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Connectedness Analysis And Investment Strategy Between Stablecoins And International Stock Indices

Ika Maradjabessy[1*] and Zaafri Ananto Husodo[2]
[1]Program Pascasarjana Ilmu Manajemen, Economi dan Bisnis, Universitas Indonesia, Depok, Indonesia

Email Address:
ika.maradjabessy@ui.ac.id, z.husodo@ui.ac.id*
[*]Corresponding Author

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Abstract: This research analyzes the dynamic connectedness between fiat-based stablecoins represented by USDC, USDP, and USDT, and gold-based stablecoins represented by DGX and GLC with indices international stocks represented by S&P500, STOXX50, Nikkei225, CSI300, and JKSE using the new method, the DCC-GARCH based dynamic, connected approach. The result shows dynamic connectedness between stablecoins and the stocks indices; this research continues to adopt the DCC-GARCH t-copula method to find investment strategies by calculating the hedging ratio and portfolio weight. Overall, this research finds evidence that portfolio construction can significantly reduce investment risk in all assets used on two assets, Nikkei225 and JKSE. In contrast, the investment strategy with portfolio weights in long positions is suitable for gold-based stablecoins GLC and DGX, where these two assets can be a diversification strategy in compiling a portfolio in long positions with all the assets used.
Keywords: Stablecoin; Stocks Indices; DCC-GARCH; T-copula DCC-GARCH.

Abstrak: Penelitian ini menganalisis *dynamic connectedness* antara stablecoin berbasis fiat yang diwakili USDC, USDP, USDT dan stablecoin berbasis emas yang diwakili DGX dan GLC dengan indeks saham internasional yang diwakili S&P500, STOXX50, Nikkei225, CSI300, dan JKSE dengan menggunakan metode baru yaitu pendekatan keterhubungan dinamis berbasis DCC-GARCH. Hasil ini menunjukkan terdapat *dynamic connectedness* antara stablecoin dan indeks saham, kemudian penelitian ini dilanjutkan menggunakan metode t-copula DCC-GARCH untuk melihat strategi investasi dengan menghitung rasio lindung nilai dan bobot portofolio antara kedua jenis aset tersebut. Hasilnya menunjukkan secara keseluruhan penelitian ini menemukan bukti yang menunjukkan bahwa konstruksi portofolio dapat secara signifikan mengurangi risiko investasi di semua aset terhadap Nikkei225 dan JKSE, sedangkan strategi investasi dengan bobot portofolio pada posisi *long* cocok untuk stablecoin berbasis emas yaitu GLC dan DGX, dimana kedua aset ini dapat menjadi strategi diversifikasi dalam menyusun portofolio pada posisi *long* dengan semua aset yang digunakan.
Kata Kunci: Stablecoin; Indeks Saham, DCC-GARCH; T-Copula DCC GARCH.

INTRODUCTION

On March 11 2020, the World Health Organization (WHO) announced the status of the Covid-19 pandemic, which was very unfavourable for the world community. The Covid-19 pandemic in December 2019 in Wuhan, China, has affected more than 200 countries. Implementing a lockdown during the COVID-19 pandemic has shaken the stability of international financial markets. (Zaremba et al., 2020) A strong relationship was found between government intervention due to the Covid-19 outbreak and higher stock market volatility. The announcement from the WHO has sent financial markets worldwide into chaos, as a global economic recession is predicted in the coming years. The day after WHO declared the financial turmoil, it was visible in the stock market (Liu et al., 2020; Okorie &

Lin, 2021) and the foreign exchange market (Aslam et al., 2020). Stock indices such as the S&P 500, FTSE-100, and Nikkei-225 plunged around 9, 11, and 4 per cent in the same period.

Besides the stock market, Covid-19 also significantly impacted the cryptocurrency market, with most cryptocurrency losses (Balcilar et al., 2022; Banerjee et al., 2022; Sui et al., 2022). The introduction contains state-of-the-art explanations of research problems that need to be answered through research activities. This section explains the theories within the scope of the research, existing phenomena, and the gap between the theories and the facts. This section also outlines the theories explaining the relationship among researched variables, relevant research results, and hypotheses. The relationships between current and previous research and contributions to modern science are also explained.

Since then, many assets have undergone in-depth research regarding haven, hedging and diversification characteristics. The cryptocurrency market has developed rapidly, among other investment instruments secured with cryptography, so it is almost impossible to carry out double spending or counterfeiting. Bitcoin has increased in value from nearly $0 in October 2009 to over $27,236 in October 2023 (CoinMarketCap.com, 2023). However, Bitcoin is characterized by high volatility, which makes it difficult for investors to get a stable rate of return or maintain value. Mixed findings come from examining Bitcoin's hedging capabilities, where Bitcoin serves as a hedge for Chinese and North American markets, as demonstrated by (Chan et al., 2019) and (Stensas et al., 2019) for emerging markets. At that point, research conducted by (Klein et al., 2018) produced contradictory findings, where the potential use of Bitcoin as a haven has generated more controversy due to its extreme volatility.

In this context, stablecoins were introduced as an alternative to traditional cryptocurrencies and investments in other capital markets. Due to their different technological conceptions, stablecoins are very different from traditional cryptocurrencies in general, both in design and investor perception. As the name suggests, stablecoins are designed to be price-stable cryptocurrencies and differ from traditional cryptocurrencies in terms of investor perception. Due to their clustering mechanism, stablecoins bridge fiat currencies with traditional cryptocurrencies.

