

# CAN A MEME COIN SERVE AS A HEDGE? A GARCH-BASED EMPIRICAL ASSESSMENT OF DOGECOIN VERSUS THE FIVE LARGEST CRYPTOCURRENCIES IN THE INDONESIAN CAPITAL MARKET

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## ABSTRACT

This research aims to evaluate whether Dogecoin, a popular meme cryptocurrency, can outperform the five largest cryptocurrencies based on market capitalization (Bitcoin, Ethereum, Tether, Binance Coin, and Solana) as a hedging asset in the Indonesian capital market. Using the GARCH model, this study analyzes daily closing prices from 2022 to 2024 for the mentioned cryptocurrencies and the Composite Stock Price Index (JCI) to determine their correlation and effectiveness as a hedge asset. The results show that although Bitcoin fails to function as a hedge or diversification asset, Ethereum, Tether, and Binance Coin show significant negative correlations with JCI, making them effective as hedge assets. In contrast, Solana and Dogecoin show a significant positive correlation, indicating their role as diversification assets rather than hedge assets. These findings provide new insights for investors and investment managers in Indonesia, so that they can select strategic assets for hedging and diversification purposes during market uncertainties such as the COVID-19 pandemic and the geopolitical conflict of the Russian-Ukrainian War. This research fills a gap in the understanding of the potential of meme coins like Dogecoin compared to mainstream cryptocurrencies as hedging assets in emerging markets like Indonesia.

**Keywords:** Cryptocurrency, Dogecoin, Hedging Assets, Indonesian Capital Market, GARCH, Diversification

**JEL Classification Code:** F21, G11, G15

## INTRODUCTION

The rapid evolution of cryptocurrency—from its origins as a decentralized peer-to-peer electronic cash system proposed by Nakamoto (2008) to the emergence of NFTs, exchange-traded funds (ETFs), stablecoins, and even community-driven meme tokens—has transformed the global digital asset landscape. While Bitcoin was initially designed to serve as an alternative financial asset free from government intervention, investors today engage with a wide spectrum of crypto assets for various purposes, including diversification, hedging, and safe-

haven strategies (Yousaf et al., 2022). As of Q1 2024, global cryptocurrency market capitalization reached USD 2.9 trillion, reflecting a 64.5% increase from the previous year (CoinGecko, 2024). This surge highlights not only the rapid expansion of the industry but also its growing integration into mainstream financial behavior.

In Indonesia, similar growth patterns are evident. The Commodity Futures Trading Regulatory Agency (Bappebti) reported that the number of registered crypto asset users surpassed 18.25 million in 2023, with an annual transaction value of IDR 149.25

trillion (Bappebti, 2023). Despite this large user base, crypto trading volume remains relatively small compared to the Indonesian capital market. In the same year, the Indonesia Stock Exchange (IDX) recorded a total stock trading value of IDR 2,569 trillion, based on an average daily trading value of IDR 10.75 trillion across 239 trading days (IDX, 2023). Crypto trading therefore accounts for only about 5.8% of the value of equity transactions. This discrepancy indicates that although public interest in crypto is rising, capital market investors in Indonesia may not yet fully understand or utilize cryptocurrencies as potential hedging instruments—contrasting with trends observed in advanced economies where crypto assets increasingly feature in portfolio risk-management strategies.

Findings from previous studies further demonstrate that the hedging capability of cryptocurrencies varies across markets and time periods. For instance, Stensås et al. (2019) reported that Bitcoin acted as a hedge in Brazil, Russia, India, and South Korea. Jeribi and Snene Manzli (2020) identified Ripple, Dash, and Monero as hedge assets prior to the COVID-19 pandemic, while Jana and Sahu (2023) concluded that stablecoins may function as safe-haven assets during periods of heightened uncertainty. Studies in other regions also found that Bitcoin exhibited hedging properties (Hussain Shahzad et al., 2020), and that major cryptocurrencies such as ETH and BNB may serve as portfolio diversifiers or safe havens under pandemic-driven volatility (Riahi et al., 2024). Conversely, several studies argue that cryptocurrencies lack reliable hedging characteristics. Aslanidis et al. (2019) and Melki and Ghorbel (2023) both found that cryptocurrencies do not effectively hedge or serve as safe havens for equity markets. Similarly, Charfeddine et al. (2020) suggested that although digital assets may provide diversification benefits, their hedging capacity remains limited. These inconsistent empirical findings present a

clear research gap motivating further investigation.

