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# Regulating Crypto Assets: Understanding Stablecoins' and Unbacked Crypto Assets' Systemic Implication on the Financial Market

**Obed Juan Benito**[1]
**Maulana Ahmad Rayhan Al Jausyan**[2]

## ABSTRACT

To bring clarity to the emerging regulatory concerns, this study employs GARCH and TVP-VAR models to compare stablecoins and unbacked crypto assets' profiles and their systemic implications to the financial market. Using daily price data, it reveals that stablecoins are more stable than unbacked crypto assets while both are having weak connectivity at the same time. Moreover, stablecoins exert a more significant systemic impact on the financial market. The time-varying analysis also indicates high connectivity between crypto assets and traditional financial assets during crisis such as Covid-19. These findings inform regulatory frameworks, ensuring stability in the financial system while promoting fintech innovation.

**Keywords :**
Crypto Assets, Stablecoin, Financial Market, Risk, Regulation.
JEL Code: G15, G18, G32, C58, D81

The Ministry of Finance of the Republic of Indonesia; Jakarta; Indonesia
[1]E-mail: obed.juanbenito@kemenkeu.go.id, [2]E-mail: maulana.araljausyan@kemenkeu.go.id

## 1. INTRODUCTION

Regulating crypto assets presents a significant challenge for regulators worldwide, considering its novelty in transforming the financial system. Most countries have only been able to regulate crypto service entities and have not gone beyond that (Bains, Ismail, Melo, & Sugimoto, 2022; WEF, 2023; PwC, 2023; Hammond & Ehret, 2022). Despite the lack of holistic regulation, the crypto asset ecosystem is growing rapidly, especially in developing countries (Bains et al., 2022). In Indonesia, the total value of crypto asset transactions reached Rp 800 trillion in 2021. Additionally, the number of crypto investors has even surpassed stock investors, reaching approximately 17 million in 2023 (Ministry of Trade of the Republic of Indonesia, 2023).

With the increasing interest and exposure to the global financial market, there is an urgent need for a comprehensive regulatory framework. The collapses of Terra-Luna and FTX in 2022 severely shook the crypto asset industry, resulting in billions of dollars in losses. Volatility, accountability, and governance issues were found to be the causes of these crypto asset failures (WEF, 2023; Bains et al., 2022; Jalan & Matkovskyy, 2023). If not controlled promptly, crypto asset instability could even create a systemic shockwave throughout the financial market (Wu and Leung, 2023; Li and Huang, 2020). However, the impact of various regulations related to crypto assets that have emerged in the past decade is still not entirely clear in influencing their activities. Therefore, further study is necessary to understand their market activity (Feinstein and Werbach, 2021; Shanaev, Sharma, Ghimire, & Shuraeva, 2020; Borri and Shaknov, 2020).

The latest update on comprehensive crypto asset regulation adopts a global risk-based regulatory approach for two main categories: stablecoins and unbacked crypto assets (Basel Committee on Banking Supervision, 2021; Bains et al., 2022). Tied to underlying assets, stablecoins tend to be more stable and secure for adoption into the financial system. However, market capitalisation and public interest are found to be greater for unbacked crypto assets, which have the opposite characteristics. Both types also offer different functions, with stablecoins often used as hedging instruments and mediums of exchange, while unbacked crypto assets are frequently used as investment instruments.

**Table 1. Crypto Assets Regulations in Various Countries (PwC, 2023)**

| No | Key Regulations | Countries that have adopted* |
|---|---|---|
| 1 | Regulatory Framework | Japan, Switzerland, France, Germany, Singapore, Malaysia, Indonesia** |
| 2 | Anti-Money Laundering (AML) and Combating the Financing of Terrorism (CFT) | United States, United Kingdom, Switzerland, France, Germany, Singapore |
| 3 | Travel Rule | United States, United Kingdom, Switzerland, France, Germany, Singapore |
| 4 | Stablecoins used for Payments | Japan, Switzerland, Bahamas, Cayman Islands, Mauritius |

*This list is only a sample and does not cover all countries that have adopted the regulations.

**Indonesia has officially enacted the Financial Sector Development and Reinforcement Law (UU P2SK), which serves as the initial framework for cryptocurrency asset regulation in 2023.

To assist financial authorities worldwide, this study aims to compare the risk profiles, exposures, and systemic implications of both types of crypto assets on the financial market. Understanding the risks (Chen, 2022), interconnections among crypto assets (Akhtaruzzaman, Boubaker, Nguyen, & Rahman, 2022), and the extent to which crypto assets impact the financial market (Li and Huang, 2020) will help regulators determine the regulation needed and the level of regulatory aggressiveness required to protect market stability while fostering innovation (WEF, 2023; Haji, 2022).

The paper is organised as follows: section 2 presents a comprehensive literature review. Section 3 describes the data and methodology employed in the study. Section 4 presents the results and discusses them in detail. Section 5 outlines the conclusions drawn from the findings. And the final section provides policy recommendations based on the study insights.

## 2. Literature Review

There have been numerous attempts to analyse the risk of crypto assets. Maciel (2020) and Obeng (2021) utilised modified GARCH models to analyse the Value-at-Risk of several crypto assets. Other studies have employed Historical Simulation and Monte Carlo models for the same purpose (Likitratcharoen Chudasring, Pinmanee, & Wiwattanalamphong, 2023; Mba, Mwambi, & Pindza, 2022; Uyar and Kahraman, 2019; Koutmos, 2018). Chen (2022) even employed Deep Learning methods to predict the price movements of Bitcoin. Most of the previous studies depicted high risk and volatility in observed unbacked crypto assets.

Furthermore, in recent years, there has been significant scholarly focus on the phenomenon of risk spillovers within the cryptocurrency market. Akhtaruzzaman et al. (2022) observed the interconnectedness of cryptocurrencies to analyse how risks are distributed among crypto assets during the COVID-19 crisis. On the other hand, Zhang and Ding (2021) sought a deeper understanding of risk spillovers in the cryptocurrency market by incorporating time and frequency variables. Xu, Zhang, & Zhang (2021) used the Systemic Risk Receiver (SRR) and Systemic Risk Emitter (SRE) indices to depict the interconnections among crypto assets. Among various studies, the market capitalisation level of a crypto asset tends to be a determining factor for its stability and influence on other crypto assets.

Systemic risk among crypto assets is not the only concern in recent studies. With its increasing use and size, scholars also attempt to understand the correlation and implications of crypto assets for the broader financial market. Urom, Abid, Guesmi, & Chevallier (2020) examined the risk correlation between Bitcoin and traditional financial assets, such as stock indices and strategic commodities. Fareed, Abbas, Madureira, & Wang (2022) found a significant relationship between Bitcoin and the Carbon Efficient Index (CEI) during economic crises like COVID-19. On the other hand, Li and Huang (2020) did not find a significant risk relationship between several crypto assets and traditional financial assets. However, recent studies on the relationship between stablecoins (Wu and Leung, 2023) and Bitcoin (Elsayed, Gozgor, & Lau, 2022) with traditional financial assets have yielded significant results.

Various models and methods can be utilised to analyse the risk of cryptocurrencies. The Generalised AutoRegressive Conditional Heteroskedasticity (GARCH) model is found to be the most popular to analyse volatility as it is used in recent studies (Chen, Huang, & Liang, 2023; Cheikh, Zaied, & Chevallier, 2020; Ngunyi, Mundia, & Omari, 2019; Kyriazis, Daskalou, Arampatzis, Prassa, & Papaioannou, 2019; Kim, Jun, & Lee, 2021; Ampountolas, 2022). On the other hand, the Vector Auto Regression model (VAR) with many modifications such as QVAR and TVP-VAR are the most common method used to analyse spillovers and connectedness among assets (Yen & Ha, 2023; Le, 2023; Chowdhury, Abdullah, & Masih, 2023; Cao & Xie, 2022; Ha, 2023; Ha & Nham, 2022; Foglia & Dai, 2022). According to previous studies, these models are found to be very insightful.

To address the research gap identified by regulators, this study attempts to combine the three aforementioned approaches to risk analysis (risk profiling, interconnection, and systemic implications for the financial market) through a comparison of stablecoins and unbacked crypto assets. To the best of our knowledge, this study is the first to comprehensively compare stablecoins with crypto assets. The main and unique contributions of this study are as follows: First, it takes a comparative perspective (stablecoin vs. unbacked crypto assets) rather than focusing solely on one or a few major crypto assets as previous studies have done. Second, unlike Li and Huang (2020), this study utilises the latest data, including the period when crypto market capitalisation experienced significant growth since late 2020 (Wu and Leung, 2023; Elsayed et al., 2022). Third, we provide a holistic understanding through the combination of the three approaches to risk analysis, rather than adopting a single approach. Fourth, we utilise the latest and most advanced method namely the Generalised AutoRegressive Conditional Heteroskedasticity (GARCH) model and the Time Varying Parameter Vector Autoregression (TVP-VAR) model to analyze the risk. Lastly, we provide deeper analysis specifically on how these two categories of crypto assets impacted Indonesia's financial market. Thus, regulators can comprehend the vulnerabilities of each type of crypto asset and determine the necessary risk management strategies.

## 3. Research Methods

### A. Data

The data used in this research includes daily closing price for various types of assets, including cryptocurrencies, such as USD Tether (USDT), USD Coin (USDC), DAI, Binance USD (BUSD), True USD (TUSD), Bitcoin (BTC), Ethereum (ETH), Binance (BNB), Ripple (XRP), and Cardano (ADA). Other than that, we also use daily closing price data for precious metals like Gold and Silver, various currencies from different countries including Euro (EUR), Pound Sterling (GBP), Swiss Franc (CHF), Singapore Dollars (SGD), Japanese Yen (JPY), South Korean Won (KRW), Chinese Yuan (CNY), Hong Kong Dollars (HKD), Indonesian Rupiah (IDR), and stock indices from various countries such as United States (S&P 500), United Kingdom (FTSE), Germany (GDAXI), French (CAC 40), Switzerland (SASMI 20), Japan (N225), South Korea (KS11), China (SSE), Hong Kong (HSI), Singapore (STI), and Indonesia (IDX). The data covers a daily period from June 30, 2020, to June 30, 2023, with a total of 36,998 data points. Daily price movements are then used to analyse the return volatility of each type of crypto assets. The data was obtained from coinmarketcap.com, Yahoo Finance, and investing.com.

