IRJEMS International Research Journal of Economics and Management Studies
ISSN: 2583 – 5238 / Volume 5 Issue 6 May 2026 / Pg. No: 23-37
Paper Id: IRJEMS-V5I6P103, Doi: 10.56472/25835238/IRJEMS-V5I6P103

Original Article

Volatility Spillovers between Bitcoin and Indonesian Stock Markets: Evidence from Islamic and Conventional Equity Indices

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Received Date: 13 May 2026 Revised Date: 27 May 2026 Accepted Date: 30 May 2026 Published Date: 04 June 2026

Abstract: *This study examines the volatility spillover effects between Bitcoin and Indonesian stock markets while assessing the effectiveness of Sharia screening in insulating Indonesian Islamic stocks from external crypto shocks, relative to conventional equity markets during periods of financial stress. Using daily data from January 2018 to December 2024, the study employs GARCH (1,1), Granger causality, Dynamic Conditional Correlation (DCC-GARCH), and the Diebold–Yilmaz spillover index to analyze volatility persistence, return transmission, and market connectedness between Bitcoin, the Indonesian Stock Exchange Index (IDX), and the Jakarta Islamic Index (JII). The findings highlight that volatility persistence strengthened following the COVID-19 pandemic, while Granger causality results reveal a unidirectional transmission running from Bitcoin to Indonesian equity markets during the post-COVID period. DCC-GARCH estimates further show weak but increasing time-varying correlations between Bitcoin and both stock indices, suggesting a gradual strengthening of market integration. However, the Islamic stock index does not exhibit significantly lower correlation or spillover exposure relative to the conventional market during periods of heightened Bitcoin volatility. Overall, the findings suggest that Sharia screening alone may provide limited insulation from cryptocurrency-related financial contagion during turbulent market conditions.*

Keywords: *Bitcoin (BTC), Volatility Spillover, Islamic Equity Markets, Indonesia, Sharia Screening, Financial Contagion, GARCH (1.1), DCC-GARCH.*

I. INTRODUCTION

The rise of cryptocurrencies and other digital assets has changed global financial markets in recent years. While Bitcoin and other cryptocurrencies offer high returns at extreme volatility and speculative risk, they have drawn massive investor interest. While research on cryptocurrency adoption is scarce, given the relatively short time span since inception compared to more established asset classes, it has expanded rapidly in emerging economies like Indonesia, characterised by millions of active participants in the digital asset markets[1], supported by mass media coverage and (social) internet. Nevertheless, this faster diffusion also leads to a knowledge gap about how cryptocurrency markets affect traditional financial systems, especially stock markets [2]. To our knowledge, existing empirical literature points to the existence of return and volatility spillovers from cryptocurrency markets to equity markets during times of financial crisis (as in 2020 with COVID-19). As an example, Chandra (2024) showed that Bitcoin is accordingly much more volatile than the Jakarta Stock Exchange, though volatility spillovers from Bitcoin to Indonesian equities were still low [3]. This calls for an understanding of such cross-market dynamics, which is instrumental for managing portfolio risk and ensuring financial stability.

Indonesia has one of the world's largest Islamic financial markets. The Islamic equity markets are based on Sharia rules, which prohibit interest (Riba) and excessive uncertainty (Gharar), as well as restrict speculative transactions (Maisir), thus leading to different risk characteristics than conventional markets [18]. These principles may offer some protection against the transmission of volatility shocks from high speculative markets like cryptocurrencies on a theoretical level. However, empirical evidence remains mixed. While some studies show that Islamic markets behave like safe havens in times of financial distress [4], other works indicate that Islamic and conventional markets face significant cross-market risk transmission during periods of crisis period [5],[6].

Although expansion of the literature on volatility spillovers and financial connectedness is noticeable in the context of international finance, almost all existing studies solely pursue developed economies or mere traditional financial systems. As a result, academic research on dynamic interactions between cryptocurrency markets and Islamic and conventional equity markets in emerging economies like Indonesia is limited. Most importantly, it is not obvious that Sharia screening affords substantial protection against cryptocurrency shocks during times of high market volatility.

In addition, COVID-19 was a structural inflexion point in global capital markets, ushering unprecedented volatility across asset classes and altering investor behaviour globally. As the Jakarta Composite Index and Retail Index (Jakarta Islamic Index) were heavily pressured in Indonesia during this period, an extreme massive fall in price trend on Bitcoin related to panic selloffs and surge of speculative expansions. Taking these structural adjustments into consideration, further exploration in terms of the pre-and post-pandemic framework might yield us a better understanding of whether or not the volatility persistence and spillover dynamics and return transmission mechanisms have strengthened over the entire trading days after such pandemic shock.

Consequently, this paper investigates the spillover volatility between Bitcoin and Indonesian stock markets while comparatively analysing if Sharia screening formulation prevails in insulation from shock due to cryptocurrency over conventional equity. Econometric techniques such as GARCH (1,1), Dynamic Conditional Correlation (DCC-GARCH) and Granger-causality tests and the Diebold–Yilmaz spillover index are used to realise this objective. This study thus adds to the limited research regarding cryptocurrency spillovers, particularly emerging Islamic financial markets and expands the amount of knowledge on financial interconnectedness, contagion and portfolio risk management in times of uncertainty.

II. LITERATURE REVIEW

A) Prior Research

- *Cryptocurrency Spillovers and Volatility Dynamics:* Previous work indicates that connectedness between cryptocurrency and equity markets increases in times of financial stress[21]. For instance, Sinlapates et al. During the COVID-19 pandemic, Wang et al. (2023) reported significant two-way bidirectional volatility spillovers between Bitcoin and stock markets, indicative of a higher level of financial interdependence during crisis periods. [7] In the same way, Ibrahim et al. (2024) also found that cryptocurrency markets can deliver shocks to traditional financial markets mostly due to increased investor uncertainty and speculative behaviour [8]. On the contrary, Indonesian studies such as Chandra (2024) [3] find significantly higher Bitcoin volatility compared to the Jakarta Stock Exchange, but their results indicate only limited spillover from Bitcoin to Indonesia. The results are mixed, highlighting that the extent of cryptocurrency contagion may not be homogeneous over markets and time.
- *Islamic Finance and Market Stability:* It can be argued that the principles of Islamic finance do not allow excessive uncertainty (gharar) and speculative activities. This theoretically gives an Islamic financial market a better ability to weather tumultuous periods in the economy compared to a traditional, interest-based system facing economic burdens. Islamic securities are then well decoupled from conventional markets, and Islamic [4] securities may ameliorate the extreme risk and instability through the systemic nature of COVID-19 events, Kenourgios, Naifar, and Dimitriou (2016). On the other hand, studies like Elsayed et al. Jabeen and Dufour [5] found widespread risk transmissions and connectedness from Islamic markets to conventional ones (and vice versa) during times of worry, thus showing the interdependence of the financial markets.
- *Volatility Spillovers in the Context of Emerging Markets:* Although previous studies involving cryptocurrency spillover and financial contagion have been similarly increasing [7], [9], they are mainly based on empirical evidence from developed economies or a broad regional market index. Hence, the few Indonesian-focused studies existing, e.g. Chandra (2024), Hugo Prasetyo Winotoatmojo (2026), exclusively look at overall connectedness between crypto assets and the broad Indonesian capital market, with almost no comparative focus on the relation of Islamic and conventional equity indices. What is more crucial is the lack of empirical evidence on whether Sharia screening negatively decreases exposure to cryptocurrency-induced volatility spillovers in Indonesia. This study thus adds to extant literature by conducting a comparative analysis of volatility dynamics and spillover effects among bitcoin, the Indonesian Stock Exchange (IDX) and the Jakarta Islamic Index (JII) between pre- and post-COVID periods.

