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CAUSAL RELATIONSHIPS AMONG BITCOIN, ETHEREUM, AND THE STOCK AND FOREIGN EXCHANGE MARKETS OF BRICS-T COUNTRIES

BRICS-T ÜLKELERİNDEKİ HİSSE SENEDİ VE DÖVİZ PİYASALARI İLE BİTCOİN VE ETHEREUM ARASINDAKİ NEDENSEL İLİŞKİLER[1]

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ABSTRACT

This study investigates causality-in-variance relationships between crypto-assets (Bitcoin and Ethereum) and traditional financial assets (stock indices and exchange rates) in BRICS-T countries over the 2016–2024 period. The evidence points to low levels of interconnectedness. For the Bitcoin-based specifications, statistically significant causality is detected only from Bitcoin to the USD/CNY and USD/ZAR exchange rates, while no causal link is found in the other directions or pairs examined. By contrast, in the Ethereum-based models a bidirectional causal relationship is identified between Ethereum and the South African equity market, and unidirectional causality is found running from Ethereum to the Chinese equity market as well as to the USD/CNY and USD/ZAR exchange rates. Overall, these results indicate limited interaction between crypto-assets and conventional financial markets. The findings underscore the importance for investors of accounting for these weak cross-market linkages in decision-making processes; crypto-assets are no longer isolated instruments, and identifying their (selective) interactions with other financial assets is increasingly

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consequential.

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Bu çalışma, 2016–2024 dönemi için BRICS-T ülkelerinde kripto varlıklar (Bitcoin ve Ethereum) ile geleneksel finansal varlıklar (hisse senedi endeksleri ve döviz kurları) arasındaki Varyansta nedensellik ilişkilerini incelemektedir. Elde edilen bulgular, düşük seviyede bağlantılar bulunduğunu ortaya koymaktadır: Bitcoin ile oluşturulan modellerden elde edilen sonuçlara bakıldığında, yalnız Bitcoin'den USD/CNY ve USD/ZAR değişkenlerine doğru bir nedensellik olduğu tespit edilmiştir. Diğer modellerde herhangi bir nedensel bağlantının olmadığı tespit edilmiştir. Diğer taraftan, Ethereum modellerinde yalnız Güney Afrika hisse senedi piyasası ile Ethereum arasında karşılıklı bir nedensel ilişki tespit edilmiştir. Ayrıca Ethereum'dan Çin hisse senedi piyasasına, USD/CNY ve USD/ZAR döviz kuruna doğru bir nedensellik olduğu tespit edilmiştir. Bu sonuçlar, kripto varlıklar ile geleneksel finansal piyasalar arasında düşük düzeyde etkileşim olduğunu göstermektedir. Ulaşılan sonuçlar yatırımcıların karar alma süreçlerinde piyasa türleri arasındaki düşük seviye etkileşimleri dikkate almalarının önemini vurgulamaktadır. Kripto varlıklar artık izole yapılar olmaktan çıkmış, diğer finansal araçlarla aralarındaki etkileşimin tespiti giderek daha önemli hale gelmeye devam etmektedir.

1. INTRODUCTION

With the acceleration of globalisation, digitalisation and worldwide economic integration, interactions among financial assets have intensified. The economic uncertainties triggered by the global financial crisis—first felt in the United States in November 2008 and later transmitted to the financial markets and economies of both developed and emerging countries—provided fertile ground for the emergence of crypto-assets (Norman, 2017; Toplu, 2021). Following the introduction in 2008 of Bitcoin—the first crypto-asset based on blockchain technology—by the pseudonymous Satoshi Nakamoto, a multitude of alternative crypto-assets have been launched (Bouri, Gupta, Tiwari, & Roubaud, 2017).

Although crypto-assets were originally designed as alternative means of payment, they have increasingly been adopted primarily as investment instruments (Blau, 2017; Baur, Hong, & Lee, 2018; Corbet, Lucey, Urquhart, & Yarovaya, 2019). Traditional fiat currencies perform three core functions—serving as a medium of exchange, a unit of account and a store of value. Crypto-assets, by contrast, do not fully embody all of these characteristics. While divisibility, portability and suitability for exchange bring them closer to the concept of money, their issuance outside central banks, lack of a comprehensive legal framework, limited acceptance as legal tender and inability to preserve value over long periods set them apart from conventional money. Hence, in legal terms crypto-assets are presently regarded not as money but as assets (Abramowicz, 2016). Consistent with this view, empirical studies by Glaser, Zimmermann, Haferkorn, Weber, and Siering (2014) and by Gümüş and Erkuş (2019) also emphasise that crypto-currencies do not possess all the essential attributes of money and are instead treated by investors chiefly as speculative investment vehicles.

Crypto-assets confer several advantages on their users. Foremost among these is the presence of a strictly capped supply—21 million units in the case of Bitcoin—generated by predefined algorithms operating under transparent rules. Such a structure renders crypto-assets relatively immune to inflationary pressures and, by extension, potentially more effective than traditional currencies in limiting inflation (Güleç et al., 2018). In addition, the financial autonomy they afford has heightened investor interest: holders can manage their funds and execute transactions without recourse to third-party intermediaries or a central authority, thereby fostering a sense of independence and control (Brand, 2016). Because crypto-assets are accessible wherever an internet

connection exists, operate around the clock, rely on decentralised networks, and eliminate intermediary fees, transactions can be completed rapidly and at minimal cost (Yanar et al., 2021).

Notwithstanding these benefits, crypto-assets also entail notable drawbacks. The displacement of central banks' monopoly over money creation can erode the effectiveness of monetary policy, disrupt established tax regimes, and—given the absence of a responsible authority—expose individuals to significant losses in the event of theft or operational failure. Furthermore, the inherent difficulty of managing aggregate liquidity could, in principle, foster an inflationary environment. Finally, the anonymity embedded in most crypto-asset protocols complicates efforts to curb illicit activities such as money laundering and the financing of terrorism, risks that are repeatedly underscored in the literature (Demir, 2021; Karyağdı & Yolci, 2023).