The initial stage of data processing involved classifying the crypto assets into two categories: stablecoins and unbacked crypto assets. Stablecoins are characterised by those who has underlying assets which include USDT, USDC, DAI, BUSD, and TUSD. On the other hand, unbacked crypto assets are characterised by those who do not have underlying assets which include BTC, ETH, BNB, XRP, and ADA (Bains et al., 2022). The selection of these crypto assets was based on their market capitalisation size on exchanges; thus, they represent each category. To assess the systemic implication on the financial market, these variables are calculated as the first logarithmic difference between two consecutive observations (Elsayed et al., 2022). The subsequent stage involved data processing using the methodology that will be explained as follows.

## B. Method

### B.I. Calculating Daily Return

Return is the gain obtained from an investment policy to a certain asset. Return can be formulated as follows:

$$R_t = \frac{X_t}{X_{t-1}} \tag{1}$$

where $R_t$ is return in period t, $X_t$ is the price of crypto assets at time t, and $X_{t-1}$ is the price of crypto assets at time t-1. The daily return of each asset is used to analyse their volatilities and interconnections to each other using GARCH and TVP-VAR model (Elsayed, Gozgor, & Yarovaya, 2022; Elsayed et al., 2022).

### B.II. Unit Root Test

Stationary data is data that exhibits constant mean, variance, and autocovariance (at various lags) regardless of when the data is formed or used. In other words, with stationary data, time series models can be considered more stable. One formal concept used to determine the stationarity of data is through unit root tests. One popular test is the Augmented Dickey-Fuller (ADF) Test, which was developed by David Dickey and Wayne Fuller. If a time series data is non-stationary at order zero, $\mathrm{I}(0)$, then the stationarity of the data can be explored through subsequent orders to achieve the level of stationarity at the nth order first difference or $\mathrm{I}(1)$, or the second difference or $\mathrm{I}(2)$, and so on.

### B.III. Classical Assumption Tests

Classical assumption tests are conducted to examine the cause-and-effect relationship of the data, allowing the validity of the data to be determined and potential biases to be avoided. We employ several tests such as normality test, autocorrelation test, and heteroskedasticity test to perform classical assumption testing with the purpose of ensuring the validity of the data and mitigating potential biases with $\alpha = 0{,}05$. This study utilises the Jarque-Bera test for normality test, the Breusch-Godfrey Serial Correlation LM test for the autocorrelation test, and the Autoregressive Conditional Heteroskedasticity (ARCH) test for the heteroskedasticity test.

### B.IV. Generalised Autoregressive Conditional Heteroskedasticity (GARCH)

There are three time series data models used in this study to model returns, namely:

a) Autoregressive (AR) Model
The general form of the AR(*p*) model is:

$$R_t = \emptyset_1 R_{t-1} + R_{t-2} + \cdots + \emptyset_p R_{t-p} + \varepsilon_t \tag{2}$$

b) Moving Average (MA) Model
The general form of the MA($q$) model is:

$$R_t = \varepsilon_t - \emptyset_1 \varepsilon_{t-1} - \emptyset_2 \varepsilon_{t-2} - \cdots - \emptyset_q \epsilon_{t-q} \quad (3)$$

c) Auto Regressive Moving Average (ARMA) Model
The general form of the ARMA($p,q$) model is:

$$R_t = \emptyset R_{t-1} + \emptyset_2 R_{t-2} + \cdots + \emptyset_p R_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \cdots - \theta_q \epsilon_{t-q} \quad (4)$$

The AR(p), MA(q), and ARMA(p,q) models assume constant variance over time, while economic data, including cryptocurrency closing prices, tend to exhibit rapid fluctuations over time, resulting in non-constant residual variances. In such conditions, modeling of the residual variance is necessary, and this is addressed using the Autoregressive Conditional Heteroskedasticity (ARCH) approach, first introduced by Engle (1982), which was later developed into the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model by Bollerslev (1986). Generally, the GARCH (p, q) model is defined as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2, \quad (5)$$

where the variables are as follows:
$\varepsilon_t \sim N(0,1), p \geq 0, q > 0, \alpha_0 > 0, \alpha_i > 0, i = 1,2, \ldots, q$ and $\beta_j \geq 0, j = 1,2, \ldots, p$ and $\sum_{i=1}^{\max(p,q)} (\alpha_i + \beta_j) < 1$.

### B.V. Estimating Value at Risk (VaR)

Value-at-Risk (VaR) depicts the estimated maximum loss that can be incurred when investing in a particular asset. Value at Risk in the context of GARCH can be formulated as follows:

$$VaR = W.(\hat{R}_t - Z_\alpha \hat{\sigma}_t) \quad (6)$$

where W represents the simulated investment fund to be used in investing in a specific asset. $\hat{R}_t$ is the forecasted return value using GARCH, $Z_\alpha$ is the Z Score value, and $\hat{\sigma}_t$ represents the volatility value.

### B.VI. Time Varying Parameter Vector Autoregression (TVP-VAR)

After the risk profile is portrayed in terms of Value at Risk (VaR) values, the interconnectedness of risks, both among different crypto assets and towards the overall financial market, can be analysed using the Time Varying Parameter Vector Autoregression (TVP-VAR) model. This model is an extension of the Vector Autoregression (VAR) model introduced by Diebold and Yilmaz (2009, 2012, 2014). TVP-VAR was developed by Koop and Krobilis (2014) to address the shortcomings of the previous model by capturing and allowing the dynamics of connectedness to change over time, improving the sensitivity to outlirers, elimination of the necessity to arbitrarily determine the rolling window size, and avoidance of observation loss, and thereby enhancing the accuracy and insights of estimations (Antonakakis et al., 2020, Urom et al., 2020, Elsayed et al., 2022). In general, the TVP-VAR model can be expressed as follows.

$$Y_t = \beta_t Y_{t_{-1}} + \epsilon_t \quad \epsilon_t | \Omega_t \sim N(0, S_t) \tag{7}$$

$$vec(\beta_t) = vec(\beta_{t_{-1}}) + v_t \quad v_t | \sim N(0, R_t) \tag{8}$$

$Y_t$ is a vector of variables at time $t$, $\beta_t$ is a matrix of parameters that change over time at time $t$, $Y_{t_{-1}}$ is a vector of variables at time $t_{-1}$, and $\epsilon_t$ is a vector of residuals at time $t$ that represent the unexplained portion of the data by the model. $\Omega_t$ is other relevant information at time $t$ used to define the distribution of residuals $\epsilon_t$ while $N(0, S_t)$ indicates the normality of the residual distribution with a mean of 0 and covariance matrix $S_t$ at time $t$. The $vec$ operation denotes the vectorisation of the parameters $\beta_t$, $\beta_{t_{-1}}$, and $v$ represents the other unexplained portion by these parameters. As seen in the study by Elsayed et al., (2022), the TVP-VAR can be formulated in the Moving Average form and used to compute Generalised Impulse Response Functions (GIRF) and Generalised Forecast Error Variance Decomposition (GFEVD).

$$Y_t = \sum_{j=0}^{\infty} A_{it} \in_{t_{-j}} \tag{9}$$

TVP-VAR in Moving Average

$$\theta = \frac{\sum_{t=1}^{H-1} \xi_{ij}^2}{\sum_{j=1}^{N} \sum_{t=1}^{H-1} \xi_{ij}^2} \tag{10}$$

H-step-ahead GFEVED function

$A_{it}$ is an NxN dimensional matrix and $\xi_{ij}^2$ represents the response of all variables $j$ to a shock in variable $i$. In this study, the TVP-VAR model is applied to analyse return connectedness, as it will depict the interconnections among various assets (Elsayed et al., 2022; Dahir, Mahat, Noordin, & Razak, 2020). Connectedness between variables can be assessed based on four criteria: spillovers FROM all variables j to i, spillovers from variabel $i$ TO all variables $j$, Total Connectedness Index (TCI), dan Net Spillovers (NS). The TCI value will indicate the overall connectedness between the tested assets. Meanwhile, NS represents the difference between the influence exerted (TO) and received (FROM). If NS has a positive value, then the asset is a "Transmitter". Conversely, if otherwise, the asset is a "Receiver". These four aspects are depicted in the formulas provided below.

$$C_i = \frac{\sum_{j=1, j\neq i}^{N} \theta_{ij}(H)}{N} \tag{11}$$

FROM all $j$ variables to $i$

$$C_i = \frac{\sum_{j=1, j\neq i}^{N} \theta_{ji}(H)}{N} \tag{12}$$

from $i$ TO all $j$ variables

$$C_i = \frac{\sum_{i,j=1, i\neq j}^{N} \theta_{ji}(H)}{N} \tag{13}$$

Total Connectedness Index

$$NS = C_{i_{\rightarrow j}} - C_{i_{\leftarrow j}} \tag{14}$$

Net Spillover

## B.VII. Structural Break

To achieve a deeper understanding, the connectedness of assets is analysed using structural break analysis to identify their correlation with major Covid-19 events, employing the Bai and Perron test (Telli & Chen, 2020). The Bai-Perron methodology anticipates prior structural shifts in one variable while accounting for the presence of other variables over an extended period. Bai and Perron formulate the general equation as:

$$y_t = w_t'\beta + \cdots + z_t'\delta_j + u_t$$

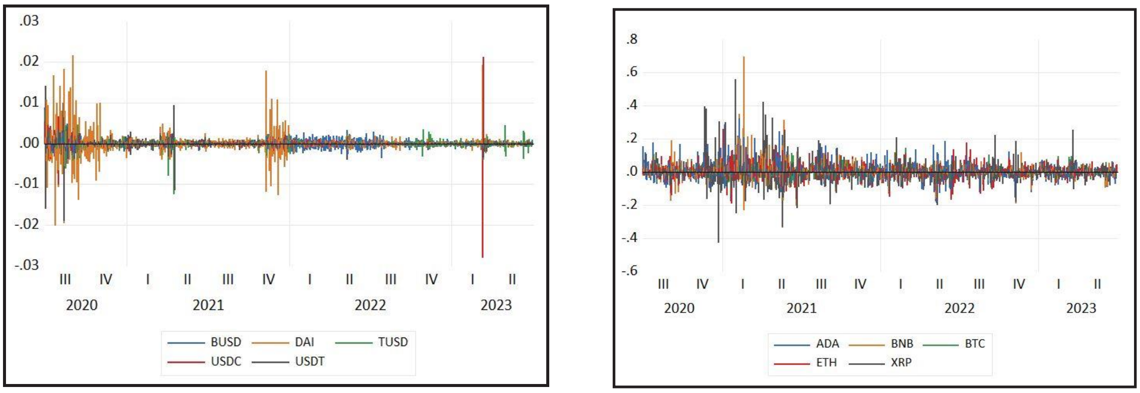
$$(t = T_{j-1} + 1, \dots, T_j)$$

For $j = 1, \dots, m+1$ and $T_0 = 0$ and $T_{m+1} = T$. Where $y_t$ is the designated dependent variable at time $t$, $w_t'$ and $z_t'$ are vectors of covariates, $\beta$ and $\delta_j$ are vectors of coefficients, and $u_t$ is the error term at time $t$. The break dates are denoted as unknowns $(T_1, \dots, T_m)$. The objective of this model is to estimate the unknown coefficients $(\beta, \delta_j, \dots, \delta_{j+1})$ along with the break dates $(T_1, \dots, T_m)$ when observations of $(y_t, w_t', z_t')$ are available.