Stablecoins are typically pegged to fiat currencies such as USD and EUR or to commodities such as precious metals, gold, and silver. Stablecoins are known for their decentralized vault, which makes them attractive to cryptocurrency users. According to (Ito et al., 2020), (1) in general, stablecoins are a stabilization mechanism achieved by controlling the proportional relationship of exchange rates between traditional cryptocurrencies and fiat currencies, and (2) pegging is an effective way to reduce asset volatility. (Sidorenko, 2020) also notes that the cryptocurrency market trend is moving towards transferring funds to several representative low-volatility digital assets, confirming stablecoins' ability to store or exchange market assets. Although stablecoins are often viewed as cryptocurrencies designed to minimize price volatility, (Chohan, 2019) notes that the question of whether stablecoins are truly stable remains unresolved. Additionally, further research is needed to determine the role of stablecoins in other cryptocurrency portfolios. As shown in research (Baur & Hoang, 2021) and (Wang et al., 2020), there are still many unanswered questions regarding the design of stablecoins and their role as safe assets compared to traditional assets or in political-economic turmoil.

The role of stablecoins, which are believed to have a more stable value compared to other traditional cryptocurrencies, and stablecoins may depend on speculative factors of supply and demand. At the same time, the stock market is faced with macroeconomic factors, such as government fiscal or monetary policies. The fact that this market depends on very different factors allows the Stablecoin market to have a dynamic relationship and hedge against market risks, thus motivating this research to research further the dynamic relationship between stablecoins and international stock indices.

Research conducted by (Wang et al., 2020) found that gold-pegged stablecoins have poor haven performance compared to fiat-based stablecoins against the underlying asset, namely cryptocurrency. Therefore, the following motivation for this research is to look further at the dynamic relationship between these stablecoins and international stock indices. Moreover, the results of previous research, which is used as a reference in this research which examines stablecoins as a hedging tool and also a diversification strategy against other assets, produces different results, so this research was carried out because of the need to understand the role and properties of stablecoins in the context of financial markets. Which continues to grow, especially in terms of diversification and hedging against other assets. The motivation for further research is also to see how stablecoins can be an effective hedge and an investment diversification strategy for international stock indices. This research was conducted using a new method, namely DCC GARCH-based dynamic connectivity or DCC GARCH based-dynamic connectedness approach, and seeing the spillover effect between stablecoins and international stock indices; this research adopted the DCC GARCH t-copula model to calculate hedging ratios, portfolio weights, and also the hedging effectiveness of stablecoins and stock indices.

As far as researchers are aware, this study is the first to examine the spillover effect between fiat and gold-based stablecoins and international stock indices using the most recent DCC-GARCH-based dynamic connectedness model developed by (Gabauer, 2020). This new approach effectively addresses the primary drawback of rolling windows analysis, which frequently needs observations and a window size selection. We can also investigate if transmission mechanisms change over time using this. The researchers then took into consideration whether these stablecoins and stock indices could be used as a portfolio investment and hedging strategy using the DCC-GARCH t-copula method proposed by (Antonakakis et al., 2020), given the results of the spillover effect between fiat and gold-based stablecoins and international stock indices. Few studies have also examined the relationship between stablecoins and global stock indices. (Kolodziejczyk, 2023), for example, employed a quantile coherency approach in his research and concluded that the stablecoins he used were only a marginal hedge against the underlying stock index or asset market.

THEORETICAL REVIEW

The first research objective in this study focuses on testing the existence of dynamic connectedness between fiat and gold-based stablecoins and international stock indices, where stablecoins are known as an alternative to traditional cryptocurrencies because of the differences in technological conception between stablecoins and traditional cryptocurrencies. Stablecoins that are considered to have more stable volatility are coins that are pegged to fiat currency and also those that are pegged to gold and precious metals. Meanwhile, the stock price index is a statistical measure that reflects the overall stock price movement of a group of stocks selected based on specific criteria and methodology and evaluated periodically. The stock price index is a group of shares with the same criteria and

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grouped using a specific methodology. The methodology is based on fundamentals, technicals or a combination of both. Moreover, the second aim of this research is to test how risk hedging performs between the variables used in this research, namely stablecoins and international stock indices. The DCC-GARCH-based dynamic connectivity method or DCC-GARCH-based-dynamic connectedness approach is used to answer this research's two objectives.

Whereas previous research conducted by (Wang et al., 2020), who examined stablecoins with traditional cryptocurrencies using DCC-GARCH, found that stablecoins can function as a haven in certain situations, while research conducted by (Jarcono et al., 2020), who examined cryptocurrencies against the movement of international stock indices found that Bitcoin can act as a hedging asset and become a diversification tool. The most recent research by (Kołodziejczyk, 2023), which examined the relationship between stablecoins and stock indices, found that stablecoins act as a weak hedge in normal conditions and a weak haven. Previous research has looked at whether cryptocurrency can be a hedging tool, but few have tested the dynamic connection between cryptocurrency and stock indexes; therefore, motivated by previous research and wanting to test the existence of dynamic connectedness or between stablecoins and stock indexes, the research It examines the dynamic connectedness between stablecoins and international stock indices and how investment strategies hedge each other's assets.

In reviewing the literature review, only a few studies have examined the role of stablecoins, previous studies such as those conducted by (Wang et al., 2020) and (Lyons & Viswanath-Natraj, 2023) regarding the role of stablecoins in traditional cryptocurrencies, then research conducted by (Ante et al., 2021) related to the influence of stablecoins on the crypto market and also research conducted by (Garcia-Jorcano & Benito, 2020) which examined Bitcoin as a diversification and hedging tool against international stock indices, then in 2023 research emerged from (Kołodziejczyk, 2023) conducting research that connects the research of (Wang et al., 2020) with (Garcia-Jorcano & Benito, 2020) to examine the role of stablecoins on traditional assets (such as shares) in various countries by using new methods to determined frequency-dependent correlations with the quantile coherence measure proposed by (Baruk & Kley, 2019). His research (Kołodziejczyk, 2023) found that stablecoins act as a weak hedge under normal market conditions and as a weak hedge when considering moments of market volatility. Motivated by previous research, which researched a lot regarding the role of stablecoins on traditional cryptocurrencies and found only a tiny amount of research on stablecoins on traditional assets such as shares, this research further examines whether there is a dynamic connectedness between stablecoins and international stock indices using a new method proposed by (Gabauer, 2020) which differs from traditional models for estimating dynamic connectedness.