Beyond conventional cryptocurrencies, the rise of meme coins originally created as satirical or community-driven digital assets adds another layer of complexity. Dogecoin, in particular, evolved from a joke into one of the top ten cryptocurrencies by market capitalization. Its adoption even extends to real economic transactions, such as purchases of Tesla vehicles, where Dogecoin is the only cryptocurrency accepted for payment on Tesla's official platform. This phenomenon raises a critical question: Can a meme-based cryptocurrency such as Dogecoin exhibit hedging properties comparable to or even exceeding traditional large-cap cryptocurrencies like Bitcoin, Ethereum, or stablecoins such as Tether? This question remains underexplored in emerging markets, including Indonesia.

During the 2022–2024 period covered in this study, global financial markets experienced unprecedented shocks, including the COVID-19 pandemic and the Russia–Ukraine geopolitical conflict. These events exerted strong downward pressure on traditional financial assets (Kumar et al., 2022; Ullah, 2023) and significantly escalated market volatility (Taera et al., 2023). In such environments, investors and portfolio managers actively seek hedging assets to mitigate systemic risks. Prior research suggests that digital assets may exhibit low or negative correlations with traditional assets during financial stress (Shahzad et al., 2019; Wang et al., 2019), making them potential hedging tools.

Modern Portfolio Theory (MPT), introduced by Markowitz in 1952, provides the theoretical foundation for this investigation. MPT posits that investors aim to maximize returns for any given level of risk and that diversification among uncorrelated or negatively correlated assets can reduce portfolio risk. Safe-haven theory further extends this concept by asserting that assets

with negative correlations during periods of market turmoil can offer protection (Hussain Shahzad et al., 2020). Under this framework, cryptocurrencies with negative dynamic correlations to equity indices may serve as hedging instruments or safe havens, whereas those with positive correlations function as diversifiers (Bouri et al., 2017). However, Kliber et al. (2019) emphasize that the diversification benefits of cryptocurrencies may weaken during severe market stress.

Given these theoretical and empirical inconsistencies, this research aims to examine whether the five largest cryptocurrencies by market capitalization—Bitcoin, Ethereum, Tether, Binance Coin, and Solana—as well as the meme coin Dogecoin, can function as hedging assets for the Indonesian capital market. By applying the GARCH model to analyze dynamic correlations with the Jakarta Composite Index (JCI), this study contributes to the growing literature on cryptocurrency performance in emerging markets and provides new insights for Indonesian investors seeking effective hedging and diversification strategies in times of uncertainty.

## LITERATURE REVIEW

### Cryptocurrencies in Financial Markets

Cryptocurrencies have evolved significantly since the introduction of Bitcoin by Nakamoto (2008), transitioning from a decentralized digital currency to an expansive asset class that includes smart-contract platforms, stablecoins, NFTs, and a wide spectrum of alternative digital tokens. The rapid growth of the cryptocurrency ecosystem has attracted retail and institutional investors globally, with many viewing cryptocurrencies as speculative assets, alternative investments, or instruments for risk management (Yousaf et al., 2022). Rising market capitalization—reaching USD 2.9 trillion in Q1 2024—indicates the increasing integration of crypto

assets into mainstream financial portfolios (CoinGecko, 2024).

Despite skepticism surrounding their intrinsic value, cryptocurrencies remain appealing due to their decentralized architecture, high liquidity, and detachment from traditional monetary policy interventions (Schilling & Uhlig, 2019). The unique market structure, characterized by 24/7 trading and high volatility, makes cryptocurrencies potentially useful for investors seeking uncorrelated assets during turbulent market conditions.

### Hedging, Safe-Haven, and Diversification Concepts

According to Modern Portfolio Theory (Markowitz, 1952), diversification is achieved by combining assets with low or negative correlations to reduce overall portfolio risk. The literature differentiates three related but distinct roles of financial assets:

- **Diversifier:** an asset that is positively but weakly correlated with another asset or portfolio under normal market conditions (Bouri et al., 2017).
- **Hedge:** an asset that is uncorrelated or negatively correlated on average with another asset.
- **Safe haven:** an asset that maintains a strong negative correlation specifically during periods of extreme market stress (Hussain Shahzad et al., 2020).