B) Theories

a. Efficient Market Hypothesis (EMH)

EMH was originally introduced by Fama in 1965. It suggests that capital markets are informationally efficient, meaning that stock prices instantaneously reflect all available information about the intrinsic value of the asset. Based on this assumption, price changes follow a random walk process which occurs in response to new information, implying that investors cannot consistently earn abnormal returns through technical analysis and security selection [11], [12]. Asset values are affected by varying forms of information; financial researchers have distinguished three versions of EMH based on how the phrase ‘all available information’ is defined. The first version is weak-form market efficiency, which suggests that current prices fully reflect information contained in the past history of the prices. The second version is semi-strong form efficiency; it posits that the current price fully incorporates all publicly available information, which includes past prices and also other sources such as earnings and dividend announcements. Lastly, the third version of EMH is the strong form-efficiency, which suggests that the current price fully reflects all existing information, both public and private.

W. Li (2024) reiterates that technological advancements such as high-frequency trading and blockchain technology have changed market dynamics significantly [11]. While these technologies can enhance market efficiency by quickly incorporating information into prices, they also possess a high potential for systemic risks such as flash crashes, challenging the validity of EMH under those conditions. In the context of crypto markets, the decentralized and transparent nature of the system theoretically enhances efficiency, but volatility, market manipulation and regulatory oversight still challenge the notion of efficiency in these markets. Empirical evidence highlights that cryptocurrencies generally fail to conform to the weak form of the EMH, with approximately 10% of the assets reflecting informational efficiency [13]. Therefore, this study adopts EMH as a theoretical benchmark rather than as an absolute principle.

b. Contagion Theory / Spillover Effect Theory

The concept of contagion in finance is defined as the propagation of shocks or volatility from one market to another, especially during periods of turmoil or instability [14]. According to Rigobon (2016), the terms contagion and spillover are often used loosely, and they are model-dependent. The author reiterates that spillover or interdependence relates to the transmission of shocks through modelled channels, meaning a transmission mechanism that is always present because of underlying financial linkages, while contagion relates to unmodelled transmission mechanisms, meaning they are associated with crises or parameter instability [15].

The financial view is mostly focused on the banking sector, but the same set of assumptions applies to international equity markets, in the sense that the financial intermediaries are actors in the capital market, not necessarily the banking sector, hence their risk appetite might force them to sell off assets of the same class, causing a cascading fall in asset values across borders [15]. While there is no single method that can fully capture the contagion and spillover dynamics, studies reveal that volatility models such as the Dynamic Conditional Correlation (DCC–GARCH) framework developed by Engle (2002) are the most accurate, as they allow researchers to trace how correlations between assets shift over time, becoming stronger during periods of turmoil and weaker when conditions stabilize [16].

Maximize for rapid information flow, speculate sentiment and do not lead with centralized power the crypto markets. Therefore, a sudden price drop in Bitcoin can rapidly change investor sentiment across different markets. Some financial stability studies have reported the spillage of volatility from crypto-assets into equity markets during the COVID-19 pandemic, indicating that cryptocurrencies are integrated into the financial system instead of segregated niches [7].

In Indonesia, contagion and spillover effects pose an interesting challenge, particularly as the country has both conventional and Islamic capital markets in addition to a relatively fast-growing cryptocurrency sector. If the volatility from Bitcoin affects indices such as the Jakarta Composite Index (IDX) or the Jakarta Islamic Index (JII), it would denote stronger interaction between digital and conventional assets. Theoretically, Islamic markets that Sharia principles bind more strictly to asset-backed investment are less prone to excessive speculation and thus should be less susceptible to contagion. But in practice, studies have shown mixed outcomes. Therefore, contagion and spillover theories help to explain how shocks transmit through the financial system and why volatility often appears to cluster across markets.

c. Islamic Finance Theory

Islamic finance theory is built on the foundational principles of Sharia law, which governs economic transactions through moral, ethical, and social guidelines. As alluded to by Mirakhor & Iqbal (2013), the key principles that guide Islamic finance and economics are fairness, transparency, and the sharing of both risk and reward between parties [17]. Compared to conventional finance, Islamic finance encourages asset-backed and equity-oriented transactions so as to ensure financial activities are underpinned by real economic value. There are three main prohibitions that shape the structure of Islamic finance, namely riba, gharar, and maysir. These principles are designed to reduce injustice, prevent excessive risk-taking, and encourage transactions rooted in fairness and clarity.

- *Riba (Prohibition of Interest):* Islamic finance is grounded on a simple yet impactful rule, that is, the prohibition of interest in all financial transactions. Based on Al-Jarhi (2017), this limits debt financing, but it does not completely eradicate interest-free loans for charitable purposes [18]. From a Sharia perspective, riba is viewed as unfair because it guarantees a return without the lender sharing in the borrower's risk or effort. This violates the idea of balance and partnership in economic exchange. Instead of interest-based lending, Islamic finance favors arrangements where profit and loss are shared between parties, such as *mudarabah* (profit-sharing) or *musharakah* (joint venture) [19]. The primary goal of Riba is to ensure that all contractual parties carry an adequate portion of risk and reward by promoting asset-backed lending, which ultimately leads to real economic growth as opposed to debt-driven growth that often increases volatility in conventional markets.
- *Gharar (Avoidance of Excessive Uncertainty):* The second key principle, gharar, refers to excessive uncertainty or ambiguity in financial transactions. In Islamic finance, contracts must be transparent, with clearly defined terms and conditions. Deals involving unclear ownership, undisclosed risks, or unknown outcomes are considered invalid. This rule

seeks to protect all parties from unfair advantage and reduce the chance of disputes or losses caused by incomplete information. For instance, selling an asset that one does not yet own or whose condition is unknown would constitute gharar [20]. In conventional markets, many complex derivatives and speculative instruments carry this kind of uncertainty. Islamic finance, by contrast, promotes clarity and fairness, which helps build trust and stability in financial relationships.