The value of crypto-assets is not directly tied to any sovereign fiat currency; rather, it is shaped largely by the level of demand expressed by investors (İçellioğlu & Öztürk, 2018). Since its inception, Bitcoin's growing recognition and widespread acceptance have enabled its use in diverse transactions for goods and services, while simultaneously attracting substantial investor interest. Consequently, marked increases in Bitcoin's market capitalisation have been observed over time. The price surges in Bitcoin, in particular, have further channelled investors' attention toward the broader crypto-asset market in pursuit of higher returns (Öztürk at al., 2018; Ilgın, 2025).

The heightened interest in crypto-assets underscores the need for investors and portfolio managers to analyse how these instruments interact with traditional financial assets and to formulate portfolio-construction strategies accordingly. Modern portfolio theory holds that incorporating assets displaying negative correlations is crucial for risk diversification. Recent turbulence in global financial markets has made it increasingly challenging for investors to assemble rational, high-return portfolios. In this context, every empirical contribution is expected to offer valuable guidance to market participants. Moreover, studies covering a large number of countries are likely to appeal to a broader investor base. The BRICS bloc—recently enlarged through the admission of new members—occupies a strategically important position in the international financial system owing to its substantial and growing weight in the world economy. Nevertheless, empirical research examining the interaction between crypto-assets and traditional financial assets in BRICS economies remains limited, suggesting that additional country-specific evidence would enrich the extant literature.

Against this backdrop, the present study investigates causal relationships between crypto-assets and conventional financial assets within the BRICS-T context (Brazil, Russia, India, China, South Africa, and Türkiye). To represent the crypto-asset market, Bitcoin and Ethereum—the two largest assets by trading volume—are included in the analysis. For each country, the leading stock-market index and the domestic currency's bilateral exchange rate against the US dollar constitute the primary traditional financial variables. The sample period spans March 2016 to August 2024. Owing to the distinct dynamics of each national financial market, separate data sets are constructed for every country; crypto-asset data are harmonised with their conventional counterparts, and individual VAR models are estimated for each economy.

The remainder of the paper is organised as follows. Section 2 reviews the literature on causal linkages between crypto-assets and traditional financial instruments. Section 3 describes the data and methodology, while Section 4 presents the empirical findings. The paper concludes with Section 5, which discusses the results and offers policy implications.

2. LITERATURE REVIEW

Owing to the sudden, large-scale fluctuations observed in their prices, the high return potential commensurate with their elevated risk, and their still imperfectly understood and hence largely unpredictable nature, crypto-assets have attracted considerable scholarly attention. A significant strand of this literature explores whether and how crypto-assets are linked to, or interact with, traditional financial assets in terms of prices and/or returns. Numerous studies document economically meaningful connections between crypto-assets and a variety of conventional asset classes. For example, statistically significant interactions have been reported between crypto-assets and foreign-exchange rates (Corelli, 2018), futures markets (Bouri et al., 2018; Ji, Bouri et al., 2019; Rehman & Apergis, 2019; Elsayed et al., 2020; Jiang et al., 2022), as well as equity markets

(Kurka, 2019) Collectively, these studies provide important insights into the dynamic relationships between crypto-assets and traditional financial markets.

Researchers have examined such linkages using a variety of empirical techniques, including vector-autoregressive (VAR) models, ARCH/GARCH-type specifications (e.g., Corbet et al., 2017; Bouri et al., 2017; Klashorst, 2018; Klein et al., 2018; Malhotra & Gupta, 2019; Elsayed et al., 2022; Gökalp, 2022; Ustaoğlu, 2022; Mensi et al., 2023) and various causality tests, such as Granger, Hatemi-J, and Toda–Yamamoto procedures. Below, selected studies that employ causality analysis to investigate the relationships between crypto-assets and traditional assets, exchange rates, or commodities (e.g., gold, oil) are summarised.

Ağan and Aydın (2018), analyse the asymmetric causal relations between Bitcoin and selected cross-currency exchange rates using the Hatemi-J (2012) methodology. Their findings indicate one-way shock transmission from Bitcoin to the yen, yuan, Canadian dollar, and US dollar pairs, whereas no causal linkage is detected between Bitcoin and either the euro or the pound sterling. İçellioğlu and Öztürk (2018) employ the Engle–Granger–Johansen cointegration framework alongside Granger causality tests to explore the interplay between Bitcoin and five major exchange rates (US dollar, euro, yen, sterling, and yuan). They report no evidence of either long-run or short-run relationships between Bitcoin and any of the currencies considered. Topaloğlu (2018) examines the Bitcoin–exchange-rate nexus by applying Gregory and Hansen's cointegration test with structural breaks and subsequent Granger causality analysis; the study uncovers a one-way positive causal effect running from the CNY/USD rate to the BTC/USD rate.

Estrada (2017) investigates the link between Bitcoin and the S&P 500 Index by means of Granger-causality tests over the 2010–2017 period and finds no evidence of causality in either direction. Erdaş and Çağlar (2018) analyse asymmetric causal relations between Bitcoin prices and gold, Brent crude oil, the US dollar, the S&P 500, and the BIST 100 by employing the Hatemi-J (2012) procedure with weekly data from November 2013 to July 2018. Their results reveal a one-way causal flow from Bitcoin prices to the S&P 500, while no causal connections emerge between Bitcoin and the other variables considered. Ahmed et al. (2023) explore causality between selected crypto-assets (Bitcoin, Ethereum, Ripple, Binance Coin, and Tether) and S&P 500 returns for the period January 2018–December 2021. Using the Granger framework, they provide empirical evidence of bidirectional causality between the S&P 500 and crypto-asset returns. Huang (2024) employs daily data spanning 1 February 2018 to 31 August 2023 to test Granger-causal relationships between crypto-assets (Bitcoin, Ethereum, Tether, Binance Coin, Cardano, and exchange-based tokens) and a set of traditional assets (gold, crude oil, the S&P 500, the 10-year US Treasury yield, and the S&P GSCI). The findings indicate that both symmetric and asymmetric causal linkages between conventional financial markets and crypto-assets are cyclical in nature and matter only in the short run.