Based on theory and empirical research that has been carried out previously, the research hypothesis is as follows:

H1: Fiat and gold-based stablecoins have dynamic connectedness with international stock indices.

With the development of new types of instruments that have become investment tools for the community, especially during crisis conditions such as the COVID-19 pandemic, many shares have fallen due to restrictions on community activities, thus hampering the economy in many countries. Cryptocurrency is a new type of investment that is developing very rapidly. However, cryptocurrency is characterized by high volatility, which makes it difficult for investors to get a stable rate of return or maintain value. Thus, there is a need for appropriate investment tools to hedge against risks in the capital market. In this condition, stablecoins were introduced as an alternative to traditional cryptocurrencies and investments in other capital markets. Previous research conducted by (Wang et al., 2020) showed that stablecoins can function as a safe haven in certain situations, although primarily only as adequate diversification under normal market conditions. (Kolodziejczyk, 2023) conducted research regarding the role of stablecoins as a means of diversification, hedging, and safe haven against traditional assets such as shares and found that the stablecoins used in the research acted as a weak hedge under normal conditions and a weak safe haven when considering dependencies. By looking at previous research, this research is also motivated to test whether stablecoins can act as a hedge against international stock indices using the latest method proposed by (Antonakakis et al., 2020), who uses Optimal DCC-GARCH Copula in his research to look at strategies effective investment and hedging.

The following is the research hypothesis, which is based on theory and prior empirical study:

H2: Fiat and gold-based stablecoins have hedging effectiveness or an effective hedge against international stock indices by looking at the hedging ratio between stablecoins and stock indices.

H3: Stablecoins become a diversification strategy for international stock indices by looking at their optimal portfolio weights.

METHODS

In this study, we analyze the returns of five stablecoins consisting of three fiat-based stablecoins (USDC, USDP, and USDT), two gold-based (DGX and GLC) and five international stock market indices (S&P500, STOXX50, Nikkei225, CSI300, and JKSE). The data covers the period from October 10 2018, to June 27 2023. The first reason for choosing this time range is limited data availability because each stablecoin included in this study was created or published differently, so data availability also varies. Moreover, this research ensures that the time series covers normal market periods. Conditions and periods of increased volatility and market tension, such as during the COVID-19 pandemic. These conditions are when safe haven properties appear, and the conditions are right to test whether market contagion occurs. This allows this research to develop insights into stablecoin behaviour. The data taken is the daily closing price of each variable converted to daily log returns.

When combining the data at the data preparation stage, this study only leaves existing observations in all series (i.e., observations missing in at least one series will be removed), bringing the number of observations in each series to 981. This study uses the R project for statistical computing and the package connectedness approach provided by Prof. David Gabauer.

Data related to stablecoins and cryptocurrencies is taken from the coinmarketcap.com database. Although many stablecoins, such as Dai, Terra USD, Binance USD, and others, are considered research or study targets, they must be ignored because the time series is not long enough.

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Regarding international stock indices data, this research uses five international stock indices; we used S&P500, which comes from the United States; STOXX50, which comes from the Eurozone, which represents 11 countries in the zone France, Germany, Austria, Belgium, Ireland, Italy, the Netherlands, Luxembourg, Spain, Portugal and Finland. Next is the Nikkei225 stock index, which comes from Tokyo; then there is the CSI300 or Shanghai Shenzhen CSI300, which comes from China; and finally, there is the JKSE or Jakarta Stock Exchange, which comes from Indonesia. For daily price data for the five indices, access via investing.com.

DCC-GARCH and the Volatility Impulse Response Function. Following the steps of research conducted by (Gabauer, 2020), this research uses Volatility Impulse Response Functions (VIRFs) to analyze Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC GARCH) to analyze the dynamic relationship between stablecoins and international stock indices. Compared with traditional methods (using a moving window to calculate dynamic connectedness), one of the advantages of the dynamic connectedness approach based on DCC-GARCH is that it does not require window size selection to take dynamic connectedness measures (Bouri et al., 2021).

The GARCH model calculates volatility as a deterministic variable, which is important for the DCC-GARCH model, by following the research methods conducted by (Hou et al., 2019) and (Zhang et al., 2022). This research uses the GARCH model to estimate volatility.

The advantages of the DCC-GARCH model compared to the BEKK model can be summarized in the following three points: First, the DCC-GARCH model can directly calculate the correlation of dynamic conditions over time. Second, using the DCC-GARCH model allows for calculating dynamic connectivity without a moving window approach, thereby avoiding the loss of observation samples (Gabauer, 2020). Finally, the DCC-GARCH model estimates the correlation coefficient of standardized residuals and directly accounts for heteroscedasticity.

To investigate the time-varying conditional volatility shown as follows:

$$y_t = c_t + \varepsilon_t, \varepsilon_t | M_{t-1} \sim N(0, H_t) \quad \text{(1)}$$

$$\varepsilon = H_t^{1/2} u_t, u_t \sim N(0, I) \quad \text{(2)}$$

$$H_t = D_t R_t D_t \quad \text{(3)}$$

$$D_t = diag(h_{11t}^{\frac{1}{2}}, \ldots, h_{KKt}^{\frac{1}{2}}) \quad \text{(4)}$$

Where M_{t-1} represents all available information from 1 to $t-1$, y_t, c_t, ε_t, and u_t are respectively $(K \times 1)$dimension vectors representing the analyzed time series, conditional mean, error term, and standardized error term. In addition, R_t, D_t and H_t are dimensional matrices $(K \times K)$that represent dynamic conditional correlation, time-varying conditional correlation, and time-varying conditional variance-covariance.