- *Maysir (Prohibition of Gambling and Speculation):* The third major restriction, maysir, prohibits gambling or speculative behaviour where profits depend mainly on chance. Transactions that resemble betting, such as short-term speculation on price movements or derivative trading without underlying assets, fall under this prohibition [21]. The idea is that wealth should be earned through productive activity, not luck or manipulation. Excessive speculation may lead to high market instability, with prices moving more on emotion than on fundamentals. This principle reflects a broader belief that stability and fairness are inseparable from ethical behavior in finance. Considering that the Jakarta Islamic Index adheres to these principles, its behavior under external shocks from excessive crypto market volatility should, in theory, differ from the conventional market. Based on the Islamic finance framework, the severity and intensity of spillover effects should be lower compared to the conventional market.

III. METHODS

A) Data and Sample

This study adopts a quantitative, explanatory time-series design using secondary daily data for Bitcoin, the IDX Composite, and the Jakarta Islamic Index (JII). To examine regime-dependent dynamics, the sample period (January 2018–December 2024) is divided into two sub-periods: pre-COVID (January 2018–February 2020) and post-COVID (March 2020–December 2024). The break point is defined on 11 March 2020, corresponding to the global financial shock following the declaration of the COVID-19 pandemic, which triggered extreme volatility across asset classes, including Bitcoin and Indonesian equity markets.

The dataset covers three price series central to Indonesia's dual financial structure: Bitcoin (BTC-USD), representing the crypto asset market. Historical prices are taken from investing.com and verified using CoinMarketCap, which maintains a consistent and widely referenced record of cryptocurrency data. The IDX composite is used as the benchmark for the conventional equity market, and the Jakarta Islamic Index (JII) represents the Islamic equity market. Daily price data for both indices are sourced from Investing.com, supplemented where necessary with figures reported by the Indonesia Stock Exchange (IDX). All price series are converted into logarithmic returns to ensure comparability and to reflect proportional rather than absolute changes. Daily frequency is maintained throughout, as it is better suited to capturing short-run volatility episodes and the rapid adjustments characteristic of crypto-equity interactions. The data is analyzed using a combination of eviews-12 and R Studio, and other necessary statistical software.

B) Model Specification

a. Univariate Generalized Heteroscedasticity Model (GARCH)

Based on Brooks (2008), the GARCH (1,1) model is sufficient to capture volatility dynamics; this study adopts this specification to capture each market's volatility properties [22]. Bitcoin (BTC), the IDX Composite, and the Jakarta Islamic Index (JII) are each modelled separately to assess whether their returns display volatility clustering and persistence. Volatility persistence is measured as the sum of the ARCH and GARCH coefficients (α + β). Values closer to unity indicate stronger long-memory behavior and slower mean reversion. Persistence estimates are compared across regimes to evaluate structural differences in volatility dynamics. A reduction in (α + β) in the post-COVID regime would suggest faster volatility decay despite potentially larger short-term shocks.

The model is specified as:

$$r_t = \mu + \varepsilon_t$$
$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Where:

- r_t = log return at time t
- μ = constant mean return
- ε_t = error term
- $\varepsilon_t|\mathcal{F}_{t-1} \sim N(0, h_t)$
- h_t = conditional variance from GARCH

Where the ARCH term (α) shows the immediate effect of new information, while the GARCH term (β) captures how long volatility shocks persist. Assets with high ($\alpha + \beta$) values exhibit long-lasting volatility episodes, a feature usually observed in both crypto and equity markets.

b. Vector Autoregression and Granger Causality

To establish whether returns in one market help predict returns in another, the study employs a VAR framework followed by Granger causality tests. The optimal lag length for the VAR model is determined using a combination of Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (BIC/SIC). According to Brooks (2008) the VAR model can be specified as follows:

$$r_{1,t} = c_1 + \sum_{i=1}^{p} \phi_{11,i}\, r_{1,t-i} + \sum_{i=1}^{p} \phi_{12,i}\, r_{2,t-i} + \varepsilon_{1,t},$$

Where:

- $r_{1,t}$ and are the return series (e.g., BTC, IDX, JII),
- c_j are constants,
- $\phi_{jk,i}$ measure how past movements in one market influence current returns in the other,
- $\varepsilon_{j,t}$ are white-noise error terms.

c. DCC-GARCH Model

To examine the evolution of volatility spillovers and correlations over time, the study utilizes the Dynamic Conditional Correlation (DCC) GARCH model presented by [16]. This framework captures how conditional covariances adjust in response to past shocks and past correlations, making it suitable for analyzing periods of financial stress, contagion events, and the potential safe-haven behavior of Islamic assets. The conditional covariance matrix is specified as:

$$H_t = D_t R_t D_t$$

Where D_t contains the conditional standard deviations from the GARCH (1,1) model, and R_t represents the time-varying correlation matrix. Lastly, the correlation dynamics follow:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha(\epsilon_{t-1}\epsilon_{t-1}{}') + \beta Q_{t-1}$$
$$R_t = \mathrm{diag}(Q_t)^{-1/2} Q_t \mathrm{diag}(Q_t)^{-1/2}$$

Where $\bar{Q}$ represents the unconditional covariance matrix of residuals, and α & β are parameters capturing the influence of lagged shocks and lagged conditional correlations on current correlations.

d. Diebold–Yilmaz Spillover Index (DYSI)

To quantify volatility transmission among Bitcoin, IDX and JII, this study employs the spillover framework proposed by Diebold et al. (2022). The approach is based on generalized forecast error variance decomposition derived from a Vector Autoregression (VAR) model. The H-step-ahead generalized forecast error variance decomposition is given by:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i{}' \Phi_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i{}' \Phi_h \Sigma \Phi_h{}' e_i\right)}$$

Where: $\theta_{ij}^{g}(H)$ measures the contribution of shocks in market j to the forecast error variance of market i. The elements are normalized so that row sums equal unity. This enables the authors to generate a connected matrix which highlights cross-market spillovers and a Total Connectedness Index as a percentage. The Total Spillover Index is defined as:

$$S^{g}(H) = \frac{\sum_{i=1}^{N} \sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100$$

IV. RESULTS AND DISCUSSION

A) Descriptive Statistics

Table 1 depicts the descriptive statistics of daily log returns for Bitcoin, the Indonesian Stock Exchange Index (IDX), and the Jakarta Islamic Index (JII). The mean returns across all markets are close to zero, indicating that daily price movements fluctuate around a relatively small average return. Bitcoin has the highest average return (0.001031) and the greatest volatility, with a standard deviation of 0.0396, compared to 0.0099 and 0.0124 for IDX and JII, respectively. The kurtosis values for each series are above 3, suggesting non-normality characteristics and the presence of frequent extreme observations. The Jarque-Bera (JB) statistic also strongly rejects normality.