Güleç et al. (2018) analyse the linkages between Bitcoin and a set of traditional markets—foreign exchange, equities, commodities, and interest rates—by applying Johansen cointegration and Granger-causality techniques; their results reveal statistically significant causal interactions between Bitcoin and all of the conventional asset classes considered. By contrast, Kaymak and Koç (2022) investigate the relationship between Bitcoin trading volumes and transactions on Borsa Istanbul (BIST) over the 2017–2021 period using the Toda–Yamamoto procedure and detect no evidence of causality in either direction. Gkillas et al. (2020), employing data from 2 December 2014 to 10 June 2018, test for Granger causality among Bitcoin, gold, and crude-oil markets and find that the ties between gold and crude oil and those between Bitcoin and crude oil are appreciably weaker than the Bitcoin–gold nexus. Aldı, Küçükkaplan, and Şahin (2025) examine ten crypto-assets in conjunction with West Texas Intermediate (WTI) crude-oil returns, using both Granger and Toda–Yamamoto tests; their evidence points to a negative bidirectional causal link between WTI and Ethereum (ETH) in the Granger framework and, likewise, between WTI and Filecoin (FIL) when the Toda–Yamamoto approach is employed.

Taken together, the extant literature has concentrated predominantly on Bitcoin, the most liquid crypto-asset, and reports mixed evidence on causal linkages between crypto-assets and traditional markets—findings

that vary with the choice of variables, countries, and sample periods. By focusing on Bitcoin and Ethereum vis-à-vis the stock and foreign-exchange markets of the BRICS-T economies, the present study addresses a gap yet to be explored in earlier research. The ensuing results are therefore expected to contribute to the empirical literature and furnish useful insights for market participants operating in these strategically important jurisdictions.

3. METHODOLOGY AND DATA

3.1. Method

In examining the estimated models, we draw on the causality-in-variance approach proposed by Hafner and Herwartz (2006). This approach is a GARCH-based procedure that tests for volatility transmission. The null hypothesis (H_0) states that there is no causality in variance between the two return series, whereas the alternative hypothesis posits the presence of causality in variance. The null hypothesis as formulated by Hafner and Herwartz (2006) is presented in the following equation.

$$H_0 : Var(\varepsilon_{it} \left| F_{t-1}^{(j)} \right.) = Var(\varepsilon_{it} \left| F_{t-1} \right.) \qquad j = 1, ..., N, i \neq j \tag{1}$$

In this specification $F_t^{(j)} = F_{t\backslash\sigma}(\varepsilon_{it}\tau \leq t)$ and ε_{it} denotes the residuals of the GARCH model.

$$\varepsilon_{it} = \xi_{it}\sqrt{\sigma_{it}^2 g_t}, g_t = 1 + z_{jt}^{'}\pi, z_{jt} = (\varepsilon_{jt-1}^2, \sigma_{jt-1}^2)' \tag{2}$$

In equation (2), the conditional variance is $\sigma_{it}^2 = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2$ and ξ_{it} denotes the standardized innovations of the GARCH model. In this specification, $\pi = 0$, corresponds to the null hypothesis of no causality in variance $(H_0 \pi = 0)$ against the alternative $(H_1 : \pi \neq 0)$. The score of the Gaussian log-likelihood for ε_{it} is given by $x_{it} = \sigma_{it}^{-2}(\partial\sigma_{it}^2 / \partial 0_i)$ and $0_i = (\omega_i, \alpha_i, \beta_i)$ by taking the derivative $x_{it}(\xi_{it}^2 - 1)/2$ is given by. Hafner and Herwartz (2006) therefore propose an LM test to assess volatility transmission between the two series.

$$\lambda_{LM} = \frac{1}{4T}(\sum_{t=1}^{T}(\xi_{it}^2 - 1)Z_{jt}^{'})v(0_i)^{-1}(\sum_{t=1}^{T}(\xi_{it}^2 - 1)Z_{jt}) \tag{3}$$

$$V(0_i) = \frac{K}{4T}(\sum_{t=1}^{T} Z_{jt}Z_{jt}^{'} - \sum_{t=1}^{T} Z_{jt}X_{it}^{'}(\sum_{t-1}^{T} X_{it}X_{it}^{'})^{-1}\sum_{t=1}^{T} X_{it}Z_{jt}^{'}), K = \frac{1}{T}\sum_{t=1}^{T}(\xi_{it}^2 - 1)^2 \tag{4}$$

The asymptotic distribution of the test statistic in Equation 4 is determined by the number of misspecification indicators in Z_{jt}. Since λ_{LM} includes two such indicators, the test is asymptotically chi-square distributed with two degrees of freedom.

3.1. Data

The purpose of this study is to investigate, within the BRICS-T context, the causal relationships between Bitcoin and Ethereum, on the one hand, and each country's leading stock-market index and the bilateral exchange rate of its national currency against the U.S. dollar, on the other. The variables employed for that purpose are listed in Table 1.

Table 1: Research Variables

Category	Variable	Abbreviation/Code Used in the Analysis
Crypto-assets	Bitcoin	BTC
	Ethereum	ETH
Stock indices	Brazil – Bovespa	BR-PP
	Russia – RTSI	RU-PP
	India – NIFTY 50	IN-PP
	China – Shanghai Composite	CN-PP
	South Africa – JSE Top 40	ZA-PP
	Türkiye – BIST 100	TR-PP
Exchange rates (against USD)	Brazil – USD/BRL	USD/BRL
	Russia – USD/RUB	USD/RUB
	India – USD/INR	USD/INR
	China – USD/CNY	USD/CNY
	South Africa – USD/ZAR	USD/ZAR
	Türkiye – USD/TRY	USD/TRY

Note: The suffix "PP" denotes stock-market (equity) variables.

Although Bitcoin—the first crypto-asset—was introduced in 2009, pronounced price dynamics did not emerge until March 2016. Ethereum, the second major crypto-asset, attained widespread recognition and corresponding price movements within an even shorter horizon. To maintain temporal comparability between the two assets, the sample period therefore commences on 10 March 2016 and extends through 30 August 2024. This study was conducted to examine the causality relationship between the aforementioned crypto-assets and traditional financial assets for the specified time period, based on the volatility spillover analysis carried out by Hitay Sarp (2025).

Daily closing prices for all variables were downloaded from Investing.com (https://tr.investing.com). Separate data sets were compiled for each model, taking into account the specific pairing of the crypto-assets with national stock-market indices and exchange rates. All estimations were performed with EViews and RATS software.