## 4. Results and Analysis

### A.I. Calculating Daily Return

**Figure 1. Comparison of Actual Return Volatility Crypto Assets**




(a) (b)

**Figure 1** illustrates the volatility of daily returns between stablecoins **(a)** and unbacked crypto assets **(b)**.

Figure 1 provides an initial overview of stablecoins and unbacked crypto assets. Using daily price movement data, the returns of both types of crypto assets can be identified. The contrast between them is quite clear. Unbacked crypto assets exhibit remarkably high daily volatility, reaching up to 10 to 20 times that of stablecoins. To gain a deeper insight, daily return data must undergo the unit root tests and classical assumption tests before being processed using the GARCH model.

### Table 2. Augmented Dickey–Fuller (ADF) Test for Crypto Assets Return

| **Null Hypothesis: Unit root (individual root process)** | | | | |
|---|---|---|---|---|
| **Method** | | **Statistic** | **Prob.** | |
| **ADF - Fisher Chi-square** | | 1225,11 | 0,00001 | |
| **ADF - Choi Z-Stat** | | -34,3753 | 0,00001 | |
| **Intermediate ADF test result (stablecoin)** | | | | |
| **Series** | **Probability** | **Lag** | **Max Lag** | **Obs** |
| **BUSD** | 0,00001 | 6 | 21 | 1088 |
| **DAI** | 0,00001 | 5 | 21 | 1089 |
| **TUSD** | 0,00001 | 6 | 21 | 1088 |
| **USDC** | 0,00001 | 7 | 21 | 1087 |
| **USDT** | 0,00001 | 11 | 21 | 1083 |

(a)

| **Null Hypothesis: Unit root (individual root process)** | | | | |
|---|---|---|---|---|
| **Method** | | **Statistic** | **Prob.** | |
| **ADF - Fisher Chi-square** | | 1316,95 | 0,00001 | |
| **ADF - Choi Z-Stat** | | -35,7771 | 0,00001 | |
| **Intermediate ADF test result (unbacked crypto assets)** | | | | |
| **Series** | **Probability** | **Lag** | **Max Lag** | **Obs** |
| ADA | 0,00001 | 0 | 21 | 1094 |
| BNB | 0,00001 | 1 | 21 | 1093 |
| BTC | 0,00001 | 0 | 21 | 1094 |
| ETH | 0,00001 | 0 | 21 | 1094 |
| XRP | 0,00001 | 0 | 21 | 1094 |

(b)

### Table 3. Breusch-Godfrey Serial Correlation LM Test Results

| Category | Crypto assets | Probability | Hypothesis | Conclusion |
|---|---|---|---|---|
| **Stablecoin** | BUSD | 0,00001 | Reject $H_0$ | Autocorrelation is present |
| **Stablecoin** | DAI | 0,00001 | Reject $H_0$ | Autocorrelation is present |
| **Stablecoin** | TUSD | 0,00001 | Reject $H_0$ | Autocorrelation is present |
| **Stablecoin** | USDC | 0,00001 | Reject $H_0$ | Autocorrelation is present |
| **Stablecoin** | USDT | 0,00001 | Reject $H_0$ | Autocorrelation is present |
| **Unbacked Crypto assets** | ADA | 0,2668 | Support $H_0$ | Autocorrelation is not present |
| **Unbacked Crypto assets** | BNB | 0,0001 | Reject $H_0$ | Autocorrelation is present |
| **Unbacked Crypto assets** | BTC | 0,6116 | Support $H_0$ | Autocorrelation is not present |
| **Unbacked Crypto assets** | ETH | 0,2381 | Support $H_0$ | Autocorrelation is not present |
| **Unbacked Crypto assets** | XRP | 0,7357 | Support $H_0$ | Autocorrelation is not present |

The results of the Augmented Dickey-Fuller (ADF) test in Table 2 indicate that there is sufficient evidence to state that the data is stationary. Consistent with this, the normality test using the Jarque-Bera test indicates that the Jarque-Bera probability values for all crypto assets are <0,05, thus rejecting $H_0$ or stating that residuals are not normally distributed. Furthermore, the results of the Breusch-Godfrey Serial Correlation LM Test can be seen in Table 3, and the ARCH test results show that the ARCH probability values for all crypto assets are $< 0{,}05$, thus rejecting $H_0$ or indicating the presence of heteroskedasticity effects in the residual model. Therefore, based on the test results indicating the presence of heteroskedasticity effects, the modeling continues using the GARCH model.

Next, the identification of the ARMA (p, q) model was performed based on the ACF and PACF plots on the correlogram, as well as the smallest values of Akaike Information Criterion (AIC) and Schwarz Criterion (SC) according to estimation and significance testing of the model at $\alpha = 0{,}05$. Based on the ARMA best-fitting models, the GARCH (1,1) model is obtained to be the best-fitting model. The ARMA models used for GARCH (1,1) modeling are depicted in Table 4.

**Table 4. ARMA Models, Mean Equation, and Variance Equation for Each Crypto Assets**

| Coin | $R_t$ | $\sigma_t^2$ |
|---|---|---|
| BUSD | $-2{,}61 * 10^{-6} + 0{,}199762R_{t-1} - 0{,}844166\varepsilon_{t-1} + \varepsilon_t$ | $8{,}89 * 10^{-9} + 0{,}346024e_{t-1}^2 + 0{,}695719\sigma_{t-1}^2$ |
| DAI | $1{,}01 * 10^{-5} + 0{,}439893R_{t-1} - 0{,}863175\varepsilon_{t-1} + \varepsilon_t$ | $2{,}72 * 10^{-8} + 1{,}355587e_{t-1}^2 + 0{,}480130\sigma_{t-1}^2$ |
| TUSD | $1{,}35 * 10^{-6} + 0{,}005R_{t-5} + 0{,}005\varepsilon_{t-1} + \varepsilon_t$ | $8{,}12 * 10^{-7} + 0{,}15e_{t-1}^2 + 0{,}6\sigma_{t-1}^2$ |
| USDC | $6{,}88 * 10^{-6} - 0{,}144649R_{t-7} - 0{,}343752\varepsilon_{t-2} + \varepsilon_t$ | $7{,}03 * 10^{-9} + 0{,}4376465e_{t-1}^2 + 0{,}106861\sigma_{t-1}^2$ |
| USDT | $1{,}17 * 10^{-5} + 0{,}470336R_{t-1} - 0{,}911346\varepsilon_{t-1} + \varepsilon_t$ | $1{,}48 * 10^{-8} + 0{,}98535e_{t-1}^2 + 0{,}452296\sigma_{t-1}^2$ |
| ADA | $7{,}59 * 10^{-4} - 0{,}608901R_{t-9} + 0{,}680422\varepsilon_{t-9} + \varepsilon_t$ | $1{,}44 * 10^{-4} + 0{,}150111e_{t-1}^2 + 0{,}807667\sigma_{t-1}^2$ |
| BNB | $1{,}805 * 10^{-3} - 0{,}160094R_{t-2} + 0{,}160287\varepsilon_{t-2} + \varepsilon_t$ | $6{,}42 * 10^{-5} + 0{,}168446e_{t-1}^2 + 0{,}821647\sigma_{t-1}^2$ |
| BTC | $1{,}757 * 10^{-3} + 0{,}066601R_{t-9} + 0{,}017075\varepsilon_{t-9} + \varepsilon_t$ | $4{,}62 * 10^{-5} + 0{,}053275e_{t-1}^2 + 0{,}909442\sigma_{t-1}^2$ |
| ETH | $2{,}4444 * 10^{-3} + 0{,}205926R_{t-8} - 0{,}280877\varepsilon_{t-8} + \varepsilon_t$ | $6{,}65 * 10^{-5} + 0{,}109199e_{t-1}^2 + 0{,}86592\sigma_{t-1}^2$ |
| XRP | $-1{,}477 * 10^{-3} + 0{,}266971R_{t-36} - 0{,}3384556\varepsilon_{t-36} + \varepsilon_t$ | $3{,}41 * 10^{-4} + 0{,}637698e_{t-1}^2 + 0{,}484795\sigma_{t-1}^2$ |

The best-fitting model in Table 4 is used to predict the return values, variances, volatilities, and Value at Risk (VaR) estimates for each crypto asset. Table 5 presents an overview of the risk profile for each crypto asset. It can be observed that stablecoins are relatively stable with an average VaR value of 2.2%. On the other hand, unbacked crypto assets exhibit high volatility and risk, with an average VaR value of 13.9%. For every investment of 100 million, stablecoin investors may incur losses of around 2.2 million daily, whereas unbacked crypto assets investors could experience losses of up to 14 million daily.

Partially, DAI stablecoin has the lowest VaR value (1.37%) among other stablecoins. This is interesting considering that DAI is a stablecoin that utilises unbacked crypto assets as its underlying asset, unlike other stablecoins. On the other hand, BTC (Bitcoin) and ETH (Ethereum) are the two assets with the lowest VaR values among the five unbacked crypto assets tested. Both of them are unbacked crypto assets with the largest market capitalisation.