Table 1: Descriptive statistics.

Statistic	BTC	IDX	JII
Mean	0.001031	0.000065	0.000263
Median	-0.000123	0.000468	0.000088
Maximum	0.177424	0.097042	0.120550

Minimum	-0.497278	-0.068050	0.081650
Std. Dev.	0.039622	0.009892	0.012417
Skewness	-1.249867	-0.175048	0.045770
Kurtosis	19.60626	12.73736	12.15505
Jarque-Bera	19940.91	6712.967	5927.011
Observations	1697	1697	1697
Our data encompasses 1, 697 observations from January 2, 2018, to 30 December 2024. This table presents a summary of daily returns descriptive statistics for Bitcoin (BTC), Indonesian Stock Exchange (IDX) and Jakarta Islamic Index (JII).			

In addition, a graphical analysis depicted in Figure 1 below shows the presence of volatility clustering across all markets, where periods of high volatility are followed by further high volatility, and relatively calm periods are followed by lower fluctuations. Bitcoin returns exhibit the most pronounced volatility, with frequent large spikes and extreme movements notably around early 2020, where a sharp negative spike can be observed, corresponding with the onset of the COVID-19 pandemic. While the IDX and JII indices also show significant structural breaks and increased fluctuations during the same period, their fluctuations remain considerably lower than Bitcoin's, highlighting the different risk profiles between crypto-assets and traditional Indonesian equity markets.

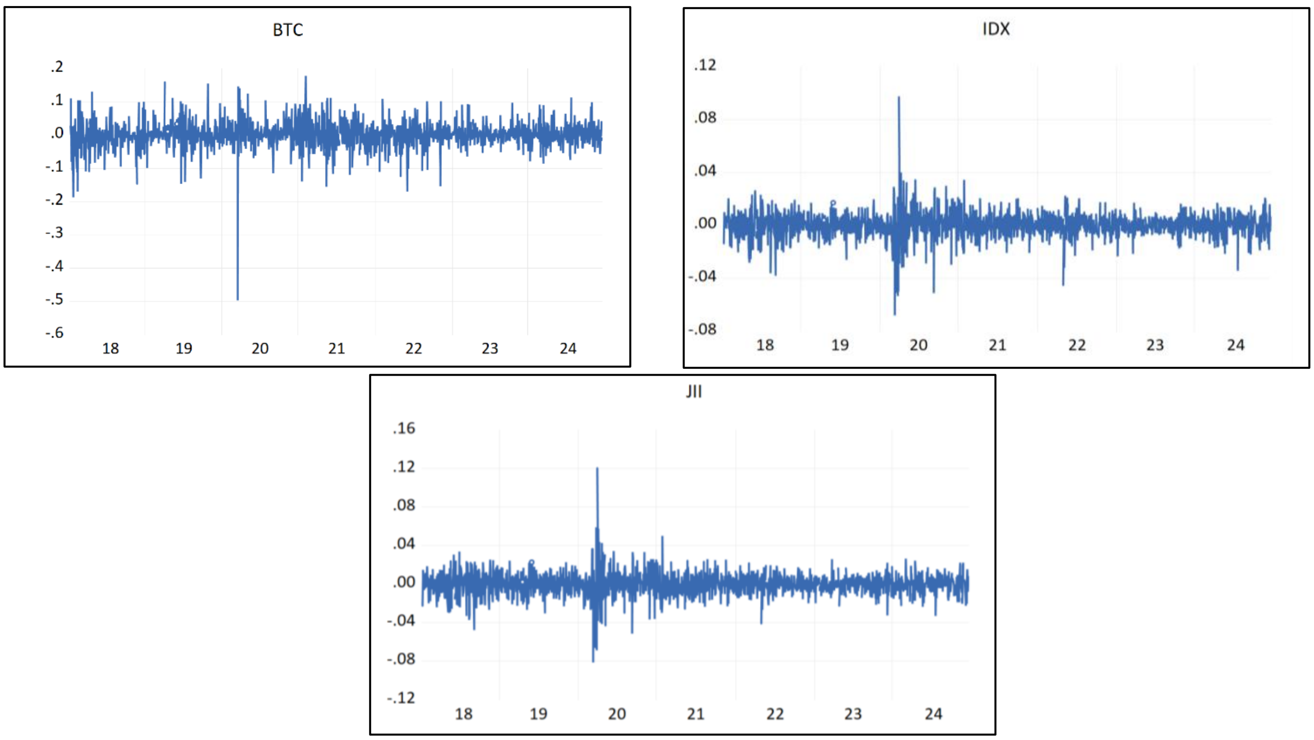

Figure 1. Daily return series for Bitcoin (BTC), the Indonesia Stock Exchange Composite Index (IDX), and the Jakarta Islamic Index (JII) from 2018 to 2024. The vertical axis represents returns, while the horizontal axis represents time in years. The figure illustrates clear volatility clustering and pronounced return fluctuations across all markets, particularly around March 2020 during the onset of the COVID-19 pandemic. Bitcoin exhibits substantially higher volatility relative to IDX and JII, reflecting the more turbulent nature of cryptocurrency markets.

B) Stationarity and ARCH Effects

Stationarity of each data series was tested using the Augmented Dickey–Fuller (ADF) test, which examines whether a time series contains a unit root, as presented in Table 2. The presence of a unit root indicates non-stationarity, and estimating time-series models using non-stationary data can lead to unreliable results and spurious regression [22]. As shown in Table 2, the ADF test statistics for all series are more negative than the corresponding critical values at the 1% significance level. Therefore, the null hypothesis of a unit root is rejected for all variables, indicating that the return series are stationary in levels.

Table 2: Unit Root Test.

Data series	ADF Statistic	1% Critical Value	Prob.
BTC	-43.745	-3.434	0.0001
IDX	-9.720	-3.434	0.0000
JII	-8.379	-3.434	0.0000
Table 2 reports the results of the Augmented Dickey–Fuller unit root tests for BTC, IDX, and JII returns. The null hypothesis of a unit root is rejected at the 1% significance level for all return series, indicating that all return series are stationary.			