To mitigate potential non-stationarity issues inherent in price series, all variables were transformed into logarithmic returns. The return series were generated according to the following expression.

$$r_t = \left[\ln(p_t) - \ln(p_{t-1})\right] \times 100 \tag{5}$$

In the expression, rt denotes the return at time t, while pt and p_{t-1} represent the closing prices of the variable at times t and t−1, respectively.

Figure 1 and 2 reports the return plots for all series examined in the study. These graphs provide a holistic view of how the return levels evolve over time, allowing both the identification of underlying trend behaviour and the visual detection of extreme movements that occur during specific sub-periods.

A visual inspection of the return plots reveals a pronounced bout of volatility at the beginning of 2020, which can be attributed to the global impact of the COVID-19 pandemic on financial markets. In addition, country-specific economic developments appear to have influenced the series. Notable examples include the effects of the Russia-Ukraine war, which began in 2022 and weighed on Russian financial markets, and the 2018 foreign-exchange crisis in Türkiye, both of which manifest as sharp movements in the graphs.

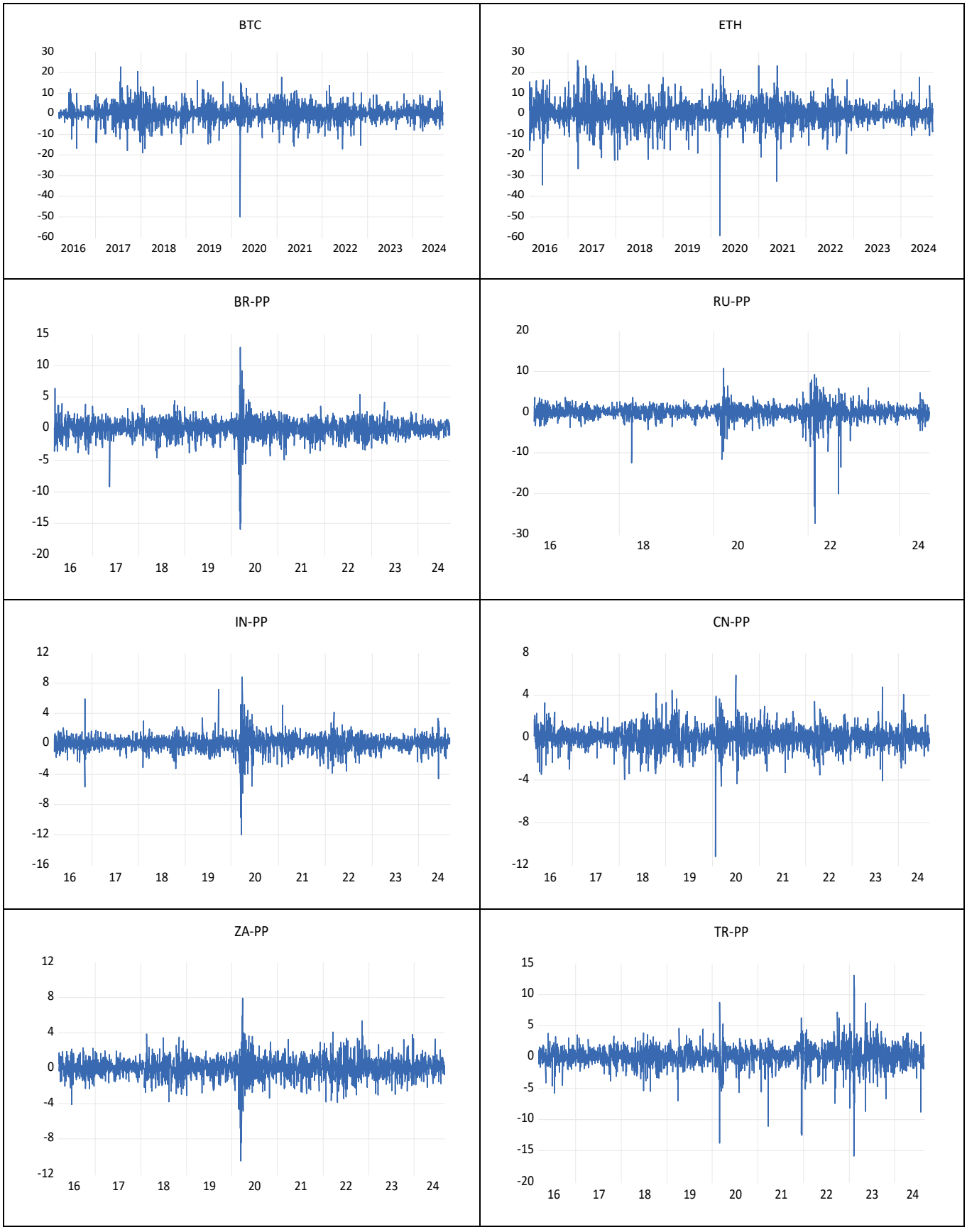

Figure 1 (part-1): Return Series Plots for the Variables

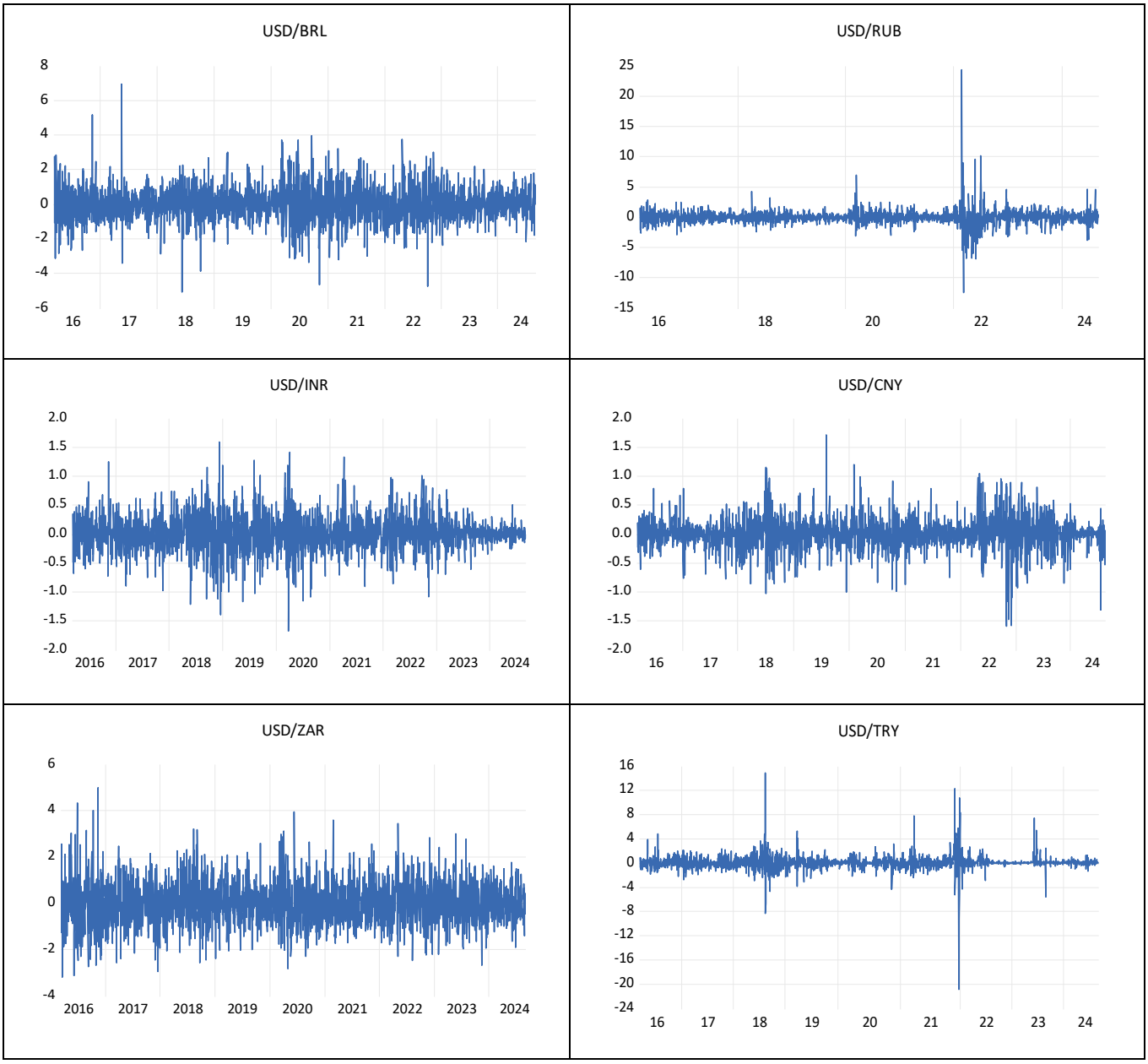

Figure 2 (part-2): Return Series Plots for the Variables

To eliminate potential asynchronicity arising from differences in each country's public holidays, commemorative days, and seasonal timing effects, every variable was processed as a separate data set, and the crypto-asset series were realigned to match the frequency and calendar of the remaining variables. On this basis, 24 distinct models were specified to capture the interactions between dependent and independent variables and to enhance the empirical performance of the analysis. For instance, the linkage between Bitcoin and Brazil's equity market (the Bovespa Index) is designated "Model 1", whereas the relationship between Bitcoin and Russia's equity market (the RTSI Index) is denoted "Model 2".