**Table 5. Risk Forecast and Value at Risk (VaR)**

| Crypto assets | Category | $\hat{R}_t$ | $\hat{\sigma}_t^2$ | $\hat{\sigma}_t$ | VaR | VaR @100Million |
|---|---|---|---|---|---|---|
| **BUSD** | Stablecoin | -0,00025 | 0,00013 | 0,01137 | -1,90% | - 1.901.642,10 |
| **DAI** | Stablecoin | -0,00004 | 0,00007 | 0,00826 | -1,37% | - 1.367.412,33 |
| **TUSD** | Stablecoin | -0,00008 | 0,00022 | 0,01492 | -2,46% | - 2.462.662,08 |
| **USDC** | Stablecoin | -0,00001 | 0,00025 | 0,01596 | -2,64% | - 2.638.050,47 |
| **USDT** | Stablecoin | -0,00005 | 0,00029 | 0,01705 | -2,82% | - 2.821.443,86 |
| **ADA** | Unbacked Crypto assets | 0,00221 | 0,00813 | 0,09019 | -14,66% | - 14.660.133,40 |
| **BNB** | Unbacked Crypto assets | 0,00180 | 0,00565 | 0,07515 | -12,22% | - 12.218.603,64 |
| **BTC** | Unbacked Crypto assets | 0,00129 | 0,00223 | 0,04718 | -7,66% | - 7.655.911,20 |
| **ETH** | Unbacked Crypto assets | -0,00305 | 0,00447 | 0,06688 | -10,85% | - 10.849.520,52 |
| **XRP** | Unbacked Crypto assets | 0,00186 | 0,02135 | 0,14613 | -24,42% | - 24.416.715,78 |

## A.II. Crypto Assets' Interconnectedness

Based on the TVP-VAR model of order one and 10-step ahead forecasts derived from data spanning from June 30, 2020, to June 30, 2023, the Total Connectedness Index among crypto assets stands at 57.56%. In Figure 2, it can be observed that the TCI value decreases with the conclusion of the COVID-19 pandemic crisis. Partially, Figure 3 demonstrates that unbacked crypto assets with the largest market capitalisation such as BTC and ETH consistently tend to be the strongest net spillover transmitters as the economic crisis recovers. Meanwhile, stablecoins tend to inconsistently serve as net transmitters or net receivers during the research period.

Figure 2. Total Connectedness Index (TCI) between Crypto Assets

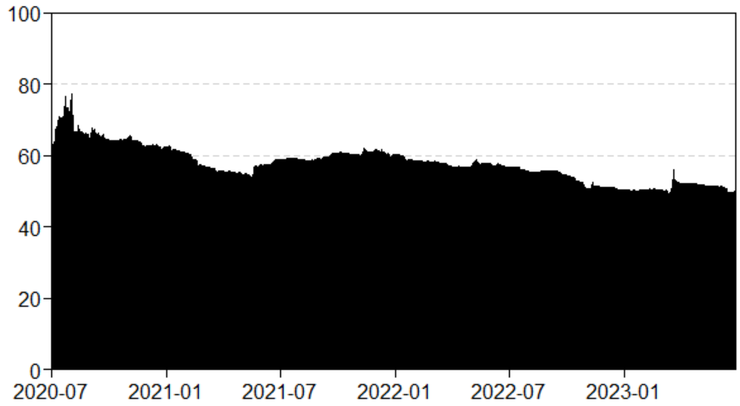



**Figure 2** illustrates the TCI of return between crypto assets during research time period.

Notes: Total connectedness is the ratio between the spillovers from all assets to each other and the spillovers from all assets to each other including its own.

Figure 3. Net Spillover of Various Crypto Assets

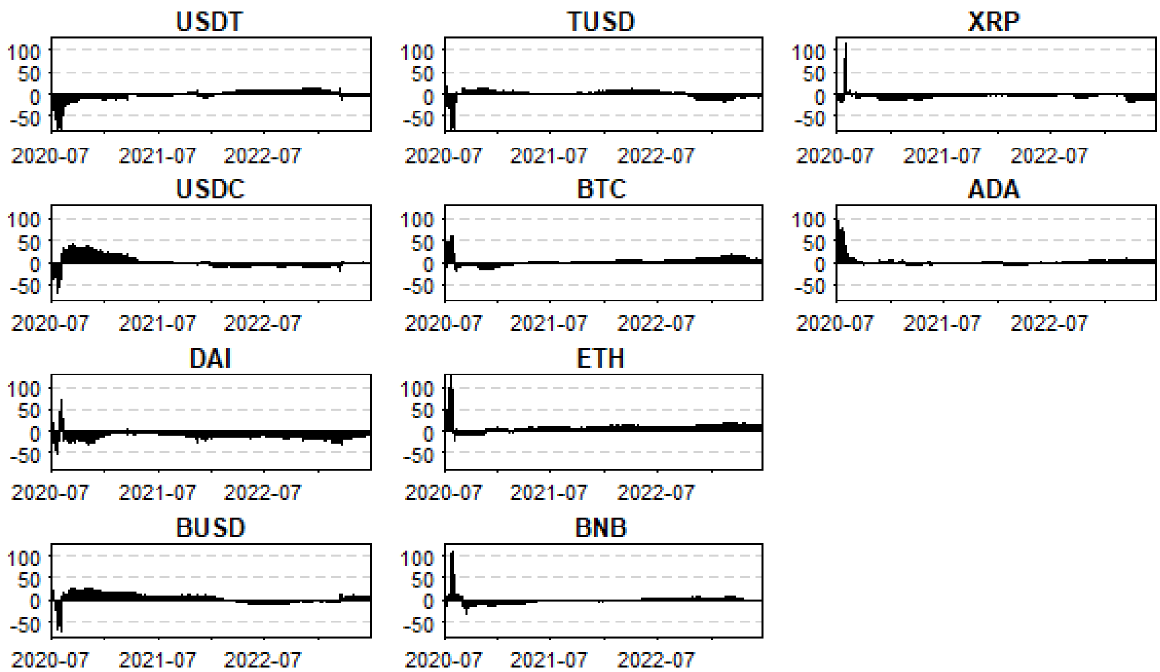



**Figure 3** illustrates the Net Spillover of each crypto assets during research time period.

Notes: Net spillover is the difference between the spillover exerted (TO) and received (FROM). If NS has a positive value, then the asset is a "Spillover-Transmitter". Conversely, if otherwise, the asset is a "Spillover-Receiver".

The return connectedness results in Table 6 indicate that return spillovers tend to occur based on categories. Significantly, stablecoins only influence their own category, as do unbacked crypto assets. These two categories do not significantly affect each other. For the stablecoins category, the strongest return spillover occurs from BUSD to TUSD with a value of 18.42%. Meanwhile, the strongest return spillover occurs from ETH to BTC with a value of 21.88%. Despite not affecting each other, the intersection between these two categories interestingly enhances connectedness. This is demonstrated with stablecoin DAI, which employs unbacked crypto assets as its underlying assets, unlike other stablecoins that use the US Dollar as their underlying asset. In Table 6, DAI experiences a quite significant spillover from BTC (2.42%), ETH (3.29%), and ADA (2.98%), with an average spillover of 2.9%, or 2 to 3 times higher than other stablecoins.

### Table 6. Return Spillover/Connectedness between Stablecoins and Unbacked Crypto Assets

| | USDT | USDC | DAI | BUSD | TUSD | BTC | ETH | BNB | XRP | ADA | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|
| USDT | | 16.27 | 1.61 | 16.43 | 18.06 | 0.71 | 0.69 | 0.78 | 0.8 | 1.52 | 57.32 |
| USDC | 16.5 | | 2.9 | 16.72 | 17.64 | 0.87 | 0.6 | 0.79 | 1.04 | 1.26 | 58.33 |
| DAI | 3.36 | 3.81 | | 1.97 | 3.55 | 2.42 | 3.29 | 1.62 | 1.46 | 2.98 | 24.46 |
| BUSD | 14.67 | 15.79 | 1.99 | | 17.33 | 0.73 | 0.62 | 0.82 | 0.84 | 1.52 | 54.32 |
| TUSD | 16.48 | 18.04 | 2.88 | 18.42 | | 1.35 | 1.22 | 1.11 | 0.87 | 1.63 | 61.99 |
| BTC | 0.54 | 0.75 | 0.64 | 0.66 | 0.8 | | 21.88 | 14.54 | 10.69 | 14.48 | 64.97 |
| ETH | 0.99 | 0.76 | 0.69 | 0.94 | 1.2 | 20.28 | | 14.27 | 13.03 | 15.62 | 67.78 |
| BNB | 0.71 | 0.72 | 0.52 | 0.8 | 0.74 | 15.57 | 15.85 | | 12.43 | 13.93 | 61.27 |
| XRP | 0.55 | 1.05 | 0.52 | 0.75 | 0.87 | 11.95 | 15.83 | 13.2 | | 14.93 | 59.66 |
| ADA | 1.5 | 1.97 | 0.79 | 1.93 | 1.78 | 14.42 | 16.65 | 13.28 | 13.25 | | 65.54 |
| TO | 55.29 | 59.61 | 12.54 | 58.61 | 61.96 | 68.31 | 76.63 | 60.41 | 54.4 | 67.88 | TCI = 57.56% |
| Inc.Own | 55.3 | 59.16 | 12.54 | 58.62 | 61.97 | 68.3 | 76.63 | 60.41 | 54.41 | 67.87 | |
| NET | -2.02 | 1.28 | -11.92 | 4.29 | -0.03 | 3.34 | 8.86 | -0.86 | -5.27 | 2.33 | |

**Table 6** summarises the TVP-VAR model of order one and 10-step ahead forecast result of return spillover/connectedness among crypto assets in a matrix.

Notes: A darker color represents a big and strong spillover while the lighter color represents the other way around. "TO" depicts directional spillovers from variable i to all j variables as the sum of all the spillovers in a certain column. "FROM" depicts directional spillovers from all j variables to variable i as the sum of all the spillovers in a certain row.

Figure 4 provides deeper insights. The arrow signs indicate the vectors or directions of spillover from one crypto asset to another. Thicker arrow signs indicate stronger spillover strength. In Figure 4, it is evident that DAI tends to receive the most return spillover. This aligns with Table 6, which shows the largest and negative net spillover value for DAI (-11.92%), making it the largest net receiver of return spillover. On the other hand, ETH (8.86%) emerges as the strongest net transmitter of return spillover. Most of the tested crypto assets exhibit TO and FROM spillover total values that are not significantly different, except for DAI, which has a difference of up to 50% (12.54% compared to 24.46%).