Anson (2002) emphasizes that safe-haven assets become particularly attractive during crises, when investors seek protection from sharp declines in traditional asset prices. In such periods, the performance of safe-haven assets tends to improve due to flight-to-quality behavior.

In the context of equity markets, an asset that consistently displays negative conditional

correlations during crises can be considered an effective hedge or safe haven. These theoretical foundations serve as the basis for evaluating the hedging potential of cryptocurrencies examined in this study.

### **Empirical Evidence on the Hedging Performance of Cryptocurrencies**

The empirical literature presents mixed findings regarding the capacity of cryptocurrencies to hedge equity market risks. Positive evidence suggests that major cryptocurrencies may serve as diversifiers or hedging instruments. Stensås et al. (2019) found that Bitcoin acted as a hedge in several emerging markets, including Brazil, Russia, India, and South Korea. Jeribi and Snene Manzli (2020) revealed that certain altcoins such as Ripple, Dash, and Monero exhibited hedging properties before the onset of the COVID-19 pandemic. During periods of heightened uncertainty, stablecoins—particularly USDT—have been shown to act as effective safe havens (Jana & Sahu, 2023). Similarly, Riahi et al. (2024) reported that ETH, BNB, BTC, and ADA performed as diversifiers, while stablecoins such as USDC and USDT offered safe-haven benefits during pandemic-driven volatility.

Conversely, a substantial body of research argues that cryptocurrencies fail to consistently provide hedging benefits. Aslanidis et al. (2019) observed that cryptocurrencies exhibit unstable correlations with equities, making them unreliable as safe havens. Melki and Ghorbel (2023) concluded that major digital currencies—including Bitcoin and Ethereum—do not effectively hedge stock markets in Eastern Europe. Charfeddine et al. (2020) further highlighted the weak and asymmetric relationship between cryptocurrencies and conventional assets, suggesting that their diversification benefits may be limited and context-dependent.

The inconsistent results across markets, time horizons, and specific crypto assets

underscore the importance of examining these relationships on a country-specific basis, particularly in emerging markets where adoption patterns differ significantly.

### **Meme Coins and the Case of Dogecoin**

Unlike utility-driven cryptocurrencies such as Bitcoin or Ethereum, meme coins emerged primarily as community-driven or humorous projects. Dogecoin, created as a parody of Bitcoin, has grown into a globally recognized digital asset supported by strong social media influence and public endorsements from high-profile figures. Its adoption in real economic activities—such as Tesla's acceptance of Dogecoin for selected purchases—demonstrates an unusual transition from internet culture to financial relevance.

Despite its popularity, academic research on meme coins remains limited. Existing studies often overlook their potential role in portfolio management, focusing instead on price speculation, social sentiment, or bubble dynamics. Jana and Sahu (2023) illustrated that Dogecoin may function only as a short-term diversifier but lacks meaningful hedging capabilities. Given its volatile and sentiment-driven nature, whether Dogecoin could act as a hedging asset in emerging markets remains an open empirical question.

The inclusion of Dogecoin in this study expands the scope of cryptocurrency research by comparing mainstream large-cap coins with a culturally driven digital asset—providing a unique angle rarely explored in the literature.

### **Research Gap and Contribution**

Previous studies offer conflicting evidence on the hedging and diversification properties of cryptocurrencies, and very few have focused on the Indonesian market—despite its rapidly growing crypto user base and significant market volatility during global crises. Additionally, empirical research has

largely neglected meme coins, particularly Dogecoin, even though it ranks among the top cryptocurrencies by market capitalization and has notable adoption in real transactions.

This study fills these gaps by:

1. **Examining six major cryptocurrencies**—Bitcoin, Ethereum, Tether, Binance Coin, Solana, and Dogecoin—within the context of the Indonesian capital market.
2. **Applying the GARCH model** to assess time-varying conditional correlations with the Jakarta Composite Index (JCI).
3. **Comparing mainstream cryptocurrencies with a meme coin**, providing new insight into whether unconventional digital assets can serve as hedges or diversifiers.
4. **Evaluating performance during periods of global uncertainty**, including the COVID-19 pandemic and the Russia–Ukraine conflict.

The findings contribute to the ongoing discourse on cryptocurrency risk management and offer practical implications for investors and portfolio managers in emerging markets.