Table 2 and 3 reports the descriptive statistics for each of the specified models. When the models are

evaluated collectively, crypto-assets are found to exhibit a higher level of risk than the corresponding benchmark variables. This is confirmed by the fact that, in every model, the standard-deviation values associated with the crypto-assets exceed those of the comparative series. Moreover, the Jarque–Bera test statistics indicate that the normality assumption is violated, implying that the probability distributions of the data sets display deviations from symmetry and differences in kurtosis.

Table 2: Descriptive Statistics (Bitcoin Models)

MODEL	VARIABLE	Mean	Max.	Min.	Std. Dev.	JB	Prob.	Obs.
1	BTC	0.23	22.76	-49.95	4.51	9962.23	0.00	2105
	BR-PP	0.04	12.83	-15.86	1.52	28147.36	0.00	2105
2	BTC	0.23	22.76	-49.95	4.47	10723.26	0.00	2120
	RU-PP	0.01	10.78	-27.21	1.96	122452.10	0.00	2120
3	BTC	0.24	22.76	-49.95	4.51	10494.46	0.00	2098
	IN-PP	0.06	8.85	-11.97	1.09	22371.83	0.00	2098
4	BTC	0.24	22.76	-49.95	4.54	9698.03	0.00	2063
	CN-PP	0.00	5.88	-11.18	1.06	5448.97	0.00	2063
5	BTC	0.23	22.76	-49.95	4.49	10109.07	0.00	2116
	ZA-PP	0.02	7.91	-10.45	1.19	4382.86	0.00	2116
6	BTC	0.23	22.76	-49.95	4.46	11149.21	0.00	2122
	TR-PP	0.12	13.04	-15.83	1.75	12895.67	0.00	2122
7	BTC	0.22	22.76	-49.95	4.40	11491.25	0.00	2206
	USD/BRL	0.02	6.93	-5.07	1.00	651.50	0.00	2206
8	BTC	0.23	22.76	-49.95	4.45	10830.46	0.00	2148
	UAS/RUB	0.01	24.30	-12.46	1.26	514557.60	0.00	2148
9	BTC	0.22	22.76	-49.95	4.39	11573.98	0.00	2211
	USD/INR	0.01	1.59	-1.68	0.31	534.72	0.00	2211
10	BTC	0.23	22.76	-49.95	4.42	11157.08	0.00	2194
	USD/CNY	0.00	1.71	-1.59	0.27	1613.81	0.00	2194
11	BTC	0.22	22.76	-49.95	4.39	11573.98	0.00	2211
	USD/ZAR	0.01	4.99	-3.20	0.97	111.52	0.00	2211
12	BTC	0.21	22.76	-49.95	4.30	12905.29	0.00	2310
	USD/TRY	0.11	14.90	-20.83	1.18	487021.00	0.00	2310

Table 3: Descriptive Statistics (Ethereum Models)