In order to determine the presence of ARCH effects in each return series, a mean equation of the form $r_t = \mu + \varepsilon_t$ was estimated using the Ordinary Least Squares (OLS) method. The residuals obtained from this equation were then subjected to the ARCH–LM test, and the results are presented in Table 3. The findings indicate that the p-values for all series are below the 1% significance level. Therefore, the null hypothesis of no ARCH effects is rejected for Bitcoin, the IDX and the JII. This confirms the presence of conditional heteroskedasticity and volatility clustering in all return series, thereby justifying the use of the GARCH (1,1) model for the subsequent analysis.

Table 3: ARCH-LM test.

Data series	F-statistic	Prob.
BTC	3.186	0.0072***
IDX	68.812	0.000***
JII	129.643	0.000***
The table reports the results of the ARCH-LM tests for BTC, IDX, and JII returns. The null hypothesis of no ARCH effects is rejected at the 1% significance level for all series, indicating the presence of conditional heteroskedasticity and volatility clustering. These findings justify the application of GARCH-based models in the subsequent analysis. Note: *** denotes rejection of the null hypothesis of no ARCH effects at the 1% significance level.		

C) Volatility Dynamics: GARCH (1,1) Results

To examine whether volatility dynamics changed following the COVID-19 pandemic, this study estimates GARCH (1,1) models for Bitcoin, the Indonesian Stock Exchange (IDX), and the Jakarta Islamic Index (JII) across the full sample, as well as pre- and post-COVID sub-periods. Volatility persistence is measured by the sum of the ARCH and GARCH coefficients ($\alpha + \beta$), as reported in Table 4. The findings presented in Panel A indicate that all three markets exhibit high volatility persistence, with $\alpha + \beta$ values close to unity, confirming the presence of volatility clustering. However, differences emerge when comparing the pre- and post-COVID periods.

For Bitcoin, volatility persistence remains consistently high, increasing slightly from 0.96 in the pre-COVID period to 0.97 in the post-COVID period. This suggests that volatility persistence in cryptocurrency markets was slightly increased by the pandemic. In contrast, the IDX shows a more pronounced change, with persistence declining from 0.98 in the pre-COVID period to 0.95 in the post-COVID period. The JII, on the other hand, exhibits only a modest change, with persistence decreasing from 0.97 to 0.96. This suggests that, although volatility persistence remains high, the overall volatility structure of the Islamic equity market is relatively stable and less prone to structural shifts across the two periods. These findings provide evidence that volatility persistence differs between the pre- and post-COVID periods.

Ultimately, these results show strong volatility persistence as all the parameters are statistically significant and close to unity for all sub-periods, suggesting that volatility shocks dissipate slowly over time and that all three markets exhibit pronounced volatility clustering. More so, all persistence measures remain below unity, indicating that volatility is mean-reverting rather than explosive.

These findings are consistent with prior evidence of persistent volatility and long-lasting shock dynamics in Bitcoin and equity markets during periods of financial stress and the COVID-19 pandemic. For instance, Saleem et al (2021) show evidence of high volatility persistence in Islamic stock indices during the COVID-19 period, suggesting that shocks to volatility dissipate gradually over time [24]. Similarly, Setiawan et al. (2021) find that volatility on the Indonesian stock markets tends to persist during the COVID-19 pandemic relative to the global financial crises of 2008, while Ünlü & Bayram (2024) document a significant increase in Bitcoin volatility during the initial period of the pandemic. Furthermore, Sinlapates et al. (2023) report significant ARCH and GARCH effects between Bitcoin and ASEAN+6 stock markets, indicating prolonged volatility transmission and persistent shock effects during the COVID-19 period [7].

Table 4: Estimation results from the GARCH (1,1) Models

	BITCOIN	**IDX**	**JII**
Panel A: Full sample Results			
Mean Equation			
μ	0.0010	0.0002	-0.0002
Variance Equation			
ω	0.000080***	0.000006***	0.000007***
α (ARCH)	0.0278***	0.1217***	0.0995***
β (GARCH)	0.9194***	0.8110***	0.8466***
Persistence (α+β)	0.95	0.93	0.95
Panel B: Pre-COVID Results			
Mean Equation			
μ	-0.0006	-0.0002	-0.0005
Variance Equation			
ω	0.000005***	0.000002	0.000004
α (ARCH)	0.0251***	0.0382***	0.0478***
β (GARCH)	0.9393***	0.9428***	0.9199***
Persistence (α+β)	0.96	0.98	0.97
Panel C: Post-COVID Results			
Mean Equation			
μ	0.0017	0.0003	-0.0001
Variance Equation			
ω	0.000003***	0.000004***	0.000004
α (ARCH)	0.0313***	0.0974***	0.0607***
β (GARCH)	0.9427***	0.8478***	0.9006***
Persistence (α+β)	0.97	0.95	0.96
Note: α and β represent the ARCH and GARCH parameters, respectively, capturing the short-run shock effects and long-run volatility persistence of the conditional variance process. The sum α + β measures the overall persistence of volatility, with values closer to unity indicating more persistent volatility dynamics. *** Statistical significance at the 1% level.			

D) Return relationships based on the Granger causality test

To assess whether return transmission dynamics changed following the COVID-19 pandemic, Granger causality tests based on a VAR (2) model were conducted for the full sample as well as pre- and post-COVID sub-periods. The results are presented in Table 5. The full sample results, as depicted in Panel A, highlight unidirectional Granger causality from Bitcoin to both IDX and JII, with no evidence of reversal causality between the two stock markets. This implies that Bitcoin drives return dynamics in Indonesian equity markets.

The pre-COVID results depicted in Panel B show no statistically significant Granger causality relationships among the variables, as all p-values are greater than 0.05, meaning that before the pandemic, Bitcoin and Indonesian stock markets operated independently, with no evidence of return transmission between them. However, post-COVID results presented in Panel C suggest Bitcoin returns significantly Granger-cause both IDX and JII at the 1% level of significance, with no evidence of reverse causality. This suggests Bitcoin became an important source of return transmission to Indonesian stock markets in the post-pandemic period.

It is important to note that Granger causality does not imply true causation, but rather indicates that past values of one variable contain useful information for predicting another [22]. In this context, movements in Bitcoin returns appear to lead those of IDX and JII. These findings motivate further investigation using DCC-GARCH and the Diebold–Yilmaz Spillover Index (DYSI), which are employed in the following sections. Overall, the findings demonstrate a clear strengthening of return transmission and Granger causality relationships in the post-COVID period relative to the pre-COVID period.