## Hypothesis Development

Based on Modern Portfolio Theory and safe-haven theory, this study proposes the following hypotheses:

- **H1:** Bitcoin (BTC) acts as a hedging asset against the Indonesian stock market.
- **H2:** Ethereum (ETH) acts as a hedging asset against the Indonesian stock market.
- **H3:** Tether (USDT) acts as a hedging asset against the Indonesian stock market.
- **H4:** Binance Coin (BNB) acts as a hedging asset against the Indonesian stock market.
- **H5:** Solana (SOL) acts as a hedging asset against the Indonesian stock market.
- **H6:** Dogecoin (DOGE) acts as a hedging asset against the Indonesian stock market.

A negative and significant coefficient indicates hedging or safe-haven potential, while a positive significant coefficient indicates a role as a diversification asset.

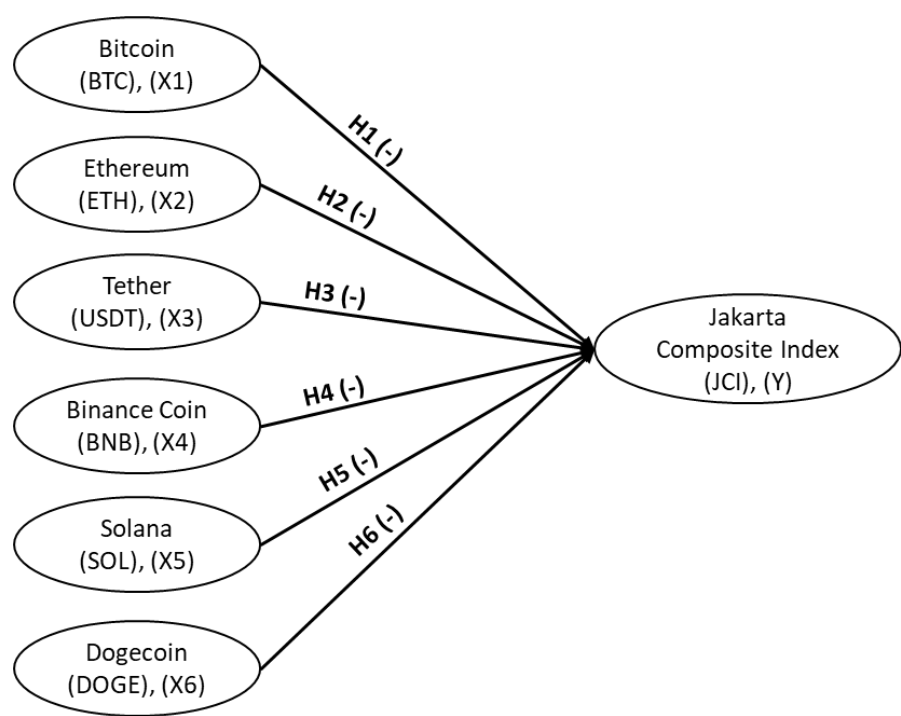


Figure 1. Conceptual Framework

METHODOLOGY

Data Description

This study uses daily time-series data covering the period from **January 2022 to December 2024**. The dataset consists of six major cryptocurrencies—Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), Solana (SOL), and Dogecoin (DOGE)—and the **Jakarta Composite Index (JCI)** as the benchmark of the Indonesian capital market. All cryptocurrency and equity index data were obtained from the **Bloomberg Terminal**, ensuring consistency and accuracy in the data collection process.

The selected cryptocurrencies represent the largest digital assets by global market capitalization (Forbes, 2023), while Dogecoin was included due to its position within the top ten cryptocurrencies and its unique characteristics as a meme-based asset. JCI was chosen as the dependent variable because it reflects the aggregated performance of more than 900 listed companies in Indonesia, making it a

comprehensive indicator of equity market conditions.

In line with prior research (Klein et al., 2018; Smales, 2019), cryptocurrency observations recorded during weekends were removed to ensure alignment with equity market trading days, resulting in a harmonized dataset across all variables.

Daily returns were computed using the logarithmic return formula:

$$R_t = \frac{(P_t - P_{t-1})}{P_{t-1}}$$

(1)

Where,  $R_t$  is the daily return of cryptocurrency and the composite stock price index at time  $t$ ;  $P_t$  And are  $P_{t-1}$  respectively the closing price of the cryptocurrency and the composite stock price index at time  $t$  and  $t - 1$ .