**Figure 4. Directional Spillovers/Connectedness between Crypto Assets**

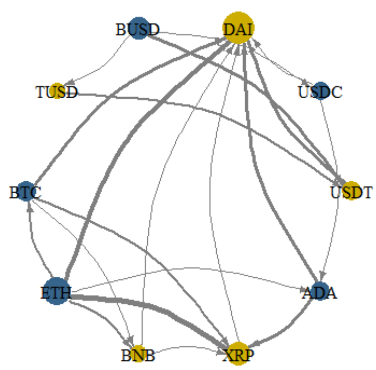



**Figure 4** illustrates the network plot among crypto assets from the TVP-VAR model of order one and 10-step ahead forecasts.

Notes: The arrow represents the directions of spillovers. The thicker the arrow, the stronger the spillover transmitted. The yellow ones are the Net Receivers (crypto assets with negative net spillover value) while the blue ones are the Net Transmitters (crypto assets with positive net spillover value).

# Table 7. Return Spillover/Connectedness between Assets in The Global Financial Market

| Crypto | USDT | USDC | DAI | BUSD | TUSD | BTC | ETH | BNB | XRP | ADA | Gold | Silver | EUR | GBP | CHF | SGD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| USDT | | 8.97 | 5.49 | 9.02 | 11.32 | 2.06 | 0.2 | 0.2 | 0.25 | 0.25 | 0.59 | 0.69 | 7.12 | 0.28 | 2.98 | 3.26 |
| USDC | 9.27 | | 3.56 | 8.06 | 9.96 | 1.85 | 0.33 | 0.3 | 0.26 | 0.3 | 0.69 | 0.49 | 10.4 | 0.29 | 2.69 | 3.04 |
| DAI | 5.76 | 3.18 | | 3.06 | 5.91 | 1.16 | 0.59 | 0.63 | 0.45 | 0.49 | 0.73 | 0.91 | 7.69 | 0.73 | 3.2 | 3.53 |
| BUSD | 8.84 | 8.96 | 3.27 | | 10.76 | 1.4 | 0.3 | 0.43 | 0.25 | 0.28 | 0.73 | 0.57 | 7.02 | 0.28 | 2.3 | 2.37 |
| TUSD | 10 | 9.13 | 4.56 | 9.15 | | 2 | 0.35 | 0.33 | 0.24 | 0.29 | 0.6 | 0.73 | 7.57 | 0.27 | 3.12 | 3.02 |
| BTC | 2.71 | 2.15 | 1.71 | 1.88 | 2.83 | | 10.94 | 6.94 | 6.14 | 7.62 | 1.28 | 1.44 | 4.51 | 0.48 | 2.53 | 2.36 |
| ETH | 1.75 | 1.4 | 1.99 | 1.63 | 2.16 | 11.7 | | 8.91 | 8.02 | 9.47 | 0.87 | 1.22 | 3.29 | 0.71 | 2.02 | 1.66 |
| BNB | 1.78 | 1.56 | 2.68 | 1.81 | 2.25 | 8.31 | 9.09 | | 6.88 | 7.79 | 0.92 | 1.08 | 3.86 | 0.51 | 2.27 | 1.94 |
| XRP | 1.89 | 1.4 | 2.03 | 1.54 | 2.19 | 8.37 | 10.02 | 8.27 | | 9.88 | 0.61 | 1.08 | 2.89 | 0.5 | 1.75 | 1.31 |
| ADA | 2.35 | 1.52 | 3.71 | 1.89 | 2.75 | 8.05 | 9.2 | 7.44 | 7.65 | | 0.91 | 1.35 | 3.28 | 0.62 | 2.13 | 1.8 |
| Gold | 1.73 | 2.35 | 1.88 | 1.96 | 2.01 | 1.81 | 1 | 0.98 | 0.54 | 0.77 | | 17.21 | 5.63 | 0.98 | 2.4 | 2.21 |
| Silver | 2.68 | 1.52 | 3.02 | 2.25 | 2.84 | 2.2 | 1.56 | 1.38 | 1.07 | 1.6 | 16.66 | | 2.73 | 1.12 | 2.35 | 2.51 |
| EUR | 5.02 | 4.99 | 5.47 | 3.17 | 5.61 | 1.61 | 0.43 | 0.25 | 0.39 | 0.5 | 1.25 | 0.83 | | 1.2 | 2.99 | 3.14 |
| GBP | 2.19 | 2.16 | 2.48 | 1.82 | 2.7 | 1.91 | 1.78 | 0.93 | 0.98 | 1.71 | 2.78 | 2.93 | 4.88 | | 5.59 | 8.09 |
| CHF | 3.33 | 2.61 | 2.96 | 2.35 | 3.77 | 1.91 | 0.78 | 0.58 | 0.51 | 0.94 | 3.3 | 2.89 | 7.53 | 3.66 | | 7.95 |
| SGD | 3.05 | 2.8 | 2.94 | 2.22 | 3.17 | 1.96 | 1.01 | 0.76 | 0.8 | 0.81 | 2.3 | 2.25 | 9.8 | 4.56 | 6.47 | |
| JPY | 2.62 | 2.79 | 2.75 | 2.41 | 2.89 | 1.45 | 0.51 | 0.5 | 0.45 | 0.58 | 3.79 | 2.95 | 5.4 | 3.34 | 7.57 | 6.84 |
| KRW | 3.44 | 3.31 | 3.86 | 2.45 | 4.16 | 2.05 | 0.98 | 0.95 | 0.62 | 0.8 | 1.49 | 1.17 | 9.76 | 1.52 | 4.87 | 6.78 |
| CNY | 4.12 | 2.6 | 4.45 | 2.94 | 4.72 | 2.41 | 1.15 | 0.75 | 0.75 | 0.93 | 2.58 | 3.21 | 4.94 | 1.24 | 4.55 | 5.57 |
| HKD | 3.11 | 2.79 | 3.26 | 2.27 | 3.93 | 1.39 | 0.46 | 0.55 | 0.64 | 0.43 | 1.39 | 1.36 | 4.96 | 0.87 | 3.49 | 3.85 |
| IDR | 4 | 4.53 | 4.92 | 2.77 | 4.85 | 2.3 | 0.88 | 0.65 | 0.81 | 0.97 | 1.42 | 1.24 | 9.29 | 0.55 | 3.87 | 4.44 |
| S&P 500 | 2.15 | 1.95 | 2.28 | 1.9 | 2.55 | 2.05 | 2.23 | 1.89 | 1.2 | 1.71 | 1.07 | 1.16 | 3.9 | 0.71 | 2.04 | 2.36 |
| FTSE 100 | 1.84 | 1.64 | 2.61 | 1.4 | 2.02 | 1.31 | 1.03 | 1.05 | 0.85 | 0.95 | 0.81 | 0.75 | 4.13 | 0.47 | 2.15 | 1.93 |
| GDAXI | 1.35 | 1.22 | 1.76 | 1.13 | 1.5 | 1.38 | 1.34 | 1.12 | 0.83 | 1.04 | 0.96 | 1.23 | 2.37 | 0.57 | 1.29 | 1.41 |
| CAC 40 | 1.25 | 1.28 | 1.66 | 1.12 | 1.46 | 1.42 | 1.24 | 1.23 | 0.71 | 1.03 | 0.72 | 0.78 | 3.18 | 0.49 | 1.76 | 1.57 |
| SASMI 20 | 2 | 2.06 | 2.22 | 1.9 | 2.36 | 2.52 | 1.59 | 1.12 | 1.35 | 1.21 | 0.82 | 0.73 | 5.33 | 0.97 | 1.92 | 2.39 |
| N 225 | 2 | 2.12 | 2.1 | 1.82 | 2.36 | 2.24 | 1.7 | 1.23 | 1.27 | 1.68 | 0.8 | 0.46 | 6.39 | 0.57 | 1.96 | 1.84 |
| KS 11 | 3.04 | 2.55 | 3.04 | 2.73 | 3.75 | 1.71 | 1.19 | 0.93 | 0.6 | 0.99 | 0.99 | 1.03 | 5.58 | 0.6 | 2.24 | 2.48 |
| SSE | 2.34 | 1.98 | 3.07 | 1.85 | 2.8 | 1.75 | 1.15 | 0.52 | 0.91 | 1.24 | 0.94 | 1.18 | 4.93 | 1.41 | 2.94 | 2.92 |
| HSI | 1.73 | 1.66 | 2.09 | 1.72 | 2.08 | 1.55 | 1 | 0.67 | 0.94 | 1.06 | 1.2 | 0.64 | 5.89 | 0.97 | 1.84 | 2.17 |
| STI | 2.86 | 3.01 | 3.23 | 2.38 | 3.13 | 1.34 | 0.65 | 0.74 | 0.77 | 0.84 | 0.74 | 0.45 | 8.75 | 0.64 | 2.38 | 2.38 |
| IDX | 3.43 | 3.16 | 4.73 | 2.35 | 3.69 | 1.58 | 0.87 | 0.93 | 1.06 | 1.04 | 1.19 | 0.74 | 9.99 | 0.71 | 2.23 | 2.48 |
| TO | 103.62 | 93.35 | 95.79 | 84.95 | 118.49 | 84.74 | 65.52 | 53.16 | 48.18 | 59.20 | 55.10 | 54.75 | 182.97 | 31.83 | 91.91 | 99.57 |
| Inc.Own | 121.77 | 112.41 | 118.62 | 109.86 | 135.77 | 104.04 | 84.47 | 72.44 | 72.77 | 77.27 | 84.33 | 82.87 | 212.74 | 50.16 | 108.65 | 112.21 |
| NET | 21.77 | 12.41 | 18.62 | 9.86 | 35.77 | 4.04 | -15.53 | -27.56 | -27.23 | -22.73 | -15.67 | -17.13 | 112.74 | -49.84 | 8.65 | 12.21 |