Following the research conducted by (Zhang et al., 2022) in the first step, components are estimated with a GARCH model for each series, and then, can define the parameters of one shock and one persistence are as follows:

$$h_{ii,t} = \omega + \alpha\varepsilon_{i,t-1}^2 + \beta h_{ii,t-1} \quad (5)$$

Where α and β are non-negative shock and persistence parameters, α β satisfies the condition (α + β) less than 1.

In the second step, dynamic conditional correlation can be calculated as follows:

$$R_t = diag\left(q_{iit}^{-\frac{1}{2}}, \dots, q_{KKt}^{-\frac{1}{2}}\right) Q_t diag\left(q_{iit}^{-\frac{1}{2}}, \dots q_{KKt}^{-\frac{1}{2}}\right) \quad (6)$$

$$Q_t = (1 - a - b)\bar{Q} + a u_{t-1} u_{t-1} + b Q_{t-1} \quad (7)$$

Q_t and $\bar{Q}$ are positive definite matrices of dimension $(K \times K)$, each representing the variance-covariance matrix of the conditional unconditional standard residuals. Similarly, a and b are non-negative shock and persistence parameters. a, b satisfy the condition $(a + b)$ less than one is met. Q_t and R_t can vary over time. Otherwise, this model will change to a Constant Conditional Correlation – Generalized Autoregressive Conditionally Heteroscedastic (CCC-GARCH) model where R_t is always constant (Bollerslev, 1990).

The dynamic linkage methodology developed by (Diebold & Yilmaz, 2012, 2014) based on Generalized Impulse Response Functions (GIRFs) is generally used in traditional volatility spillover analysis. In that research study, GIRF is defined as the effect of j steps forward of a shock in each variable y_t on variable j: $GIRF(J, \gamma_{j,t}, M_{t-1}) = E(y_{t+J} | \varepsilon_{j,t} = \gamma_{j,t}, M_{t-1}) - E(y_{t+J} | \varepsilon_{j,t} = 0, M_{t-1})$, where $\gamma_{j,t}$ is the shock in the jth variable. It is noted that J-step-ahead means predicting the outcome after J days, and in this study, J is set to be ten days in the dynamic analysis of this study. In contrast to traditional VAR models, the advantage of GIRF is that it is not affected by the ordering of variables.

Inspired by GIRF, VIRF, developed by (Gabauer, 2020), is an abbreviation for a shock on each variable H_t on conditional volatility variables j and J step-ahead and can be expressed as follows:

$$\phi^g = VIRF(J, \gamma_{j,t}, M_{t-1}) = E(H_{t+J} | \varepsilon_{j,t} = \gamma_{j,t}, M_{t-1}) - E(H_{t+J} | \varepsilon_{j,t} = 0, M_{t-1}) \quad (8)$$

Where M_{t-1} represents all available information from 1 to t-1, H_{t+J} represents the time-varying conditional variance-covariance of the forecast period J.

The essence of VIRF is to use the DCC-GARCH model (Engle & Sheppard, 2001) to predict conditional variance-covariance, which can be done iteratively in three steps. The first step is that the conditional volatility $(D_{t+h} | M_t)$will be predicted using the univariate GARCH (1,1) model as follows:

$$E\left(h_{ii,t+h} | M_t\right) = \sum_{i=0}^{h-1} \omega(\alpha + \beta)^i + (\alpha + \beta)^{h-1} E\left(h_{ii,t+h-1} | M_t\right), h = 1, 2, \dots, n \quad (9)$$

Meanwhile, in the second step, we can predict $E(Q_{t+h} | M_t)$ by:

$$E(Q_{t+h} | M_t) = (1 - a - b)\bar{Q} + aE(u_{t+h-1} u'_{t+h-1} | M_t) + bE(Q_{t+h-1} | M_t), h = 1, 2, \dots, n \quad (10)$$

where $E(u_{t+h-1}u_{t+h-1}|M_t) \approx E(Q_{t+h-1}|M_t)$ (Engle, RF., Sheppard, 2001), which can help predict dynamic condition correlation and conditional variance-covariance in the last step:

$$E(R_{t+h}|M_t \approx diag[\, E\,(q_{iit+h}^{-\frac{1}{2}}|M_t),\dots,E\,(q_{KKt+h}^{-\frac{1}{2}}|M_t)\,]$$
$$E(Q_{t+h})diag[\, E(q_{iit+h}^{-1/2}|M_t),\dots,E(q_{KKt+h}^{-1/2}|M_t)\,] \dots\dots(11)$$

$$E(H_{t+h}|M_t) \approx E(D_{t+h}|M_t)E(R_{t+h}|M_t)E(D_{t+h}|M_t)\dots\dots(12)$$

Dynamic Linkage Approach Based on DCC-GARCH. Generalized Forecast Error Variance Decomposition (GFEVD) $\Psi_{ij}^{g}.t$ (J) is calculated based on VIRF. GFEVD can be interpreted as the variance shared by one variable explaining others. These variance shares are normalized so that each row sums up to one, meaning all variables together explain 100 per cent of the variable's forecast error variance (Gabauer, 2020). The calculation process is as follows:

Paired Directional Connectedness:

$$\tilde{\Psi}_{ij.t}^{g}(J) = \frac{\sum_{t=1}^{J}\Phi_{ij,t}^{2,g}}{\sum_{j=1}^{K}\sum_{t=1}^{J-1}\Phi_{ij,t}^{2,g}}\dots\dots(13)$$

Where $\sum_{j=1}^{K}\tilde{\Psi}_{ij.t}^{g}(J) = 1$ and $\sum_{j=1}^{K}\tilde{\Psi}_{ij.t}^{g}(J) = K$. The denominator represents the aggregate cumulative impact of all shocks, while the numerator represents the cumulative effect of the shock.