This transformation stabilizes variance and addresses skewness—both crucial for volatility modeling using GARCH-type specifications.

## Econometric Framework

To examine the dynamic relationship between cryptocurrency returns and the Indonesian equity market, this study employs the **Generalized Autoregressive Conditional Heteroskedasticity (GARCH)** model introduced by Engle (2002). This model is widely used in financial econometrics to capture time-varying volatility and conditional correlations, especially for high-frequency data that exhibit volatility clustering and heteroskedasticity.

The conditional variance equation for a standard GARCH(1,1) model is expressed as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (2)$$

$\sigma_t^2$  is the conditional variance at time t

$\mu_{t-1}^2$  is the squared residual at time t-1

$\sigma_{t-1}^2$  is the conditional variance at time t-1

A **GARCH(p, q)** model generalizes this into:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \dots + \alpha_p \mu_{t-p}^2 \quad (3)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \dots + \alpha_p \mu_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \beta_q \sigma_{t-q}^2 \quad (4)$$

This study adopts the **GARCH(1,1)** specification, selected based on the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC), which produced the lowest values among all tested models—indicating superior fit and parsimony.

## Variable Specification

The study's variables are categorized as follows:

Dependent Variable:

- **JCI (Jakarta Composite Index)**  
Represents the daily closing value of Indonesia's primary stock market index.

Independent Variables:

- **BTC (XBTUSD):** Bitcoin
- **ETH (XETUSD):** Ethereum
- **USDT (XDT):** Tether (stablecoin)
- **BNB (XBIUSD):** Binance Coin
- **SOL (XSOUSD):** Solana
- **DOGE (XDGUSD):** Dogecoin

All variables are measured in daily closing prices (USD-denominated for cryptocurrencies).

## Stationarity and Diagnostic Testing

Before estimating the GARCH model, all variables underwent the **Augmented Dickey–Fuller (ADF)** test to ensure stationarity. The results confirmed that all return series were stationary at the first difference level (( p < 0.05 )), validating their suitability for volatility modeling.

Additional diagnostic checks were performed:

- **Normality test**
- **Homoscedasticity test**
- **Autocorrelation assessment (Durbin–Watson)**

No major violations were detected after transformation, confirming that the data met the necessary assumptions for GARCH estimation.

## Analytical Procedure

The methodological steps used in this study include:

1. **Data collection** from Bloomberg Terminal.

2. **Data cleaning**, including weekend removal and alignment of trading days.
3. **Return calculation** using logarithmic transformation.
4. **Stationarity testing** via ADF.
5. **Model selection** using AIC/SIC criteria.
6. **Estimation of GARCH(1,1)** to examine conditional correlations.
7. **Coefficient interpretation** to determine hedging, safe-haven, or diversification roles.
8. **Hypothesis testing** based on significance levels.

This approach allows for the identification of dynamic volatility spillovers between cryptocurrencies and the Indonesian equity market.

## RESULT AND DISCUSSION

### Descriptive Statistics

The dataset comprises **334 daily observations** for all variables, including the Jakarta Composite Index (JCI) and six cryptocurrencies. Table 2 summarizes the descriptive statistics for each return series. The JCI shows relatively low volatility compared to cryptocurrencies, which is consistent with equity market characteristics in emerging economies. Meanwhile, Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Solana (SOL), and Dogecoin (DOGE) demonstrate substantially higher standard deviations, reflecting the inherent volatility of digital asset markets.

Skewness and kurtosis statistics indicate non-normal return distributions, a pattern commonly observed in financial time-series data due to fat tails and volatility clustering. The Jarque–Bera test results further confirm non-normality across all variables, justifying the application of GARCH-type models for volatility estimation.

### Stationarity Test Results

The Augmented Dickey–Fuller test (ADF) was performed to ensure stationarity of all return series. All variables rejected the null hypothesis of non-stationarity at the 5% significance level, confirming that each return series is stationary at the first difference. This satisfies the requirements for estimating conditional volatility using the GARCH model.