These results are partially supported by prior studies, which document Bitcoin as a volatility or return transmitter to Asian stock markets, particularly during the COVID-19 period. Consider Sinlapates et al. (2023), Kakinuma (2022), and Zeng et al. (2023) as examples [7], [27], [28]. In contrast to these broader studies, our results show that prior to the COVID-19 pandemic, Bitcoin and Indonesian equity indices were effectively disconnected, but that post-COVID Bitcoin returns Granger-cause IDX and JII, with no reverse causality. This extends the literature by documenting a structural strengthening of return transmission from Bitcoin to an emerging, largely Islamic equity market.

Table 5: Results for the Granger causality tests

Null Hypothesis	χ^2-stat	Prob.
Panel A: Full Sample		
IDX does NOT Granger-cause BTC	1.315	0.5181
JII does NOT Granger-cause BTC	1.608	0.4476
BTC does NOT Granger-cause IDX	10.399***	0.0055
JII does NOT Granger-cause IDX	1.549	0.4609
BTC does NOT Granger-cause JII	9.662***	0.0080
IDX does NOT Granger-cause JII	0.143	0.9310
Panel B: Pre-COVID		
IDX does NOT Granger-cause BTC	1.695	0.4286
JII does NOT Granger-cause BTC	0.965	0.6172
BTC does NOT Granger-cause IDX	0.395	0.8206
JII does NOT Granger-cause IDX	0.230	0.8913
BTC does NOT Granger-cause JII	0.305	0.8588
IDX does NOT Granger-cause JII	1.892	0.3884
Panel C: Post-COVID		
IDX does NOT Granger-cause BTC	3.831	0.1473
JII does NOT Granger-cause BTC	3.257	0.1962
BTC does NOT Granger-cause IDX	18.447***	0.0001
JII does NOT Granger-cause IDX	2.053	0.3583
BTC does NOT Granger-cause JII	16.678***	0.0002
IDX does NOT Granger-cause JII	1.028	0.5982

Note: The table reports pairwise Granger causality test results based on a VAR (2) model. The null hypothesis states that the lagged values of one variable do not Granger-cause another variable. The results indicate stronger return transmission from Bitcoin to Indonesian stock markets during the post-COVID period.

*** denotes statistical significance at the 1% level.

E) DCC-GARCH Results

To further examine whether the strengthening of return transmission observed in the Granger causality analysis is accompanied by changes in market integration, a DCC-GARCH (1,1) model is estimated for the full sample as well as the pre- and post-COVID sub-periods and the results are presented in Table 6. Panel A indicates that the dynamic correlations between Bitcoin and Indonesian stock markets are positive but relatively low, with mean values of 0.045 for BTC–IDX and 0.052 for BTC–JII. In contrast, the correlation between IDX and JII is substantially higher, confirming strong co-movement within domestic equity markets as expected. Both estimated DCC parameters are statistically significant, with $\alpha + \beta$ close to 1, implying strong persistence of correlations over time.

Looking at the pre-COVID scenario represented in Panel B, we find that both IDX and JII correlations to Bitcoin are virtually zero, implying that cryptocurrency and Indonesian stock markets had largely operated in isolation. The short-run DCC parameter (α) is also found to be statistically insignificant, which suggests that correlations are not quite persistent and thus, correlated volatility does respond slowly to new shocks. Alternatively, Panel C, which presents the post-COVID period, shows higher correlations with mean values of BTC–IDX and BTC–JII, increasing up to 0.067 and 0.079, respectively. This increment indicates an enhancement of co-movement between Bitcoin and Indonesian equity markets. Moreover, both DCC parameters during this period are statistically significant, indicating that correlations not only progressively increase but also respond more dynamically to new information and remain very persistent. All these findings align with Chandra (2024), Balcı et al. And Hugo Prasetyo Winotoatmojo (2026), who has arrived at the conclusion that time varying correlations between Bitcoin and Indonesian Stock markets increase long-run, especially during stress periods, signifying increasing co-movements and so increasing potential loss of diversification benefits [3], [29], [10].

A Newey–West adjusted t-test was performed on the difference between BTC–JII and BTC–IDX correlations to evaluate differences across the correlations. Since the DCC model generates a series of dynamic correlations with potential time-varying variance and serial dependence, we use a Newey–West heteroskedasticity and autocorrelation consistent (HAC) estimator for robust inference (Newey & West 2014). Results of the HAC test in Table 7 indicate that the mean difference was positive (and given that a strict inequality was effective) and is statistically significant at the 1% level, which suggests that JII has a slightly higher co-movement with Bitcoin compared to IDX in the post-COVID period. The results indicate that dynamic conditional correlations vary across market regimes and differ between the Islamic and conventional stock markets.

Table 6: Results for DCC-GARCH (1,1)

Panel A: DCC Results for the full Sample		
DCC Parameters		
Parameter	Estimate	t-stat
α (DCC)	0.0336	2.91***
β (DCC)	0.9392	36.45***
α + β	0.9728	
Mean Dynamic Correlations		
Pair	Mean Correlation	
BTC–IDX	0.0453	
BTC–JII	0.0517	
IDX–JII	0.8495	
Panel B: DCC Results for Pre-COVID Period		
DCC Parameters		
Parameter	Estimate	t-stat
α (DCC)	0.0199	0.61
β (DCC)	0.8746	22.57***
α + β	0.8945	
Mean Dynamic Correlations		
Pair	Mean Correlation	
BTC–IDX	0.0027	
BTC–JII	-0.0055	
IDX–JII	0.9248	
Panel C: DCC Results for Post-COVID Period		
DCC Parameters		
Parameter	Estimate	t-stat
α (DCC)	0.0333	3.48***
β (DCC)	0.9134	34.04***
α + β	0.9467	
Mean Dynamic Correlations		
Pair	Mean Correlation	
BTC–IDX	0.0671	
BTC–JII	0.0789	
IDX–JII	0.8160	

Notes: α and β represent the short-run shock sensitivity and persistence parameters of the Dynamic Conditional Correlation (DCC) process, respectively. The sum α + β measures the persistence of dynamic correlations, with values closer to unity indicating highly persistent correlation dynamics over time.

The results suggest relatively weak integration between Bitcoin and Indonesian stock markets during the pre-COVID period, while the post-COVID period indicates stronger and more persistent co-movement dynamics.

Mean correlations represent the average dynamic conditional correlations estimated between market pairs.