Furthermore, using GFEVD, the total connectedness index (TCI) can be calculated as follows:

Total Connectedness Index (TCI):

$$C_t^{g}(J) = \frac{\sum_{i,j=1,i\neq j}^{K}\tilde{\Psi}_{ij.t}^{g}(J)}{K}\dots\dots(14)$$

In general, the TCI reflects the average share of the forecast error variance of a variable that is explained by all other variables, or, in other words, how much shocks in one variable affect the average of all other variables.

Once we obtain the TCI, we can determine the total directional connectedness TO of other variables, which means the spillover transmitted from variable i to variable j by:

Total Directional Connectedness (TO):

$$C_{i\rightarrow j,t}^{g}(J) = \frac{\sum_{j=1,i\neq j}^{K}\tilde{\Psi}_{ji.}^{Tg}(J)}{\sum_{j=1}^{K}\tilde{\Psi}_{ji.t}^{g}(J)}\dots\dots(15)$$

Then, the total directed connectedness FROM other variables, which represents the overflow variable i receives from variable j, can be determined by:

Total Directional Connectedness (FROM):

$$C_{i\leftarrow j,t}^{g}(J) = \frac{\sum_{j=1,i\neq j}^{K}\tilde{\Psi}_{ji.}^{Tg}(J)}{\sum_{j=1}^{K}\tilde{\Psi}_{ji.t}^{g}(J)}\dots\dots(16)$$

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Finally, the total directed connectedness of variable i is the difference between the total directed connectedness (TO) and the total directed connectedness (FROM). If variable I have a positive (negative) value of the total directional connectedness, it indicates that variable i is a transmitter (receiver) of net shocks. This can be calculated by:

Net Total Directional Connectedness:

$$C^{g}_{i,t} = C^{g}_{i\rightarrow j,t}(J) - C^{g}_{i\leftarrow j,t}(J) \qquad (17)$$

Optimal Hedging and Portfolio Strategy Based on DCC GARCH Copula. Following (Antonakakis et al., 2020) and (Evrim Mandacı et al., 2020), this study uses the DCC GARCH t-copula model to calculate conditional covariance and dynamic conditional correlation, which are applied to calculate the optimal hedging ratio and portfolio weights. Using the t-copula model in financial analysis and econometrics has several advantages that make it a valuable tool in modelling dependencies between random variables. The following are several reasons why copulas are used in this research. Firstly, copulas allow for the modelling of nonlinear dependencies between random variables. This is important because the relationship between stablecoins and stock indexes may not be linear, and copulas can capture more complex relationships. Second, copulas provide flexibility in modelling various extreme and asymmetric dependencies. This makes it possible to model relationships that traditional statistical methods may not capture. Third, with copula, this research can separate the marginal distribution model from the dependency model. This makes it possible to model the distribution of each variable separately from the dependencies of those variables. Moreover, copulas can finally be used to model extremity in the distribution of random variables. Thus, using copulas in this research can provide a more flexible approach and capture more complex dependencies between these variables.

Since this study has explained the structure of the DCC-GARCH model in detail in Section 4.3.1, this section will not repeat the DCC-GARCH model here. This study uses dynamic connectivity based on the basic DCC-GARCH model by (Engle, 2002) with standard errors following the multivariate Student's t distribution. This study uses a model with a copula function (Sklar, 1959) rather than the Student's t distribution to estimate the optimal hedge ratio and optimal portfolio weights. (Patton, 2006) proposed copula theory as a flexible tool for modelling dependencies between N random variables, showing that N-marginal distribution functions and copulas are combined to produce an N-dimensional joint distribution function. FX1, …, XN is defined as the joint distribution function of the random variables X1, …, In this situation, the unique N-dimensional copula distribution function C can be defined as:

$$F_{X1,\dots,\chi_N} = C(F_{X1}(\chi_1),\dots,F_{X1}(\chi_N)) \qquad (18)$$

$$C(u_1,\dots,u_N) = F_{X1,\dots,XN}\left(F^{-1}_{X1}(u1),\dots,F^{-1}_{XN}(uN)\right) \qquad (19)$$

(Patton, 2006) applies copula theory to the case of multivariate conditionals, enabling asymmetric modelling of time-varying conditional dependencies between time series. The density of Student's t-copula function with shape parameter θ is used to build the DCC GARCH t-copula model as follows:

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$$C(u_1, \ldots, u_N | R_t, \theta) = t\theta\left(F_{X1}^{-1}(u_1|\bullet_1), \ldots, F_{X1}^{-1}(u_N|\bullet_N)\right) = \int_{-\infty}^{F_1^{-1}(u_1)} \ldots \int_{-\infty}^{F_N^{-1}(u_N)} \frac{\Gamma(\theta + N/2)}{\Gamma(\theta/2)(\theta\pi)^{N/2}|R_t|^{1/2}}\left(\left(1 + \frac{1}{\theta} z'_t R_t^{-1} z_t\right)\right)^{(\theta+N)/2} dz_1, \ldots, dz_N \quad (20)$$

where $F_{X1}^{-1}(u_1|\bullet_1)$ is the conditional distribution, and $\bullet_i$ denotes the estimated parameters of the univariate GARCH model. This shows differences in the marginal distribution of the fundamental univariate GARCH model in the DCC-GARCH t copula model.