MODEL	VARIABLE	Mean	Max.	Min.	Std. Dev.	JB	Prob.	Obs.
13	ETH	0.26	39.25	-58.99	6.28	5671.14	0.00	2105
	BR-PP	0.05	12.83	-15.86	1.53	28147.36	0.00	2105
14	ETH	0.25	39.25	-58.99	6.25	6081.93	0.00	2120
	RU-PP	0.01	10.79	-27.22	1.96	122452.10	0.00	2120
15	ETH	0.26	40.16	-58.99	6.27	6348.88	0.00	2098
	IN-PP	0.06	8.85	-11.97	1.09	22371.83	0.00	2098
16	ETH	0.26	39.25	-58.99	6.36	5447.16	0.00	2063
	CN-PP	0.00	5.88	-11.18	1.06	5448.97	0.00	2063
17	ETH	0.25	39.25	-58.99	6.24	5703.00	0.00	2116
	ZA-PP	0.02	7.91	-10.45	1.19	4382.86	0.00	2116
18	ETH	0.25	45.18	-58.99	6.21	7575.76	0.00	2122
	TR-PP	0.12	13.04	-15.83	1.75	12895.67	0.00	2122
9	ETH	0.24	39.25	-58.99	6.13	6714.49	0.00	2206
	USD/BRL	0.02	6.93	-5.07	1.01	651.5037	0.00	2206
20	ETH	0.25	39.25	-58.99	6.20	6275.42	0.00	2148
	USD/RUB	0.01	24.30	-12.46	1.26	514557.60	0.00	2148
21	ETH	0.24	39.25	-58.99	6.12	6766.01	0.00	2211
	USD/INR	0.01	1.59	-1.68	0.31	534.72	0.00	2211
22	ETH	0.24	39.25	-58.99	6.16	6523.54	0.00	2194
	USD/CNY	0.00	1.71	-1.59	0.27	1613.81	0.00	2194
23	ETH	0.24	39.25	-58.99	6.12	6766.01	0.00	2211

	USD/ZAR	0.01	4.99	-3.20	0.97	111.52	0.00	2211
24	ETH	0.23	39.25	-58.99	5.98	7309.91	0.00	2310
	USD/TRY	0.11	14.90	-20.83	1.18	486968.10	0.00	2310

4. RESULTS

Establishing the stationarity of the series employed in this study i.e., verifying the absence of unit roots is essential for generating reliable results and avoiding spurious regressions. Accordingly, unit-root tests were carried out prior to the empirical analysis; if a series were found to contain a unit root, differencing would be required to achieve stationarity. To assess unit-root properties, the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests, both widely used in the literature, were applied. Lag lengths were selected using the Schwarz information criterion (SIC).

As shown in Table 4, the ADF and PP test statistics computed under models with an intercept, with an intercept and trend, and without either yield probability values below 0.05 for all series. These results indicate that the return series are level-stationary, i.e., they are integrated of order zero, I(0).

Table 4: Unit-Root Test Results

BITCOIN MODELS		**ADF**	**PP**	**ETHEREUM MODELS**		**ADF**	**PP**
MODEL	**VARIABLE**	**With Intercept & Trend**	**With Intercept & Trend**	**MODEL**	**VARIABLE**	**With Intercept & Trend**	**With Intercept & Trend**
1	BTC	-47.5358*	-47.5227*	13	ETH	-46.4118*	-46.4725*
	BR-PP	-16.1435*	-51.4922*		BR-PP	-16.1435*	-51.4922*
2	BTC	-47.1124*	-47.1156*	14	ETH	-46.5892*	-46.6198*
	RU-PP	-23.6276*	-45.3287*		RU-PP	-23.6276*	-45.3287*
3	BTC	-47.0118*	-46.9994*	15	ETH	-45.7527*	-45.7731*
	IN-PP	-49.2109*	-49.1713*		IN-PP	-49.2109*	-49.1713*
4	BTC	-46.4222*	-46.4634*	16	ETH	-46.1591*	-46.1694*
	CN-PP	-47.2471*	-47.3704*		CN-PP	-47.2471*	-47.3704*
5	BTC	-47.5120*	-47.5139*	17	ETH	-46.5530*	-46.6200*
	ZA-PP	-46.2421*	-46.2415*		ZA-PP	-46.2421*	-46.2415*
6	BTC	-47.0056*	-47.0370*	18	ETH	-45.9331*	-46.0011*
	TR-PP	-49.4157*	-49.3728*		TR-PP	-49.4157*	-49.3728*
7	BTC	-48.3176*	-48.3129*	19	ETH	-47.5263*	-47.5594*
	USD/BRL	-50.0814*	-50.2087*		USD/BRL	-50.0814*	-50.2087*
8	BTC	-47.3713*	-47.3727*	20	ETH	-46.8456*	-46.8772*
	UAS/RUB	-15.4655*	-45.8015*		USD/RUB	-15.4655*	-45.8015*
9	BTC	-48.3552*	-48.3509*	21	ETH	-47.5638*	-47.5968*
	USD/INR	-36.0936*	-47.5068*		USD/INR	-36.0936*	-47.5068*
10	BTC	-48.2307*	-48.2340*	22	ETH	-47.3510*	-47.3847*
	USD/CNY	-48.1133*	-48.2020*		USD/CNY	-48.1133*	-48.2020*
11	BTC	-48.3552*	-48.3509*	23	ETH	-47.5638*	-47.5968*
	USD/ZAR	-46.1504*	-46.1432*		USD/ZAR	-46.1504*	-46.1432*
12	BTC	-49.3630*	-49.4251*	24	ETH	-48.2935*	-48.3884*
	USD/TRY	-34.0904*	-43.0788*		USD/TRY	-34.0893*	-43.0802*

* represents 1% significance level.

In order to test whether the error terms obtained from the models exhibit autocorrelation, the Ljung-Box Q test was applied. This test is used to evaluate the reliability of time series models by determining whether the error terms satisfy the white noise assumption. Table 5 presents the Ljung-Box Q statistics for lag levels 1, 5,

10, and 20. The results indicate that the error terms in all models are free from autocorrelation. On the other hand, to examine whether there is a heteroskedasticity problem in the models, the ARCH-LM test and the White heteroskedasticity test were employed. The analysis results reveal that there is a significant presence of heteroskedasticity in all models. These findings indicate that the variance exhibits time-varying characteristics during the modeling process, which may affect forecast accuracy. Therefore, it is recommended that future studies employ models such as GARCH, which are capable of capturing time-varying volatility, in order to enhance the statistical validity of the results.

