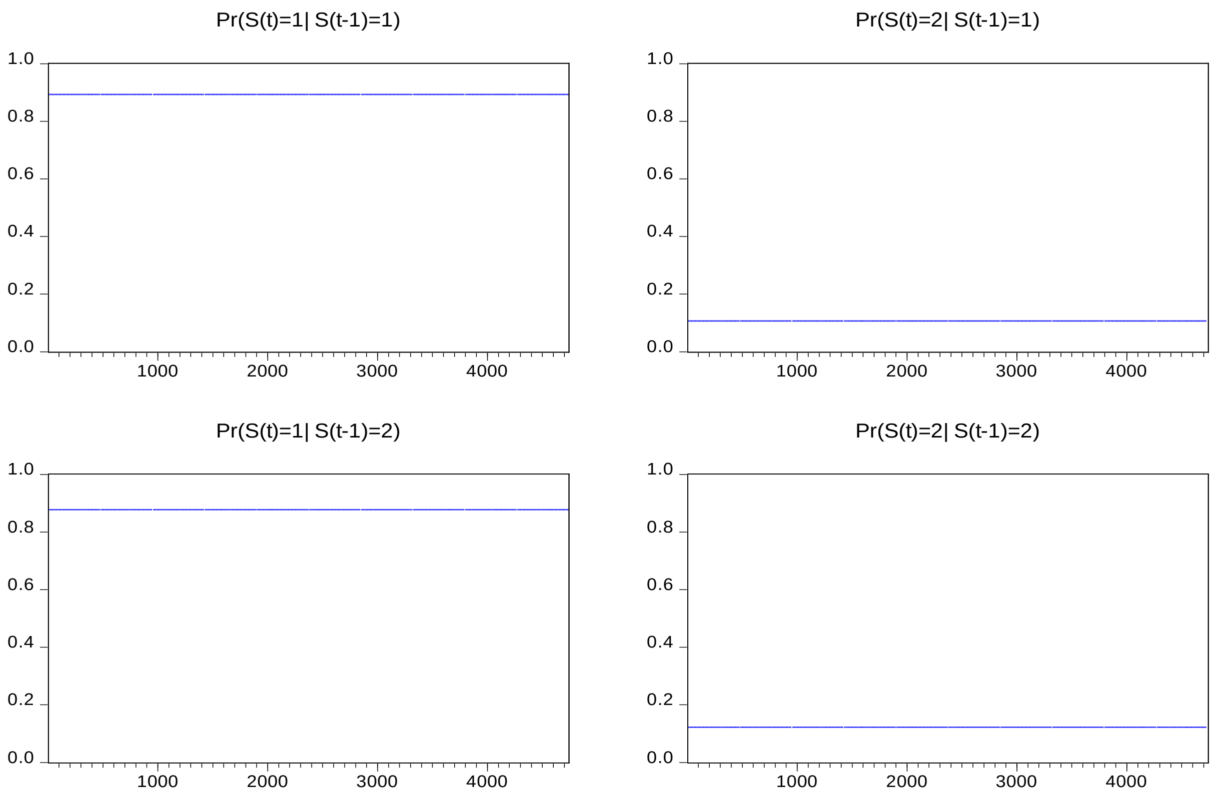
Source: Authors' elaboration using EViews 13.

Figure A.2. Transition probabilities of stock return



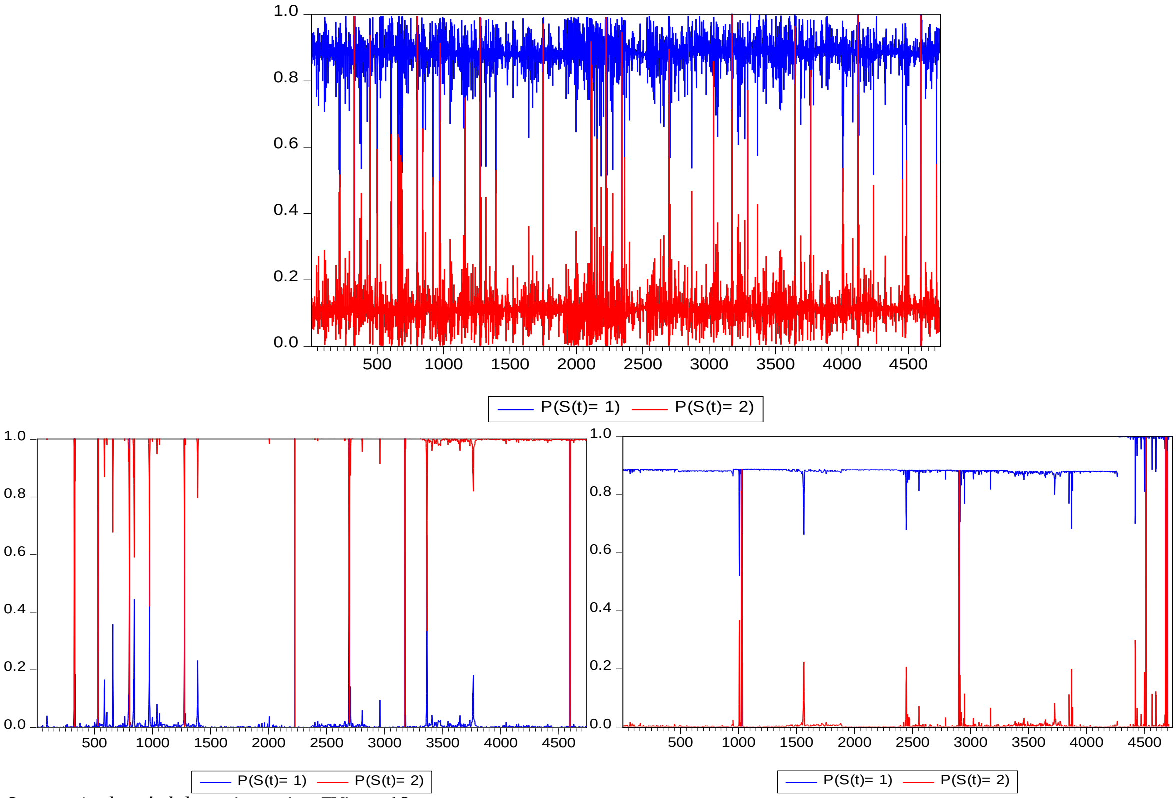
Source: Authors' elaboration using EViews 13.