Next, we used the basic DCC-GARCH model (Engle, 2002) created to estimate conditional variance and covariance. In this section, (Kroner & Sultan, 1993) use conditional variance and covariance estimates from DCC-GARCH to calculate the optimal hedging ratio (βijt), which is a ratio that shows the optimal proportion of an asset that should be hedged against an asset. Other to reduce portfolio risk maximally, where the optimal hedging ratio (βijt) can be calculated as follows:

$$\beta_{ijt} = h_{ijt} / h_{jjt} \quad (21)$$

Where h_{ijt} and h_{jjt} represent the conditional covariance of variable i and variable j and the conditional variance of i, the optimal hedge ratio calculates the cost of hedging a 1-dollar long position on variable i with a short β_ijt dollar position on variable j. This suggests that a higher conditional variance of i will lead to lower long-term hedging costs. In contrast, a higher conditional covariance of i and j will lead to higher long-term hedging costs.

$$W_{ijt} = \frac{h_{jjt} - h_{ijt}}{h_{iit} - 2h_{ijt} + h_{jjt}} \quad (22)$$

Because this research is interested in long positions, this research applies the optimal portfolio weight limits as follows:

$$W_{ijt} = \begin{cases} 0 \text{ if } W_{ijt} < 0 \\ W_{ijt} \text{ if } 0 \leq W_{ijt} \\ 1 \text{ if } W_{ijt} > 1 \end{cases} \quad (23)$$

W $_{ijt}$ represents the weight of variable i in a one-dollar portfolio of two variables, i and j, at time t. The weight of variable j is $W_{jit} = 1 - W_{ijt}$.

After obtaining the optimal hedge ratio and optimal portfolio weight, this research calculates the effectiveness of the hedge and portfolio. Following (Ederington, 1979), hedging effectiveness (HE_{ijt}) is a measure of the extent to which a hedging strategy can protect or reduce the risks associated with fluctuations in the value of assets or liabilities where hedging effectiveness (HE_{ijt}) can calculated as follows:

$$r_{\beta ijt} = x_{it} - \beta_{jit} x_{jt} \quad (24)$$

$$r_{wijt} = W_{ijt} x_{it} + W_{jit} x_{jt} \quad (25)$$

UNTAR Universitas Tarumanagara
Jurnal Manajemen
e-JM
E-ISSN: 2549-8797
ISSN: 1410-3583

$$HE_{ijt} = 1 - \frac{[(Var(r_{\beta ijt}), Var(r_{wijt}))}{Var(r_{unhedged})]} \qquad (26)$$

Where $(Var(r_{\beta ijt}), Var(r_{wijt}))$ represents the optimal hedge ratio or hedge portfolio variance of the optimal portfolio weight strategy. $Var(r_{unhedged})$ is the variance of the unhedged position between variable i and variable j. In fact, HE measures the percentage reduction in the variance of an unhedged position. The higher the HE shows, the more significant the decrease. (Antonakakis et al., 2020) found that the (Brown & Forsythe, 1974) test showed remarkable results in testing the significance of HE, so this study uses the (Brown & Forsythe, 1974) test to check the significance of HE and determine whether one of the investments This approach succeeded in reducing variation.

RESULTS

In this study, the data used is daily return data from stablecoins represented by USDC, USDP, USDT, DGX, and GLC and for international stock indices represented by S&P500, STOXX50, NIKKEI225, CSI300, and JKSE index return data in the period October 10 2018 to June 27 2023. Stablecoin return data is taken from coinmarketcap.com, and international stock index data is accessed from investing.com.

Table 1. Descriptive Statistics of Research Variables

	N	Mean	Median	Max	Min	Std. Dev	Skewness	Kurtosis	JB	ADF
USDC	981	-0.001	-0.001	4.244	-3.723	0.390	1.052**	40.597**	57960**	-13.825**
USDP	981	-0.001	0.001	4.891	-5.218	0.410	-0.088	54.870**	109976**	-15.324**
USDT	981	0.000	-0.001	5.339	-5.257	0.400	0.379**	70.348**	185427**	-13.559**
DGX	981	-0.005	-0.039	187	-151	11	2.676**	118.055**	542265**	-13.486**
GLC	981	-0.074	-1.120	155	-114	20	1.063**	13.846**	4993.9**	-10.597**
S&P500	981	0.043	0.087	9	-13	1.500	-0.865**	15.189**	6195.4**	-9.1709**
STOXX50	981	0.026	0.096	8.834	-13	1.500	-1.009**	15.039**	6091.4**	-9.4592**
Nikkei225	981	0.033	0.083	6.889	-6.273	1.300	-0.114**	5.490**	255.66**	-10.334**
CSI300	981	0.016	0.018	7.426	-8.207	1.400	-0.230**	6.286**	449.99**	-9.9627**
JKSE	981	0.014	0.045	9.704	-6.805	1.100	-0.078**	12.740**	3878.9**	-9.6505**

Note: JB represents (Jarque & Berra's, 1987) normality test, ADF represents Augmented Dickey and Fuller Root Test, ** indicates rejection of the null hypothesis at the 1 per cent significance level.
Source: Processed data, 2023

Table 1 shows descriptive statistics for the return series. In this research, each variable has a total of 981 observations or 981 daily return data per each variable.