| Crypto | JPY | KRW | CNY | HKD | IDR | S&P 500 | FTSE 100 | GDAXI | CAC 40 | SASMI 20 | N 225 | KS 11 | SSE | HSI | STI | IDX | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| USDT | 1.75 | 3.83 | 3.4 | 1.28 | 4.28 | 1.6 | 1.08 | 0.58 | 0.85 | 0.66 | 1.21 | 2.53 | 0.55 | 0.52 | 2.42 | 2.64 | 81.84 |
| USDC | 1.83 | 3.87 | 2.7 | 1.29 | 4.78 | 1.81 | 0.97 | 0.52 | 0.81 | 0.73 | 1.25 | 2.72 | 0.56 | 0.65 | 2.45 | 2.51 | 80.94 |
| DAI | 1.19 | 5.1 | 5.1 | 2.35 | 4.89 | 2.02 | 1.67 | 0.6 | 0.76 | 0.88 | 1.75 | 2.9 | 1.05 | 1.11 | 3.25 | 4.53 | 77.17 |
| BUSD | 1.93 | 2.97 | 2.84 | 1.23 | 3.53 | 1.73 | 0.98 | 0.6 | 0.85 | 0.73 | 1.35 | 2.75 | 0.59 | 0.7 | 2.4 | 2.16 | 75.09 |
| TUSD | 1.64 | 4.24 | 3.58 | 1.56 | 4.7 | 1.88 | 0.92 | 0.57 | 0.79 | 0.7 | 1.46 | 3.15 | 0.62 | 0.57 | 2.43 | 2.58 | 82.72 |
| BTC | 1.4 | 2.61 | 2.62 | 1.14 | 2.51 | 2.13 | 1.05 | 1.11 | 1.21 | 1.79 | 1.01 | 1.81 | 0.77 | 0.71 | 1.67 | 1.65 | 80.71 |
| ETH | 0.88 | 1.79 | 2.32 | 1.21 | 1.62 | 2.7 | 1.47 | 1.48 | 1.52 | 1.62 | 1.28 | 1.63 | 1.01 | 0.78 | 1.45 | 1.5 | 81.05 |
| BNB | 0.89 | 2.7 | 2.6 | 1.34 | 2.15 | 3.11 | 1.9 | 1.39 | 1.79 | 1.48 | 1.44 | 2.03 | 0.83 | 0.72 | 1.64 | 1.98 | 80.72 |
| XRP | 0.79 | 1.64 | 2.25 | 1.18 | 1.59 | 1.78 | 1.44 | 1.18 | 1.16 | 1.75 | 1.01 | 1.32 | 1.33 | 0.73 | 1.18 | 1.34 | 75.41 |
| ADA | 0.98 | 2.18 | 3.3 | 1.54 | 2.26 | 2.54 | 1.51 | 1.3 | 1.39 | 1.46 | 1.35 | 1.77 | 1.15 | 0.87 | 1.45 | 2.27 | 81.94 |
| Gold | 0.97 | 2.19 | 1.84 | 1.53 | 1.92 | 2.68 | 1.48 | 1.24 | 1.35 | 1.01 | 1.16 | 2.53 | 0.78 | 1.56 | 2.19 | 2.88 | 70.78 |
| Silver | 1.05 | 1.95 | 3.58 | 1.75 | 1.75 | 2.35 | 1.41 | 1.58 | 1.26 | 1.04 | 1.08 | 1.97 | 1.4 | 0.94 | 1.43 | 1.85 | 71.88 |
| EUR | 1.01 | 3.86 | 3.05 | 1.59 | 4.81 | 2.33 | 0.92 | 0.62 | 0.82 | 0.83 | 1.68 | 3.48 | 0.6 | 0.76 | 3.36 | 3.66 | 70.23 |
| GBP | 3.06 | 3.57 | 3.26 | 2.12 | 2.06 | 4.36 | 1.81 | 2.77 | 2.57 | 1.59 | 1.65 | 2.59 | 1.38 | 1.49 | 2.48 | 1.99 | 81.67 |
| CHF | 3.96 | 5.82 | 4.46 | 2.1 | 4.14 | 2.62 | 1.36 | 1.04 | 1.62 | 1.08 | 1.33 | 2.28 | 1.23 | 0.86 | 2.09 | 2.22 | 83.25 |
| SGD | 3.64 | 6.51 | 4.42 | 1.89 | 4.08 | 3.28 | 1.79 | 1.92 | 2.01 | 1.43 | 1.46 | 2.59 | 1.29 | 1.74 | 2.27 | 2.13 | 87.36 |
| JPY | | 4.43 | 3.79 | 1.87 | 3.35 | 1.86 | 2.05 | 0.98 | 1.94 | 0.83 | 1.78 | 1.99 | 0.86 | 0.96 | 1.9 | 1.84 | 77.28 |
| KRW | 2.08 | | 4.52 | 1.85 | 4.97 | 3.15 | 2.07 | 1.57 | 2.1 | 1.23 | 1.7 | 3.58 | 1.13 | 2.2 | 2.81 | 2.72 | 85.88 |
| CNY | 2.02 | 5.5 | | 2.62 | 4.12 | 2.84 | 1.51 | 1.17 | 1.27 | 0.91 | 1.6 | 2.82 | 1.86 | 1.66 | 2.63 | 2.13 | 81.57 |
| HKD | 1.44 | 4.08 | 3.66 | | 3.27 | 2.3 | 1.23 | 0.94 | 0.96 | 0.77 | 1.29 | 2.29 | 1.04 | 2.66 | 2.49 | 2.23 | 65.40 |
| IDR | 1.6 | 5.42 | 3.93 | 1.71 | | 3.06 | 2.03 | 1.57 | 2.43 | 1.22 | 2.08 | 3.35 | 0.9 | 1.27 | 2.93 | 3.04 | 84.04 |
| S&P 500 | 0.98 | 2.38 | 2.53 | 1.78 | 2.6 | | 5.38 | 7.37 | 7.34 | 4.51 | 4.72 | 4.6 | 0.69 | 1.73 | 3.52 | 2.57 | 83.84 |
| FTSE 100 | 1.08 | 2.34 | 2.18 | 1.47 | 2.44 | 6.09 | | 9.03 | 11.07 | 6 | 3.57 | 3.51 | 0.57 | 2.3 | 4.01 | 2.67 | 83.26 |
| GDAXI | 0.71 | 1.46 | 1.79 | 1.57 | 1.62 | 8.84 | 10.02 | | 14.41 | 9.19 | 3.08 | 2.95 | 0.47 | 1.42 | 2.53 | 1.44 | 82.01 |
| CAC 40 | 0.95 | 1.89 | 1.6 | 1.08 | 2.36 | 8.09 | 11.26 | 13.3 | | 7.62 | 3.66 | 3.34 | 0.41 | 1.95 | 2.96 | 2.06 | 83.43 |
| SASMI 20 | 0.93 | 2.32 | 2.06 | 1.3 | 2.14 | 5.4 | 6.78 | 9.97 | 8.79 | | 2.28 | 2.3 | 0.84 | 1.08 | 2.08 | 1.74 | 80.48 |
| N 225 | 1.25 | 2.19 | 2.26 | 1.34 | 2.8 | 6.7 | 4.3 | 4.96 | 5.24 | 4 | | 6.88 | 1.07 | 2.99 | 3.97 | 3.12 | 83.61 |
| KS 11 | 1.19 | 2.79 | 2.98 | 1.9 | 3.39 | 5.62 | 3.36 | 3.21 | 3.56 | 1.68 | 6.02 | | 1.32 | 3.94 | 5.57 | 4.32 | 84.29 |
| SSE | 1.35 | 3.12 | 3.88 | 1.95 | 2.81 | 2.39 | 1.49 | 1.07 | 1.17 | 1.53 | 2.33 | 3.62 | | 9.21 | 2.18 | 1.87 | 71.88 |
| HSI | 0.86 | 2.21 | 2.14 | 1.37 | 2.16 | 3.61 | 3.39 | 2.17 | 3.07 | 1.85 | 4.07 | 6.59 | 6.88 | | 6.63 | 3.78 | 77.98 |
| STI | 1.12 | 2.97 | 2.42 | 1.73 | 3.34 | 4.51 | 4.24 | 2.91 | 3.92 | 1.54 | 3.74 | 5.89 | 0.89 | 4.33 | | 4.81 | 82.66 |
| IDX | 0.95 | 3.45 | 2.69 | 1.33 | 3.77 | 3.18 | 2.56 | 1.25 | 1.93 | 0.83 | 2.86 | 5.15 | 0.56 | 2.88 | 5.56 | | 79.11 |
| TO | 45.46 | 101.37 | 93.73 | 49.96 | 96.21 | 106.56 | 83.41 | 79.96 | 89.95 | 62.52 | 66.23 | 96.91 | 34.64 | 55.25 | 85.97 | 78.22 | TCI = 79.67% |
| Inc.Own | 68.18 | 115.49 | 112.16 | 84.56 | 112.17 | 122.71 | 100.15 | 97.95 | 106.51 | 82.04 | 82.62 | 112.62 | 62.75 | 77.27 | 103.31 | 99.11 | |
| NET | -31.82 | 15.49 | 12.16 | -15.44 | 12.17 | 22.71 | 0.15 | -2.05 | 6.51 | -17.96 | -17.38 | 12.62 | -37.25 | -22.73 | 3.31 | -0.89 | |

**Table 7** summarises the TVP-VAR model of order one and 10-step ahead forecast result of return spillover/connectedness among various assets in the global financial market.

Notes: A darker color represents a big and strong spillover while the lighter color represents the other way around. “TO” depicts directional spillovers from variable i to all j variables as the sum of all the spillovers in a certain column. “FROM” depicts directional spillovers from all j variables to variable i as the sum of all the spillovers in a certain row.

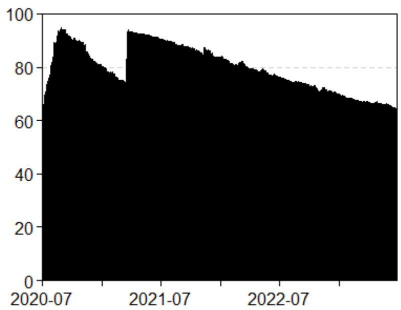
### A.III. Systemic Implication on the Financial Market

Table 7 presents the outcomes of the TVP-VAR model applied to various assets within the global financial market. This was done using order one and 10-step ahead forecast, utilising data covering the period from June 30, 2020, to June 30, 2023. The Total Connectedness Index (TCI) value for the tested 32 assets is recorded at 79.67%. Broadly, the asset with the strongest net spillover transmitter to the overall financial market is the Euro (EUR), with a value of 112.74%. On the other hand, the greatest net spillover receiver from the overall financial market is the Great British Pound (GBP) at -49.84%.