### Model Selection

Four GARCH specifications—GARCH(1,1), GARCH(1,2), GARCH(2,1), and GARCH(2,2)—were evaluated using AIC and SIC criteria. The **GARCH(1,1)** model exhibited the lowest AIC and SIC values, making it the most parsimonious and statistically efficient specification for capturing volatility dynamics in this study. This is consistent with Engle’s (2002) argument that GARCH(1,1) typically provides excellent performance in modeling financial market volatility.

### GARCH(1,1) Estimation Results

Table 5 presents the GARCH estimation results. The coefficients reveal important insights into the conditional correlations between each cryptocurrency and the Indonesian equity market.

### Mean Equation Coefficients

- **Bitcoin (BTC):**  
The coefficient (−0.000456) is negative but statistically insignificant ( $p = 0.9442$ ). This suggests that BTC movements have no meaningful hedging effect against JCI fluctuations. Despite being the largest cryptocurrency, Bitcoin does not provide stable hedging properties in the Indonesian context.
- **Ethereum (ETH):**  
ETH shows a significant negative coefficient (−0.055709,  $p < 0.001$ ),

indicating a strong inverse relationship with JCI returns. Thus, ETH acts as an effective hedging asset.

- **Tether (USDT):**  
USDT has a large and significant negative coefficient ( $-1.579613$ , ( $p = 0.0388$ )), suggesting robust hedging capability, consistent with its nature as a USD-pegged stablecoin.
- **Binance Coin (BNB):**  
BNB exhibits a significant negative coefficient ( $-0.009711$ , ( $p < 0.001$ )), confirming its function as a hedge.
- **Solana (SOL):**  
SOL shows a highly significant positive coefficient ( $0.052640$ , ( $p < 0.001$ )), indicating a strong comovement with JCI—thus functioning as a diversification asset rather than a hedge.
- **Dogecoin (DOGE):**  
DOGE also demonstrates a significant positive coefficient ( $0.007656$ , ( $p < 0.001$ )), suggesting that Dogecoin behaves as a diversification asset, not a safe haven.

### Variance Equation Coefficients

The variance dynamics further validate the GARCH model:

- The ARCH term **RESID(-1)(^2)** ( $1.217949$ , ( $p < 0.001$ )) indicates strong sensitivity to recent shocks.

- The GARCH term **GARCH(-1)** ( $-0.115904$ , ( $p = 0.0242$ )) shows a negative but significant effect, implying relatively fast mean reversion in volatility.
- Together, the ARCH and GARCH components confirm volatility clustering—a typical characteristic of financial return series.

The adjusted R-squared of **0.5804** indicates that the model explains over 58% of JCI volatility, which is considered substantial for financial time-series modeling.

### Discussion

#### Performance of Bitcoin in the Indonesian Market

Although Bitcoin exhibits a negative sign, the coefficient is statistically insignificant, meaning BTC does **not** provide meaningful hedging benefits. This aligns with findings from Jiang et al. (2021), who concluded that Bitcoin is unreliable as a hedge for equity markets. Bitcoin's high volatility and inconsistent correlation patterns reduce its risk-mitigation potential—especially in emerging markets such as Indonesia.

Additionally, because BTC's correlation with JCI is weak and unstable, it cannot be classified as a diversification asset either. This reinforces Jana and Sahu's (2024) finding that Bitcoin is unsuitable for diversification under both normal and crisis conditions.

**Table 1. GARCH Test**

| Variable          | Coefficient | Std. Error | z-Statistic | Prob.  |
|-------------------|-------------|------------|-------------|--------|
| C                 | 9.160772    | 0.003509   | 2610.677    | 0.0000 |
| XBT               | -0.000456   | 0.006524   | -0.069973   | 0.9442 |
| XET               | -0.055709   | 0.009238   | -6.030458   | 0.0000 |
| XDT               | -1.579613   | 0.764384   | -2.066516   | 0.0388 |
| XBI               | -0.009711   | 0.002560   | -3.793743   | 0.0001 |
| XSO               | 0.052640    | 0.000979   | 53.78875    | 0.0000 |
| XDG               | 0.007656    | 0.001920   | 3.988193    | 0.0001 |
| Variance Equation |             |            |             |        |
| C                 | 2.98E-05    | 6.48E-05   | 4.603944    | 0.0000 |