Dynamic Connectedness. To analyze the dynamic connectedness between fiat-based stablecoins (USDC, USDP, and USDT) and gold (DGX and GLC) and international stock indices represented by the S&P500, STOXX50, Nikkei225, CSI300, and JKSE, this research uses software statistics-oriented programming, namely R Studio, using R code provided by Prof. David Gabauer on Github, which produced the results in **Table 2.**

Table 2 shows the average dynamic linkage of each fiat-based stablecoin return (USDC, USDP and USDT), gold-based stablecoin return (DGX, GLC) and also international stock index returns (S&P500, STOXX50, NIKKEI225, CSI300, JKSE). The values in the ith row and jth column are pairwise directional relationships, which show that the spillover effect is transmitted from variable j to variable i and vice versa. The FROM value represents the spillover effect that a market receives from all other markets, excluding the diagonal value (the value of the market itself). On the other hand, TO is a spillover effect

UNTAR Universitas Tarumanagara
Jurnal Manajemen e-JM
E-ISSN: 2549-8797
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transmitted from one market to another, excluding the diagonal value (the value of the market itself). While "Inc. Own" is the value of TO added to the diagonal value of the market itself. "NET Directional Connectedness" refers to the difference between a variable's TO value and the FROM value. "NPDC Transmitter" refers to the net pairwise directional connectedness transmitter, which counts the number of times one variable dominates another variable. TCI represents the total connectedness index or total connectedness index, which is the sum of the TO values or FROM values divided by N-1 (the number of variables minus one).

Table 2. Average Dynamic Connectedness

	USDC	USDP	USDT	DGX	GLC	S&P 500	STOXX 50	Nikkei 225	CSI300	JKSE	FROM
USDC	51.830	9.060	7.210	5.260	23.530	0.860	0.200	0.290	1.090	0.680	48.170
USDP	3.710	39.490	6.220	4	43.799	0.230	0.210	1.640	0.610	0.090	60.510
USDT	5.340	11.450	59.670	2.170	20.160	0.100	0.290	0.370	0.350	0.120	40.330
DGX	0	0	0	95.170	4.670	0.050	0.030	0.010	0.030	0.020	4.830
GLC	0	0	0	0.400	99.590	0	0	0	0	0	0.410
S&P500	0.060	0.010	0.010	12.610	19.320	42.960	16.070	3.550	3.160	2.250	57.040
STOXX50	0.020	0.010	0.020	10.700	13.510	17.870	44.450	7.580	3.450	2.390	55.550
NIKKEI225	0.020	0.070	0.020	7.130	18.360	2.890	5.110	54.790	7.710	3.900	45.210
CSI300	0.060	0.030	0.020	8.440	14.680	2.590	2.720	8.900	59.750	2.820	40.250
JKSE	0.080	0.020	0.010	15.230	22.790	4.150	3.790	9.020	5.520	39.390	60.610
TO	9.280	20.650	13.500	65.930	180.820	28.740	28.420	31.370	21.920	12.270	412.910
Inc.Own	61.110	60.140	73.170	161.100	280.420	71.710	72.860	86.160	81.670	51.660	TCI
NET Directional connectedness	-38.890	-39.860	-26.830	61.100	180.420	-28.290	-27.140	-13.840	-18.330	-48.340	41.290
NPDC Transmitter	0	2	1	8	9	5	4	7	6	3	

Source: Processed data, 2023

Jurnal Manajemen
e-JM
E-ISSN: 2549-8797
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This research refers to (Bilgin & Yilmaz, 2018) to create a dynamic linkage table network, as shown in **Figure 1**, to better visualize the dynamic linkage table.

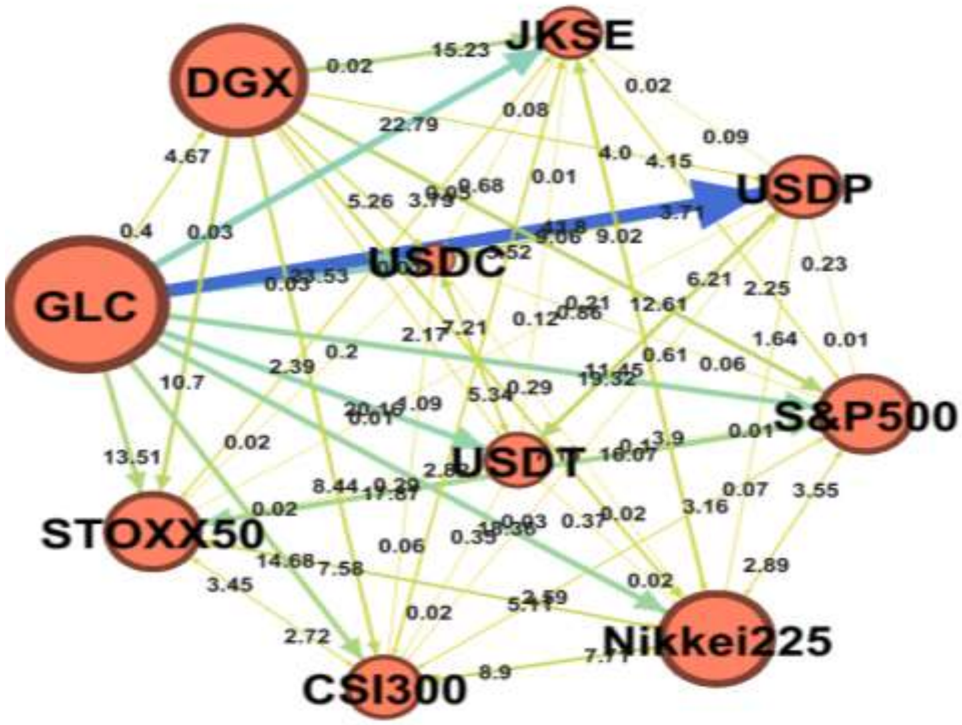

Figure 1. Average Dynamic Connectivity Network Of The Spillover Series in **Table 2**
Source: Processed data Gephi, 2023

Figure 2 depicts the total volatility of dynamic connectedness, which ranges between 30 and 80 per cent. This shows that the linkage between fiat and gold-based stablecoins and international stock indices varies over time, a fact usually masked by the static nature of the TCI.