*** denotes statistical significance at the 1% level.

Table 7: Difference in Dynamic Correlations (Post-COVID, HAC Test)

Variable	**Estimate**	**Std. Error**	**t-stat**	**p-value**
BTC–JII − BTC–IDX	0.0119	0.0035	3.37***	0.0008

Notes: The table shows the (HAC) test results for the difference between BTC–JII and BTC–IDX dynamic correlations during the post-COVID period. HAC consistent standard errors are used to account for potential heteroskedasticity and serial correlation in the estimated dynamic correlation series.

*** denotes statistical significance at the 1% level. Standard errors are HAC consistent

F) Capturing the Volatility Spillover Effects Using the Diebold-Yilmaz

Table 8 presents the connectedness matrix obtained using the Diebold–Yilmaz methodology. Panel A reports the spillover effects for the full sample covering the period from 01/01/2018 to 12/31/2024. The diagonal values (99.5% for BTC, 55.3% for IDX and 55.3% for JII) suggest that all markets are primarily influenced by their own shocks. The off-diagonal elements highlight cross-market spillovers. Bitcoin contributes 0.2% to both IDX and JII, while IDX contributes 0.5% to BTC and 44.3% to JII. Similarly, JII contributes 0.4% to BTC and 44.3% to IDX. Most importantly, the results indicate a Total connectedness index (TCI) of 30%, indicating a moderate degree of volatility spillovers among the markets. This suggests that approximately 30% of forecast error variance is attributable to cross-market volatility transmission, while the remaining variation is driven by own-market shocks.

In the pre-COVID period (Panel B), the TCI is slightly higher at 31.3%, reflecting a comparable level of interconnectedness. The results indicate that volatility spillovers were already present prior to the pandemic, with Indonesian equity markets (IDX and JII) contributing the majority of spillovers within the system, while Bitcoin played a relatively limited role.

In the post-COVID period (Panel C), the TCI decreases marginally to 30.0%, suggesting that the overall degree of volatility transmission did not increase following the pandemic. Although minor changes are observed in the directional spillovers, the magnitude of total connectedness remains broadly stable across the two sub-periods. These results suggest that Total volatility spillovers between Bitcoin and Indonesian stock markets did not increase in the post-COVID period. Similarly, Chandra (2024) shows evidence of volatility spillover between Bitcoin and the Indonesian stock market, where Bitcoin acts as the receiver rather than the transmitter.

However, these results differ from broader ASEAN studies (see Komarudin & Magfiroh, 2025, for example), which report substantial increases in total connectedness during periods of crisis. Utilizing the Diebold–Yilmaz framework, the authors show that spillovers between cryptocurrencies and ASEAN stock markets rose significantly during COVID-19 and the 2022 crypto crisis, with total connectedness exceeding 60% during peak stress periods [31]. In contrast, the present study finds that connectedness between Bitcoin and Indonesian equity markets remained relatively moderate and stable across sub-periods. These differences might be attributable to the scope of this present study, which is Indonesian-focused and captures a more concentrated market structure with fewer cross-border contagion channels compared to the broader ASEAN system. Nonetheless, the results are supported by Hugo Prasetyo Winotoatmojo (2026), who reports a Total connected Index of approximately 29.5% between major cryptocurrencies and the Indonesian capital market [10]. The study also shows that the Indonesian capital market is primarily driven by its own shocks despite exposure to cryptocurrency-related volatility transmission.

Table 8: Connectedness Matrix from the Diebold–Yilmaz Spillover Index

Panel A: Full Sample				
	BTC	IDX	JII	From Others
BTC	99.5	0.2	0.2	0.5
IDX	0.5	55.3	44.3	44.7
JII	0.4	44.3	55.3	44.7
Contribution to others	0.9	44.5	44.5	89.9
Total Connectedness Index (TCI)				30.0%
Panel B: Pre-COVID Period				
BTC	99.0	0.6	0.4	1.0
IDX	0.0	53.6	46.3	46.4
JII	0.0	46.4	53.5	46.5
Contribution to others	0.1	47.0	46.8	93.9
Total Connectedness Index (TCI)				31.3%
Panel C: Post-COVID Period				
BTC	98.7	0.7	0.6	1.3
IDX	1.1	55.6	43.3	44.4
JII	0.9	43.3	55.7	44.3
Contribution to others	2.1	44.0	43.9	90.0
Total Connectedness Index (TCI)				30.0%
Note: The table depicts the connectedness matrix obtained using the Diebold–Yilmaz framework. Diagonal elements represent own-market shocks, while off-diagonal elements represent spillovers transmitted across markets. “From Others” measures volatility received from other markets, whereas “Contribution to Others” measures volatility transmitted to other markets. TCI denotes the Total Connectedness Index.				

G) Conditional Safe Heaven

To examine whether the Islamic stock market remains relatively insulated from Bitcoin during periods of extreme volatility, dynamic conditional correlations between Bitcoin and Indonesian stock markets are estimated using a DCC-GARCH model. Periods of extreme Bitcoin volatility are identified using the 90th percentile of the full-sample conditional variance. The analysis then compares pairwise correlations between Bitcoin and both the Islamic (JII) and conventional (IDX) markets across the pre- and post-COVID periods. To assess statistical significance, Newey–West heteroskedasticity and autocorrelation consistent (HAC) tests are conducted. The results are presented in Tables 9 and 10, respectively.

In the pre-COVID period, the correlation between BTC and JII (0.0373) is slightly higher than that with IDX (0.0337), indicating no evidence of reduced co-movement. In contrast, in the post-COVID period, the correlation between BTC and JII (0.0770) is lower than that with IDX (0.0859), suggesting a modest reduction in co-movement under conditions of heightened volatility. The test for statistical significance indicates that the differences are not statistically significant in either period (p-values > 0.05), suggesting that the observed variations are small and not robust. Therefore, during periods of extreme Bitcoin volatility, the Islamic stock market does not exhibit lower dynamic conditional correlation with Bitcoin than the conventional stock market. Although the correlations between Bitcoin and both Indonesian equity indices remain relatively low, the differences between the Islamic and conventional markets are economically small and statistically insignificant.

The findings are partially supported by broader evidence from ASEAN markets, which suggests Bitcoin may exhibit regime-dependent hedge characteristics. Panyagometh (2024), for example, reports relatively low and often statistically insignificant dynamic correlations between Bitcoin and ASEAN stock indices before and during the COVID-19 pandemic [32]. However, the present study finds that although Bitcoin correlations with Indonesian equity indices remain relatively low, the Islamic stock index does not exhibit significantly lower correlation relative to the broader conventional market. This highlights that while co-movements between Bitcoin and ASEAN equity markets remain limited, Sharia screening alone may not provide substantial additional insulation from cryptocurrency-related shocks.