|                    |           |                       |           |        |
|--------------------|-----------|-----------------------|-----------|--------|
| RESID(-1)^2        | 1.217949  | 0.223299              | 5.454347  | 0.0000 |
| GARCH(-1)          | -0.115904 | 0.051428              | -2.253717 | 0.0242 |
| R-squared          | 0.588007  | Mean dependent var    | 8.842115  |        |
| Adjusted R-squared | 0.580447  | S.D. dependent var    | 0.025304  |        |
| S.E. of regression | 0.016390  | Akaike info criterion | -6.120935 |        |
| Sum squared resid  | 0.087841  | Schwarz criterion     | -6.006829 |        |
| Log likelihood     | 1030.782  | Hannan-Quinn criter.  | -6.066910 |        |
| Durbin-Watson stat | 0.169049  |                       |           |        |

Source: data processed

$$JCI_t = 9.160772 - 0.000456BTC_t - 0.055709ETH_t - 1.579613USDT_t - 0.009711BNB_t + 0.052640SOL_t + 0.007656DOGE_t$$
$$\sigma^2_t = 2.98E - 05 + 1.217949\varepsilon^2_{t-1} - 0.115904\sigma^2_{t-1}$$

Table 2. Hypothesis Testing

| Hypothesis | Asset        | Expected Sign | Result        | Interpretation                |
|------------|--------------|---------------|---------------|-------------------------------|
| H1         | Bitcoin      | Negative      | Not supported | Neither hedge nor diversifier |
| H2         | Ethereum     | Negative      | Supported     | Hedge                         |
| H3         | Tether       | Negative      | Supported     | Strong hedge / safe haven     |
| H4         | Binance Coin | Negative      | Supported     | Hedge                         |
| H5         | Solana       | Negative      | Not supported | Diversifier                   |
| H6         | Dogecoin     | Negative      | Not supported | Diversifier                   |

Hedging Effectiveness of ETH, USDT, and BNB

The negative and statistically significant coefficients for Ethereum, Tether, and Binance Coin indicate that these assets serve as **effective hedging instruments** for the Indonesian stock market.

- **Ethereum (ETH):**  
ETH behaves countercyclically relative to JCI, consistent with prior research suggesting ETH may act as a safe haven during the COVID-19 pandemic (Caferra & Vidal-Tomás, 2021).

- **Tether (USDT):**  
With the largest negative coefficient, USDT emerges as the strongest hedging asset in this study. Its stability and 1:1 peg to the U.S. dollar make it a natural hedge during market downturns—supporting the findings of Jana et al. (2024).
- **Binance Coin (BNB):**  
BNB’s negative coefficient, though smaller, remains statistically significant. This indicates that BNB can also reduce exposure to Indonesian equity market volatility.

These results complement earlier studies that highlight the hedging potential of certain cryptocurrencies during macroeconomic

shocks (Corbet et al., 2018; Stensås et al., 2019).

### Diversification Role of Solana and Dogecoin

Solana and Dogecoin exhibit significant positive correlations with JCI, indicating that their returns move in the same direction as the Indonesian equity market. This classifies SOL and DOGE as **diversification assets**, not hedging instruments.

- **Solana (SOL):**  
SOL's extremely strong positive relationship suggests high sensitivity to broader market sentiment, consistent with literature stating that cryptocurrencies may act as diversifiers when correlations are positive (Bouri et al., 2017).
- **Dogecoin (DOGE):**  
DOGE, despite its origins as a meme coin, exhibits diversification characteristics similar to SOL. Its movements are sentiment-driven, making it unsuitable as a hedge. This aligns with Jana and Sahu (2023), who found that Dogecoin provides only short-term diversification benefits.

### CONCLUSION

This study investigates whether major cryptocurrencies—Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), Solana (SOL), and Dogecoin (DOGE)—can serve as hedging instruments against volatility in the Indonesian capital market, represented by the Jakarta Composite Index (JCI). By employing the GARCH(1,1) model on daily data from 2022 to 2024, the results provide important empirical insights into the risk management potential of cryptocurrencies in an emerging market context.

The findings indicate that not all major cryptocurrencies function effectively as

hedging tools. **Bitcoin fails to act both as a hedge and as a diversification instrument**, reflecting its instability and inconsistent correlation structure. In contrast, **Ethereum, Tether, and Binance Coin demonstrate significant negative correlations with JCI**, confirming their role as hedging assets during periods of market stress, including the COVID-19 pandemic and the Russia–Ukraine conflict. Among these, **Tether shows the strongest hedging capability**, consistent with its stablecoin characteristics and its peg to the U.S. dollar.