Tablo 5: Diagnostic Tests

Model	Q(1)	Q(5)	Q(10)	Q(20)	White Test	ARCH-LM
BTC-USD/BRL	2.1033	7.1812	10.6770	22.6220	2.6272	14.9812
	(0.1470)	(0.2080)	(0.3830)	(0.3080)	(0.0725)	(0.0001)
BTC-USD/RUB	0.6813	9.8991	17.7800	33.7960	1.4842	6.6204
	(0.4090)	(0.0780)	(0.0590)	(0.1280)	(0.2269)	(0.0000)
BTC-USD/INR	1.5516	6.6578	10.9080	23.1570	3.8674	5.6309
	(0.2130)	(0.2470)	(0.3650)	(0.2810)	(0.0211)	(0.0000)
BTC-USD/CNY	1.3441	6.0246	10.2290	23.4640	14.7273	12.4850
	(0.2460)	(0.3040)	(0.4210)	(0.2670)	(0.0000)	(0.0004)
BTC-USD/ZAR	1.2763	6.3908	11.3740	23.7490	5.0443	11.8790
	(0.2590)	(0.2700)	(0.3290)	(0.2540)	(0.0065)	(0.0006)
BTC-USD/TRY	2.0488	6.1080	25.9250	40.6690	0.7679	7.8783
	(0.1520)	(0.2960)	(0.1040)	(0.1140)	(0.4641)	(0.0004)
ETH-USD/BRL	0.3520	4.1680	9.2477	19.2640	9.5251	36.3740
	(0.5530)	(0.5250)	(0.5090)	(0.5050)	(0.0001)	(0.0000)
ETH-USD/RUB	0.1563	6.3134	15.1780	30.7390	1.2962	11.8609
	(0.6930)	(0.2770)	(0.1260)	(0.0590)	(0.2738)	(0.0000)
ETH-USD/INR	0.3015	3.2116	8.2066	17.3580	1.4847	10.3697
	(0.5830)	(0.6670)	(0.6090)	(0.6300)	(0.2268)	(0.0000)
ETH-USD/CNY	0.2481	3.3945	8.2725	16.4760	6.3027	34.8657
	(0.6180)	(0.6390)	(0.6020)	(0.6870)	(0.0019)	(0.0000)
ETH-USD/ZAR	0.0888	3.1641	9.7065	19.0240	1.7787	33.8390
	(0.7660)	(0.6750)	(0.4670)	(0.5200)	(0.1691)	(0.0000)
ETH-USD/TRY	0.1452	8.9278	15.9220	28.2860	0.0361	18.1181
	(0.7030)	(0.1120)	(0.1020)	(0.1030)	(0.9645)	(0.0000)

According to the ARCH–LM test results, the models exhibit time-varying variance (conditional heteroskedasticity). Accordingly, the series were deemed suitable for ARCH-type specifications, and the Hafner and Herwartz (2006) framework—which models volatility within causality-in-variance tests—was implemented. First, the ARMA structures of the mean equations were determined using the AIC criterion, and the corresponding maximum lag lengths were incorporated into the models. The lag lengths for each specification are reported as degrees of freedom (df) in Tables 6 and 7. Furthermore, the model was estimated under a Student-t error distribution. For the Bitcoin-based models, the results of the Hafner and Herwartz (2006) procedure are presented in Table 6.

Tablo 6: Causality in VarianceTest Results for Bitcoin Models

Dependent >> Independent	LM Statistic	df	Prob.	Evaluation
BTC >> BR	0.542501	1	0.4614	No Causality Relationship.
BR >> BTC	0.012214	1	0.9120	No Causality Relationship.
BTC >> RU	0.418204	1	0.5178	No Causality Relationship.
RU >> BTC	0.283284	1	0.5946	No Causality Relationship.
BTC >> IN	0.138901	1	0.7094	No Causality Relationship.
IN >> BTC	0.019957	1	0.8877	No Causality Relationship.
BTC >> CN	0.173545	1	0.6770	No Causality Relationship.
CN >> BTC	0.519300	1	0.4711	No Causality Relationship.

BTC >> ZA	0.058327	1	0.8092	No Causality Relationship.
ZA >> BTC	0.331925	1	0.5645	No Causality Relationship.
BTC >> TR	0.734727	1	0.3914	No Causality Relationship.
TR >> BTC	0.398209	1	0.5280	No Causality Relationship.
BTC >> USD/BRL	0.181222	1	0.6703	No Causality Relationship.
USD/BRL >> BTC	0.014029	1	0.9057	No Causality Relationship.
BTC >> USD/RUB	0.212282	1	0.6450	No Causality Relationship.
USD/RUB >> BTC	0.060140	1	0.8063	No Causality Relationship.
BTC >> USD/INR	0.194794	1	0.6590	No Causality Relationship.
USD/INR >> BTC	0.043000	1	0.8357	No Causality Relationship.
BTC >> USD/CNY	0.564822	1	0.4523	No Causality Relationship.
USD/CNY >> BTC	**38.27407**	**1**	**0.0000*** **	**Causality Relationship Exists.**
BTC >> USD/ZAR	1.391478	2	0.4987	No Causality Relationship.
USD/ZAR >> BTC	**15.01927**	**2**	**0.0005*** **	**Causality Relationship Exists.**
BTC >> USD/TRY	0.149743	1	0.6988	No Causality Relationship.
USD/TRY >> BTC	0.013062	1	0.9090	No Causality Relationship.

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

According to the results reported in Table 6, the causality-in-variance (LM–Wald) tests indicate—within the analyzed sample and the GARCH-based auxiliary-regression framework—that Bitcoin's conditional variance is not statistically significantly affected by the volatility of most BRICS-T equity indices (BR, RU, IN, CN, ZA, TR) or by the majority of the exchange-rate pairs examined, including USD/BRL, USD/RUB, USD/INR, and USD/TRY. By contrast, significant causality is detected only from Bitcoin to USD/CNY and USD/ZAR. Overall, the findings suggest no pronounced volatility spillovers between BTC and BRICS-T stock markets or across most currency pairs; nevertheless, certain shocks in global foreign-exchange markets—particularly those involving USD/CNY and USD/ZAR—can influence Bitcoin's conditional variance.