Table 9: Dynamic Correlations during High Bitcoin Volatility

Period	BTC–IDX	BTC–JII	Difference (JII − IDX)
Pre-COVID	0.0337	0.0373	+0.0036
Post-COVID	0.0859	0.0770	−0.0089

Notes: The table reports average dynamic conditional correlations between Bitcoin and Indonesian stock markets during periods of high Bitcoin volatility identified using the 90th percentile of conditional variance estimates. Positive differences indicate higher BTC–JII correlations relative to BTC–IDX correlations.

Table 10: HAC Test of Correlation Differences during High Volatility

Period	Estimate	Std. Error	t-stat	p-value
Pre-COVID	0.0037	0.0280	0.13	0.8959
Post-COVID	−0.0089	0.0151	−0.59	0.5553

Notes: The table presents HAC test results for differences between BTC–JII and BTC–IDX dynamic correlations during periods of high Bitcoin volatility.

H) Implications of the Study

a. Theoretical Implications

The Efficient Market Hypothesis (EMH), originally proposed by Fama (1970), posits that financial markets are informationally efficient, implying that asset prices reflect all available information relevant to their intrinsic value. Arff (2001) further distinguishes the theory into weak, semi-strong and strong forms based on the nature of information incorporated into market prices. The findings of this study, which reveal low but increasing post-pandemic correlations and modest spillover effects between Bitcoin and Indonesian equity markets, suggest the presence of partial and time-varying market integration. These results are broadly consistent with the weak form of EMH, implying that financial markets gradually incorporate information transmitted from cryptocurrency markets, particularly during periods of heightened uncertainty.

Contagion or spillover effects in finance are largely defined as the propagation of shocks or volatility from one market to another, especially during periods of turmoil or instability [14]. Rigobon (2016), on the other hand, suggest that spillovers pertain to the transmission of shocks through modelled channels, meaning a transmission mechanism that is always present because of underlying financial linkages, while contagion relates to unmodelled transmission mechanisms, meaning they are associated with crises or parameter instability [15]. The findings of this study indicate that Indonesia-driven spillovers are largely contained, implying that domestic equity shocks are more important than Bitcoin shocks, while broader ASEAN studies report significant total connectedness. This refines contagion theory by showing that crypto contagion is not uniform across regions.

In addition, Islamic finance theory which is built on Sharia laws are expected to insulate Islamic transactions from external shocks due to prohibition of Riba (Prohibition of Interest), Masir (Prohibition of Gambling and Speculation) and Gharar (Avoidance of Excessive Uncertainty) [17], [18], [20] The findings of this study show that JII does not have significantly lower correlation or spillovers than IDX implying that Sharia screening alone does not guarantee extra insulation from crypto shocks and therefore these findings suggest that the insulating effect of Sharia screening may be more limited in the context of cryptocurrency-related shocks.

b. Policy Implications

The findings of this study highlight weak but still positive and significant correlations or co-movements with crypto markets. These findings suggest that regulators may need to incorporate cryptocurrencies into stress tests and macroprudential monitoring, especially during periods of crises. More so, this study identifies Bitcoin as the net receiver of volatility spillovers rather than the transmitter; hence, policies should focus on perhaps protecting domestic investors rather than creating buffers to reduce crypto contagion effects.

c. Practical Implications

The study identifies that Bitcoin offers limited but non-zero diversification for IDX and JII in normal periods, correlations rise in stress periods, and it does not act as an effective hedge for Indonesian portfolios. In regard to Islamic investors, it is important to note that JII is not significantly less exposed to Bitcoin than IDX; risk management should not solely rely on Sharia screening, instruments such as sukuk or gold may still be needed.

V. CONCLUSION

This study examined the volatility spillover effects and the impact of the COVID-19 pandemic on the connectedness and volatility dynamics between Bitcoin and the Indonesian stock market over the period 2018–2024. The Indonesian market was represented by the IDX and JII indices, which served as proxies for the conventional and Islamic equity markets, respectively.

Volatility dynamics were analyzed using the GARCH (1,1) framework. The findings revealed evidence of volatility clustering and high volatility persistence across the sampled markets, as most estimated parameters were close to unity. The results further indicated that Bitcoin and the IDX exhibited greater volatility persistence in the post-pandemic period, suggesting increased sensitivity to market shocks following COVID-19. In contrast, volatility persistence within the JII slightly declined, implying that the Islamic equity market remained relatively more stable and less susceptible to structural changes across the two periods.

Using the Granger-causality approach, the study found evidence that prior to the COVID-19 pandemic, Bitcoin and the Indonesian equity indices were largely disconnected. However, in the post-pandemic period, Bitcoin returns were found to Granger-cause both the IDX and JII, while no reverse causality was observed. These findings extend the existing literature by demonstrating a structural strengthening in return transmission from Bitcoin to an emerging market with a substantial Islamic equity component.

Furthermore, evidence obtained from the DCC-GARCH framework indicated a slight increase in contagion effects between Bitcoin and the Indonesian stock market following the pandemic. The JII exhibited a marginally higher positive dynamic correlation with Bitcoin relative to the IDX during the post-pandemic period. Although the estimated correlations remained weak and close to zero, the corresponding DCC parameters were statistically significant and therefore cannot be disregarded. These findings are broadly consistent with other Asian and Indonesian-specific studies conducted within a similar period, such as [3] and [10].

Based on the Diebold–Yilmaz framework, this study found that total volatility spillovers between Bitcoin and the Indonesian stock markets did not increase during the post-pandemic period. Surprisingly, the findings revealed that the Indonesian equity markets contributed the majority of spillovers within the system, while Bitcoin played a comparatively limited role.

Lastly, this study sought to examine the effectiveness of Islamic Sharia screening in insulating Islamic equities from external shocks, particularly those originating from cryptocurrency markets during turbulent periods. This formed the rationale for including the JII as a stand-alone market despite the broad coverage of the IDX. In this regard, the findings suggest that although Bitcoin correlations with Indonesian equity indices remained relatively low, the Islamic stock index did not exhibit significantly lower correlations relative to the broader conventional market. These findings imply that Sharia screening alone may not provide substantial additional insulation from cryptocurrency-related shocks.

Conflict of Interest

The authors declare no conflict of interest.

Funding Statement

The authors received no external financial assistance for this research.

Acknowledgment

Firstly, I would like to express my sincere gratitude to my family for their continuous support and encouragement throughout the course of this research. Secondly, I would like to acknowledge the KNB Scholarship for providing the opportunity and support that made this study possible. Finally, I extend my appreciation to my academic supervisors for their constructive criticism, guidance, and valuable insights, which greatly contributed to the quality of this work.

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