Meanwhile, **Solana and Dogecoin exhibit significant positive correlations with JCI**, suggesting that their value movements mirror those of the equity market. As such, these cryptocurrencies are more appropriate as **diversification assets** rather than safe-haven instruments. The performance of Dogecoin also reveals that meme-based cryptocurrencies—despite their popularity—lack the stability required to mitigate market downturn risks.

### Managerial Implications

The results of this study carry several practical implications for industry participants:

#### 1. Strategic Portfolio Hedging

Investment managers may incorporate ETH, USDT, or BNB to protect portfolios from downturns in the Indonesian equity market, especially during uncertain macroeconomic conditions.

#### 2. Preference Toward Stable Assets

USDT should be prioritized as a hedging instrument due to its low volatility and strong negative relationship with equity market performance.

#### 3. Timing and Risk Positioning

SOL and DOGE can be used as diversification tools, particularly when the stock market is stable or expected to perform well, given their

positive price co-movement with JCI.

#### 4. **Risk Management Practices in Indonesia**

The findings may guide Indonesian regulators and market institutions in assessing the feasibility of digital assets within risk mitigation frameworks and future financial product development.

#### 5. **Investor Education**

As cryptocurrency adoption grows rapidly in Indonesia, it is essential to communicate realistic expectations regarding which crypto assets can effectively serve as hedging instruments.

### **Theoretical Contributions**

This study advances the literature by:

- Providing evidence on the differentiated performance of cryptocurrencies in an emerging market setting.
- Highlighting the distinct behavior of meme coins such as Dogecoin compared to mainstream assets.
- Strengthening understanding of safe-haven behavior during overlapping global crises involving health and geopolitical shocks.

### **Policy Implications**

Given the increasing integration of crypto assets in Indonesia's financial landscape:

- Policymakers should acknowledge stablecoins' potential role in market stability and explore regulatory frameworks supporting responsible adoption.
- Capital market authorities may consider promoting research-driven guidelines for crypto inclusion in institutional portfolios.

### **Limitations and Future Research**

Despite providing important empirical insights into the hedging performance of cryptocurrencies in the Indonesian capital market, this study is subject to several limitations that warrant consideration in future research.

*First*, the scope of analysis is restricted to Indonesia, which may limit the generalizability of conclusions to broader regional or global markets. Financial dynamics and cryptocurrency adoption vary substantially across countries; therefore, expanding the study to include other emerging markets (e.g., ASEAN or Asia-Pacific) could yield more comprehensive perspectives.

*Second*, this research focuses only on six cryptocurrencies based on market capitalization and popularity. The crypto ecosystem is highly dynamic, with rapid shifts in market leadership and the emergence of new assets, including other meme-based tokens such as Shiba Inu or more advanced Layer-2 blockchain assets. Future research should examine a wider and more diverse set of cryptocurrencies.

*Third*, the study employs the GARCH(1,1) model to capture volatility patterns and conditional correlations. Although this model is widely used in financial econometrics, alternative or more advanced multivariate volatility models—such as DCC-GARCH, BEKK-GARCH, or wavelet coherence approaches—may better capture structural breaks and time-varying co-movements under extreme market conditions.

*Fourth*, the analysis period includes global crises such as the COVID-19 pandemic and the Russia–Ukraine conflict but excludes the effects of more recent macroeconomic shocks or regulatory policy changes specific to Indonesia's digital asset market. Extending the dataset beyond 2024 would allow the evaluation of evolving behavioral

shifts and the long-term hedging role of digital assets.

*Finally*, this study relies solely on market price data and does not incorporate behavioral and macroeconomic factors such as investor sentiment, liquidity volatility, exchange rates, or monetary policy announcements. Integrating these determinants into the modeling framework may reveal deeper insight into the drivers of crypto–equity interactions.

In light of these limitations, future studies are encouraged to employ multi-market comparisons, diversified asset selections, advanced econometric techniques, and additional explanatory variables. Such approaches will enrich the understanding of whether and when cryptocurrencies—especially unconventional assets like meme coins—can function as credible components of risk-mitigation strategies in emerging capital markets.

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