The results of the Hafner and Herwartz (2006) procedure for the Ethereum-based models are reported in Table 7.

Tablo 7: Causality in Variance Test Results for Ethereum Models

Dependent >> Independent	**LM Statistic**	**df**	**Prob.**	**Evaluation**
ETH >> BR	1.678804	1	0.1951	No Causality Relationship.
BR >> ETH	0.114155	1	0.7355	No Causality Relationship.
ETH >> RU	0.315812	1	0.5741	No Causality Relationship.
RU >> ETH	0.797428	1	0.3719	No Causality Relationship.
ETH >> IN	0.293612	1	0.5879	No Causality Relationship.
IN >> ETH	0.553336	1	0.4570	No Causality Relationship.
ETH >> CN	0.112989	2	0.9451	No Causality Relationship.
CN >> ETH	**52.71058**	**2**	**0.0000*** **	**Causality Relationship Exists.**
ETH >> ZA	**13.40229**	**5**	**0.0199** **	**Causality Relationship Exists.**
ZA >> ETH	**14.42179**	**5**	**0.0131** **	**Causality Relationship Exists.**
ETH >> TR	2.104656	1	0.1469	No Causality Relationship.
TR >> ETH	0.081181	1	0.7757	No Causality Relationship.
ETH >> USD/BRL	0.092896	1	0.7605	No Causality Relationship.
USD/BRL >> ETH	0.028698	1	0.8655	No Causality Relationship.
ETH >> USD/RUB	0.027531	1	0.8682	No Causality Relationship.
USD/RUB >> ETH	0.213628	1	0.6439	No Causality Relationship.
ETH >> USD/INR	0.261541	1	0.6091	No Causality Relationship.

USD/INR >> ETH	0.122880	1	0.7259	No Causality Relationship.
ETH >> USD/CNY	0.008870	1	0.9250	No Causality Relationship.
USD/CNY >> ETH	**18.73164**	**1**	**0.0000*** **	**Causality Relationship Exists.**
ETH >> USD/ZAR	2.031524	2	0.3621	No Causality Relationship.
USD/ZAR >> ETH	**17.92739**	**2**	**0.0001*** **	**Causality Relationship Exists.**
ETH >> USD/TRY	0.228998	1	0.6323	No Causality Relationship.
USD/TRY >> ETH	0.090327	1	0.7638	No Causality Relationship.

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

The findings reported in Table 7 indicate that, within the GARCH-based auxiliary-regression framework, the causality-in-variance (LM–Wald) tests for Ethereum reveal a limited number of volatility spillovers that are asymmetric in direction: while no statistical significance is observed for its relationships with the BR, RU, IN, and TR equity indices or with the USD/BRL, USD/RUB, USD/INR, and USD/TRY exchange-rate pairs, bidirectional causality in variance is detected between Ethereum and the South African stock market, and unidirectional causality running from Ethereum to the Chinese stock market as well as to the USD/CNY and USD/ZAR exchange rates. Overall, the evidence suggests that volatility transmission mechanisms are concentrated at the country/currency level and, rather than indicating broad market integration, exhibit a selective and asymmetric pattern.

5. CONCLUSION

In this study, the causal relationships between crypto-assets and the leading stock indices and exchange rates of the BRICS-T countries were examined using the Hafner and Herwartz (2006)–based causality-in-variance test, which explicitly accounts for volatility in the series. The findings reveal that there are certain causal linkages between the analyzed stock markets, exchange rate markets, and the selected cryptocurrencies.

The empirical results indicate statistically significant causality running from Bitcoin to the USD/CNY and USD/ZAR exchange rates, whereas no causal relationship is detected between Bitcoin and the other variables. Examining the Ethereum results, a bidirectional causality relationship is identified with the South African equity market. In addition, unidirectional causality is detected running from Ethereum to the Chinese equity market and to the USD/CNY and USD/ZAR exchange rates. Taken together, these findings indicate that the causal linkages between Ethereum and the BRICS-T equity and foreign-exchange markets are limited in scope

The findings obtained in this study vary depending on the countries' economic dynamics, income levels, investor profiles, governance structures, financial market development levels, and technological infrastructures. Therefore, the results should be evaluated in consideration of country-specific dynamics. The outcomes are in line with the significant causality findings reported by Güleç, Çevik, and Bahadır (2018), who examined the relationships between Bitcoin and exchange rates, stock markets, commodity markets, and interest rates. Similarly, the unidirectional relationships identified by Wijk (2013), Ağan and Aydın (2018), and Gkillas, Bouri, Gupta, and Roubaud (2020) also support the findings of this study. On the other hand, the results reported by Kaymak and Koç (2022), who found no significant relationship between variables, and Ahmed, Sarkodie, and Leirvik (2023), who identified bidirectional causality, do not overlap with the findings of this research.

The presence of causal relationships between cryptocurrencies and certain national markets necessitates a reassessment of investors' portfolio diversification strategies. The increasing influence of high-volume digital assets such as Bitcoin and Ethereum on traditional markets requires that these assets be considered not merely as alternative investment tools but also as market-moving instruments. It is crucial for investors to closely monitor developments not only in cryptocurrency markets but also in the corresponding stock and exchange rate markets of the relevant countries for effective risk management. Sudden fluctuations in cryptocurrency prices have the potential to influence capital movements and exchange rates, particularly in developing countries. Therefore, it is essential for regulatory authorities to adopt a more holistic perspective toward these markets and to strengthen monitoring and oversight mechanisms.

The findings of this study demonstrate that cryptocurrencies are becoming increasingly influential within the global financial system. In this context, future research incorporating longer time series and alternative analytical techniques could provide a deeper understanding of the causal dynamics underlying these relationships. Moreover, examining the impacts of structural breaks, global crises, or regulatory interventions on causality patterns could offer valuable contributions to the literature. Cryptocurrencies are no longer merely components of digital innovation; they have evolved into active elements of the global financial structure. Hence, it is critically important for both investors and policymakers to carefully monitor their effects and to develop strategic approaches to ensure market stability and efficiency.

Ethics Committee Declaration
Ethics committee declaration is not required for the study.

Author Contribution Rate Declaration
All stages of the study were carried out as a result of the joint work of the authors.

Conflict Statement
There is no conflict of interest between the authors.

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