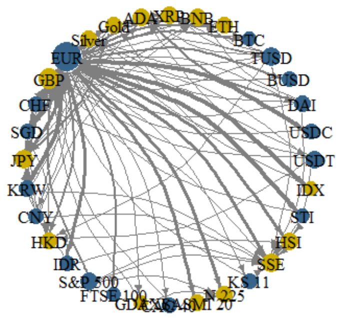
Additionally, there are noteworthy patterns in relation to crypto assets. All stablecoins are net spillover transmitters to the entire financial market, while almost all unbacked crypto assets, except for Bitcoin (BTC), act as net spillover receivers from the overall financial market. Among the tested stablecoins, True USD (TUSD) holds the largest net spillover transmitter value at 35.77%, ranking second overall among the tested assets. Conversely, Binance Coin (BNB) exhibits the largest net spillover receiver value at -27.56% among the five unbacked crypto assets.

In terms of partial analysis, stablecoins exhibit significant connectedness to several global financial assets compared to unbacked crypto assets. Notably, substantial spillovers (4-5%) are evident from stablecoins to Euro (EUR), Indonesian Rupiah (IDR), and Indonesian Stock Exchange (IDX). Meanwhile, significant spillovers (4-5%) directed towards stablecoins stem from Euro (EUR), Korean Won (KRW), Chinese Yuan (CNY), and Indonesian Stock Exchange (IDX). In contrast, unbacked crypto assets display negligible connectedness (< 3%) to any traditional financial assets. This pattern is also mirrored in the influences directed towards unbacked crypto assets, except for the spillover from Euro (EUR) to Bitcoin (BTC).

**Figure 5. Directional Spillovers/Connectedness and Total Connectedness Index (TCI) between Assets in The Global Financial Market**




(a)




(b)

**Figure 5** illustrates the Total Connectednes Index (TCI) over time **(a)** and the network plot among various assets in the global financial market from the TVP-VAR model of order one and 10-step ahead forecasts **(b).**

Notes: The arrow represents the directions of spillovers. The thicker the arrow, the stronger the spillover transmitted. The yellow ones are the Net Receivers (crypto assets with negative net spillover value) while the blue ones are the Net Transmitters (crypto assets with positive net spillover value).

Figure 5 illustrates the interconnectedness of the 32 assets within the global financial market under examination. As depicted in Figure 5, there is a decrease in the Total Connectedness Index (TCI) in tandem with the recovery from the COVID-19 pandemic crisis. However, a substantial TCI increase of around 20% is observed in mid-2021 (2$^{nd}$ wave of COVID-19), followed by a return to the same declining pattern. In line with Table 7, directional spillovers predominantly stem from Euro (EUR) currency towards all tested assets.

### A.IV. The Case of Indonesia

The influence and relationship of crypto assets on the global financial market in Table 7 and Figure 5 demonstrate a fairly significant connection with the Indonesian financial market, represented by the Indonesian Rupiah (IDR) and the Indonesian Stock Exchange (IDX). This interesting connection might have something to do with the recent Financial Sector Development and Reinforcement Bill (UU P2SK) launched by Indonesia in 2023. In order to gain a deeper understanding of their comprehensive interconnectedness, the outcomes of the TVP-

VAR modeling with order one and 10-step ahead forecasts based on various crypto assets, IDR, and IDX data spanning from June 30, 2020, to June 30, 2023, are presented in Table 8 and Figure 6.

**Table 8. Return Spillover/Connectedness between Assets in Indonesian Financial Market**

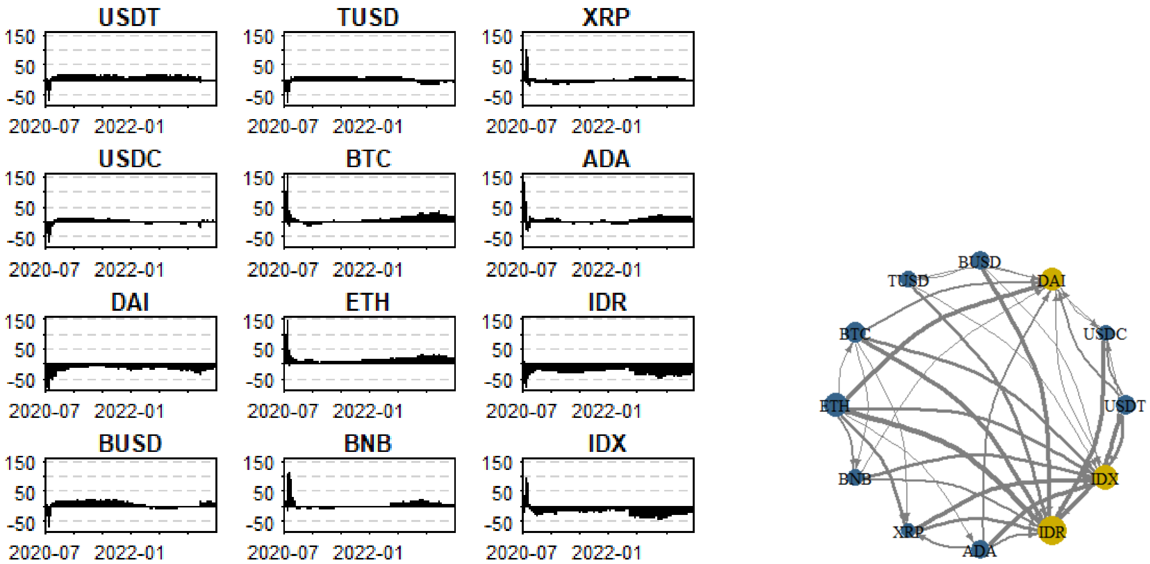
| | USDT | USDC | DAI | BUSD | TUSD | BTC | ETH | BNB | XRP | ADA | IDR | IDX | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| USDT | | 17.21 | 0.37 | 16.19 | 17.27 | 0.77 | 0.79 | 0.86 | 0.76 | 1.25 | 3.37 | 0.95 | 59.8 |
| USDC | 19.07 | | 1.67 | 16.15 | 17.43 | 0.94 | 0.76 | 0.82 | 0.95 | 1.18 | 3.86 | 0.95 | 63.77 |
| DAI | 2.01 | 2.96 | | 1.82 | 3.01 | 2.31 | 3.67 | 1.72 | 1.34 | 2.78 | 1.12 | 1.92 | 24.65 |
| BUSD | 16.28 | 14.98 | 0.99 | | 16.82 | 0.84 | 0.89 | 0.94 | 0.83 | 1.35 | 3.49 | 0.87 | 58.3 |
| TUSD | 17.44 | 17.4 | 1.7 | 17.77 | | 1.29 | 1.22 | 1 | 0.81 | 1.37 | 3.75 | 0.79 | 64.55 |
| BTC | 0.47 | 0.58 | 0.42 | 0.55 | 0.66 | | 21.87 | 14.62 | 10.71 | 14.27 | 0.36 | 0.63 | 65.13 |
| ETH | 0.66 | 0.56 | 0.77 | 0.73 | 0.76 | 20.5 | | 14.05 | 12.82 | 15.64 | 0.35 | 0.69 | 67.54 |
| BNB | 0.57 | 0.47 | 0.49 | 0.64 | 0.58 | 15.75 | 15.56 | | 12.29 | 13.72 | 0.47 | 0.65 | 61.18 |
| XRP | 0.75 | 1.03 | 0.49 | 0.89 | 1.03 | 12 | 15.22 | 12.89 | | 14.84 | 0.42 | 0.71 | 60.27 |
| ADA | 1.66 | 1.5 | 0.83 | 1.71 | 1.52 | 14.28 | 16.54 | 12.97 | 13.19 | | 0.74 | 1.1 | 66.05 |
| IDR | 6.63 | 6.94 | 1.4 | 6.54 | 6.6 | 3.76 | 3.94 | 2.22 | 2.96 | 2.84 | | 1.31 | 45.14 |
| IDX | 3.61 | 2.25 | 0.52 | 2.27 | 2.01 | 3.18 | 3.29 | 3.06 | 3.71 | 4.28 | 1.24 | | 29.43 |
| TO | 69.16 | 65.89 | 9.66 | 65.26 | 67.69 | 75.63 | 83.75 | 65.13 | 60.38 | 73.53 | 19.18 | 10.57 | TCI = |
| Inc.Own | 109.36 | 102.11 | 85.01 | 106.96 | 103.14 | 110.5 | 116.21 | 103.95 | 100.11 | 107.48 | 74.04 | 81.14 | 55.48% |
| NET | 9.36 | 2.11 | -14.99 | 6.96 | 3.14 | 10.5 | 16.21 | 3.95 | 0.11 | 7.48 | -25.96 | -18.86 | |

**Table 7** summarises the TVP-VAR model of order one and 10-step ahead forecast result of return spillover/connectedness of the crypto assets and Indonesian financial market.

Notes: A darker color represents a big and strong spillover while the lighter color represents the other way around. “TO” depicts directional spillovers from variable i to all j variables as the sum of all the spillovers in a certain column. “FROM” depicts directional spillovers from all j variables to variable i as the sum of all the spillovers in a certain row.

Based on Table 7, IDR (-25.96%) and IDX (-18.66%) represent the largest net receivers. Both stablecoins and unbacked crypto assets contribute greater spillovers to IDR and IDX compared to the spillovers they receive from these two traditional Indonesian financial assets. Nonetheless, on average, stablecoins exert a stronger influence on IDR (±6%) than unbacked crypto assets (±3%). When compared to IDX, the influence of stablecoins (±2-3%) and unbacked crypto assets (±3-4%) is relatively similar. On the other hand, the impact of IDR and IDX is more pronounced on stablecoins (±3%) than that of on unbacked crypto assets (±0.5%).

**Figure 6. Directional Spillovers/Connectedness and Net Spillover (NS) between Crypto Assets and Indonesian Financial Market**




(a) (b)

**Figure 6** illustrates the Net Spillover (NS) over time **(a)** and the network plot of the crypto assets and Indonesian financial market from the TVP-VAR model of order one and 10-step ahead forecasts **(b)**.