Figure A.3. Transition probabilities of Bitcoin returns



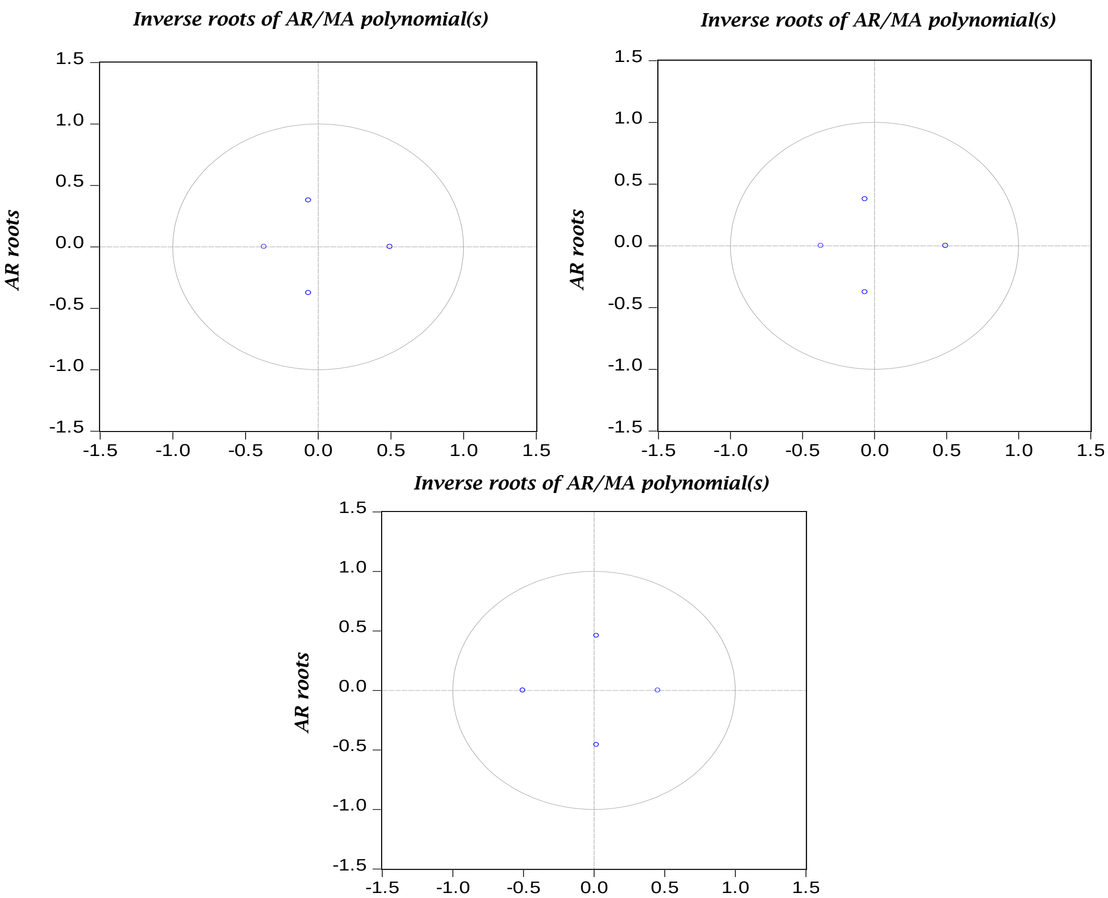
Source: Authors' elaboration using EViews 13.

Figure A.4. AR structure test for *RBTCR*, *REXR*, and *RSTR*-oil-importing countries



Source: Authors' elaboration using EViews 13.

Figure A.5. Stability plots of estimated equations for *RBTCR*, *REXR*, and *RSTR*



Source: Authors' elaboration using EViews 13.