Notes: The arrow represents the directions of spillovers. The thicker the arrow, the stronger the spillover transmitted. The yellow ones are the Net Receivers (crypto assets with negative net spillover value) while the blue ones are the Net Transmitters (crypto assets with positive net spillover value).

Figure 6 provides a clearer overview of the relationship between crypto assets and the Indonesian financial market through the visualisation of vectors and net spillover values during the research timeframe. Consistent with Figure 3, stablecoins tend to act as net receivers, while unbacked crypto assets tend to act as net transmitters during the COVID-19 pandemic crisis in 2020. During the same period, IDX experiences a sharp rise as a net transmitter with high values, while IDR becomes a net receiver and experiences a significant decline. Post-crisis, both categories of crypto assets consistently maintain their role as net transmitters towards IDX and IDR, which conversely remain consistent as net receivers throughout the research period.

### A.V. Connectedness during the Covid-19 Pandemic

**Figure 7. Structural Breaks of TCI between Assets in The Global Financial Market**

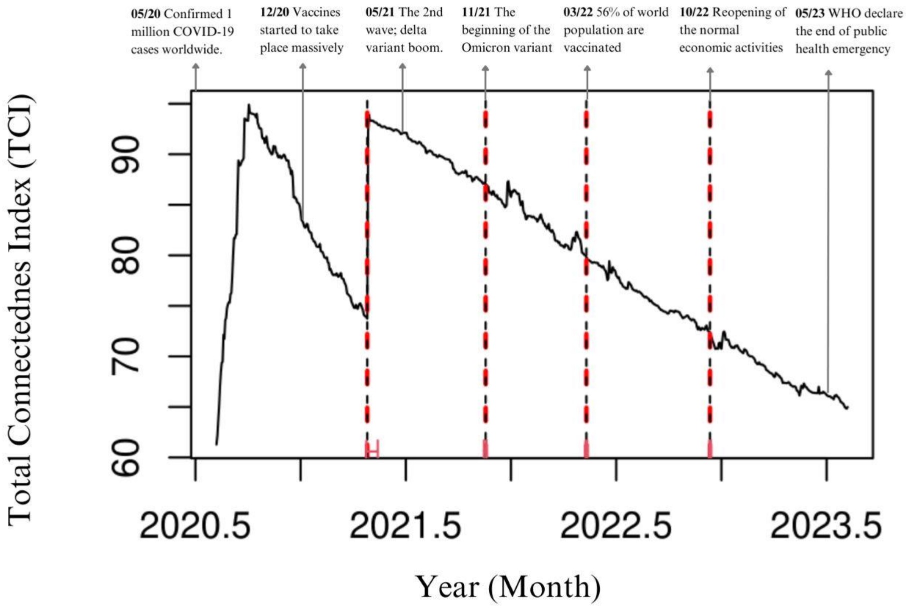



**Figure 7** illustrates the structural breaks in the Total Connectedness Index among assets in the Global Financial Market from 2020 to 2023, employing the Bai and Perron Test with four breaks (m=4).

The impact of the Covid-19 pandemic on the movement of the Total Connectedness Index (TCI) among assets in the global financial market can be comprehensively understood through structural breaks analysis. Utilising the Bai and Perron Test revealed four significant breaks $(p - value = 2.2 \ x \ 10 - 16)$, dividing the research period into five distinct phases, as depicted in Figure 7 and detailed in Table 9. Based on the analysis results, TCI values increased during the worsening stages of the Covid-19 pandemic, such as during the initial wave in early 2020 and the significant second wave in mid-2021. Conversely, improvements in the Covid-19 pandemic were aligned with a decrease in TCI values, marked by vaccination campaigns and the reopening of economic activities. TCI experienced a slight increase at the end of 2021 when the Omicron variant emerged, but promptly declined as this variant proved to be less severe than the Delta variant, which had claimed more casualties.

**Table 9. Structural Breaks of TCI between Assets in The Global Financial Market and the Related Covid-19 Major Events**

| No | Start_Period | End_Period | Break_Date | Related_Events |
|---|---|---|---|---|
| 1 | 1-Jul-2020 | 23-Mar-2021 | March 2021 | Covid-19 $2^{nd}$ Wave Delta Variant (April 2021) |
| 2 | 24-Mar-2021 | 5-Oct-2021 | October 2021 | The Beginning of Omicron Variant (November 2021) |
| 3 | 6-Oct-2021 | 22-Mar-2022 | March 2022 | More than half of the world's population are successfully vaccinated (March 2022) |
| 4 | 23-Mar-2021 | 20-Oct-2022 | October 2022 | Reopening of the normal economic activities (October 2022) |
| 5 | 21-Oct-2022 | 27-Jun-2023 | June 2023 | WHO declared the end of public health emergency (April 2023) |

**Table 7** displays the intercept values of structural breaks from the results of the Bai and Perron Test based on dates and major Covid-19 events occurring around those dates.

## A.VI. Discussion and Implications of The Findings

This study provides valuable insights for regulators and financial authorities worldwide in adopting crypto assets into their financial systems. Crypto assets with high volatility and risk should have different regulatory treatments compared to those with low volatility and risk. Additionally, the systemic implication and adoption depth of a crypto asset into the financial market will determine the level of regulatory aggressiveness required to maintain financial market stability while not impeding innovation (Haji, 2022). Insights to address this issue can be derived from the results of this study.

We employ the GARCH model to comparatively analyse the risk profiles of stablecoins and unbacked crypto assets using the Value-at-Risk technique. The results indicate that stablecoins have significantly smaller Value-at-Risk compared to unbacked crypto assets. This aligns with previous research that found unbacked crypto assets tend to be high-risk with daily VaR above 5% (Som & Kayal, 2022; Uyar & Kahraman, 2019). The unique contribution of this study is that it reveals a risk differential through the comparison, where unbacked crypto assets tend to be 6-7 times riskier than stablecoins. Moreover, the study discovers that the cross-section between stablecoins and unbacked crypto assets affects the risk level of a crypto asset, as observed in the case of DAI. For regulators, this finding can serve as a foundation for different risk management strategies between stablecoins and unbacked crypto assets, as well as cautioning against various innovations that intersect both categories.

Using the TVP-VAR model, this study finds that stablecoins and unbacked crypto assets function as separate risk sources except when they intersect (as in the case of DAI). During crises, unbacked crypto assets tend to act as net transmitters, while stablecoins play the opposite role within the crypto market. This finding aligns with previous research on unbacked crypto assets and market activity during crises (Elsayed *et al.*, 2022). This study adds insights through the novel comparison with stablecoins, which has not been extensively conducted in prior studies. Furthermore, this can serve as a basis for both crypto market participants and regulators in treating these two types of crypto assets during market bearish and bullish phases.

This comparative study also assesses their systemic implication on the global and Indonesian financial markets. In contrast to Li & Huang (2020), this study discovers a significant spillover relationship between crypto assets and traditional financial assets, particularly involving stablecoins, due to the use of post-2020 crypto market development data. This complements the research by Wu & Leung (2023) and Elsayed *et al.* (2022) by deepening the understanding of the impact of stablecoins and unbacked crypto assets on traditional financial assets. Stablecoins tend to exhibit close relationships with European currencies and, surprisingly, Indonesian. Europe is recognised as a leading financial ecosystem in crypto regulation (PricewaterhouseCoopers LLP, 2023; Basel Committee on Banking Supervision, 2021; Bains *et al.*, 2022).

Furthermore, this study sheds light on the role of stablecoins as net transmitters, in stark contrast to unbacked crypto assets acting as net receivers in the global financial market. Additionally, the overall Total Connectedness Index (TCI) tends to increase during crises and decrease as the economy moves towards normalcy. For a deeper understanding, this study employs structural break analysis, revealing significant relationships between the major movements of TCI and significant Covid-19 events. For regulators, this phenomenon can serve as a decision-making basis, particularly in measuring the required level of regulatory aggressiveness considering different penetration levels of various crypto asset types into the financial market systems.

## 5. Conclusion

### A. Conclusion

This study conducts a comprehensive and comparative risk analysis of stablecoins and unbacked crypto assets using the Generalised AutoRegressive Conditional Heteroskedasticity (GARCH) model to assess their risk profile, and the Time Varying Parameter Vector Autoregression (TVP-VAR) model to examine their systemic impact on the broader financial market. The dataset employed comprises the daily price movements of stablecoins (USDT, USDC, DAI, BUSD, TUSD), unbacked crypto assets (BTC, ETH, ADA, BNB, XRP), and various traditional financial assets spanning from June 30, 2020, to June 30, 2023, encompassing a total of 36,998 data points.

With their dominant function as hedging instruments and mediums of exchange, we observe that stablecoins tend to be significantly more stable than unbacked crypto assets. However, both of them function as separate risk sources as they do not exhibit significant connectivity. Furthermore, it turns out that stablecoins possess an overall deeper systemic influence on the financial market compared to unbacked crypto assets, characterised by a greater connectedness to certain traditional financial assets. The time-varying analysis also reveals that the interconnections between crypto assets and traditional financial assets are highly responsive to the dynamics of the economy. As a result, regulators must provide distinct regulatory treatments, taking into account not only the category of crypto assets but also considering the economic dynamics. This is because both types exhibit quite distinct characteristics, impacts, and behaviours in relation to other assets and the broader financial market.

### B. Policy Recommendation

Through the findings of this study, we present policy recommendations for regulators and financial authorities. Based on this research, regulating crypto assets requires dynamic regulations and strategies that align with the characteristics of the crypto assets and the economic dynamics. This is because the interconnections among crypto assets themselves and with the broader financial market tend to fluctuate relative to the economic dynamics. Stablecoins can serve as an initial stage of crypto asset adoption due to their value stability.

Nevertheless, any stablecoin model intended for market release should undergo a comprehensive sandbox testing to anticipate risk transmission to other financial assets or even to the entire financial market. Conversely, unbacked crypto assets need to receive more regulatory attention during market crises, as they have been shown to exert significant influence on other assets during such times, unlike stablecoins.

During periods of less economic shocks, a relaxed regulatory approach is preferable for the crypto environment, as interconnectedness and risk transmission between assets decrease. This approach is aimed at fostering innovation without jeopardising financial system stability. Consequently, a growing and concurrently stable financial sector can be realised.

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