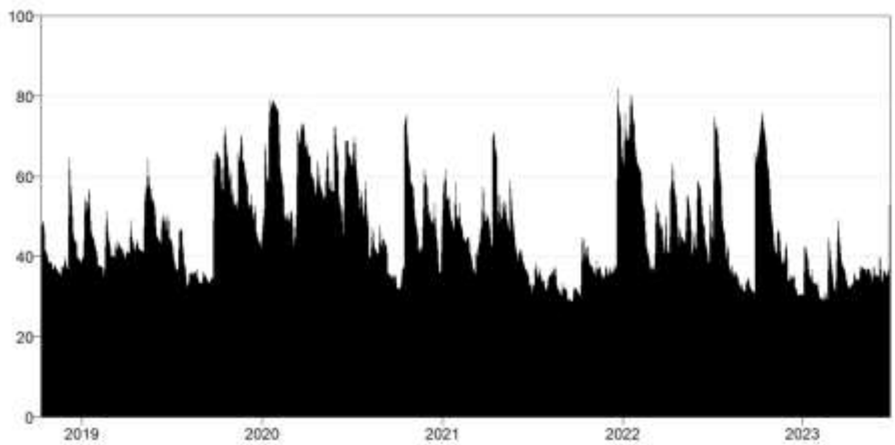

Figure 2. Total Dynamic Connectedness
Source: Processed data, 2023

Hedging Strategies. After calculating dynamic connectedness, this research finds a time-varying dynamic connectedness between fiat and gold-based stablecoins and international stock indices. Therefore, it is important to investigate investment diversification and risk management strategies. This research uses two tools, namely the hedging ratio and portfolio weight, to estimate an asset's hedging ability and calculate hedging effectiveness. Here, it is assumed that investors should hold a long position in an index when the future volatility of this index is expected to be higher than the current level of volatility. Conversely, when the future volatility of an index is expected to decrease, investors should take a short position on the index.

Table 3. Dynamic Optimal Hedging Ratio and Hedging Effectiveness

Long position/Short position	βijt	Std.Dev.	HE	p-value
USDC/USDP	0.280	0.280	0.430	0.800
USDC / USDT	0.360	0.230	0.370	0.830
USDC/DGX	0.000	0.010	-0.010	0.810
USDC/GLC	0.000	0.000	-0.060	0.950
USDC/SP500	-0.010	0.020	-0.010	0.120
USDC/STOXX50	-0.010	0.020	-0.010	0.180
USDC/Nikkei225	-0.010	0.020	-0.050**	0.010
USDC/CSI300	-0.010	0.020	-0.020	0.170
USDC/JKSE	-0.010	0.030	-0.040**	0.000
USDP/USDC	2.040	2.470	0.390	0.580
USDP/USDT	1.650	2.100	0.350	0.830
USDP/DGX	0.000	0.000	-0.010	0.810
USDP/GLC	0.000	0.000	-0.040	0.950
USDP/SP500	0.000	0.020	0.030	0.120
USDP/STOXX50	0.000	0.010	0.000	0.180
USDP/ Nikkei225	-0.020	0.020	-0.070**	0.010
USDP/CSI300	-0.010	0.010	-0.010	0.170
USDP/JKSE	0.000	0.020	-0.020**	0.000
USDT/USDC	0.450	0.300	0.390	0.580
USDT/USDP	0.290	0.280	0.490	0.800
USDT/DGX	0.000	0.010	0.010	0.810
USDT/GLC	0.000	0.000	-0.010	0.950
USDT/SP500	0.010	0.020	0.000	0.120
USDT/STOXX50	0.000	0.010	-0.010	0.180
USDT/Nikkei225	-0.01	0.010	-0.060**	0.010
USDT/CSI300	0.000	0.010	-0.010	0.170
USDT/JKSE	0.000	0.010	-0.010**	0.000
DGX/USDC	-15.210	38.830	0.000	0.580
DGX/USDP	0.430	4.690	0.000	0.800
DGX/USDT	12.800	35.310	0.000	0.830
DGX/GLC	0.060	0.090	-0.010	0.950
DGX/SP500	0.800	1.040	-0.040	0.120
DGX/STOXX50	0.490	1.040	-0.020	0.180
DGX/Nikkei225	0.060	0.800	0.000**	0.010
DGX/CSI300	0.420	0.720	0.000	0.170
DGX/JKSE	0.450	1.010	-0.020**	0.000
GLC/USDC	-20.770	29.450	-0.010	0.580
GLC/USDP	-3.140	5.560	-0.010	0.800
GLC/USDT	11.960	28.110	-0.010	0.830
GLC/DGX	0.380	0.340	0.000	0.810
GLC/SP500	1.000	0.980	0.010	0.120
GLC/STOXX50	0.290	0.910	0.000	0.180
GLC/Nikkei225	-0.520	1.200	0.000**	0.010
GLC/CSI300	0.470	1.000	0.000	0.170
GLC/JKSE	-0.650	1.390	0.000**	0.000
SP500/USDC	-1.670	2.330	0.020	0.580
SP500/USDP	0.030	0.280	0.030	0.800

Jurnal Manajemen e-JM
E-ISSN: 2549-8797
ISSN: 1410-3583

Long position/Short position	βijt	Std.Dev.	HE	p-value
SP500/USDT	2.020	2.980	-0.090	0.830
SP500/DGX	0.030	0.020	-0.020	0.810
SP500/GLC	0.010	0.010	0.030	0.950
SP500/STOXX50	0.600	0.160	0.450	0.180
SP500/Nikkei225	0.240	0.130	0.080**	0.010
SP500/CSI300	0.220	0.150	0.130	0.170
SP500/JKSE	0.310	0.140	0.090**	0.000
STOXX50/USDC	-0.430	1.530	-0.010	0.580
STOXX50/USDP	0.190	0.370	-0.020	0.800
STOXX50/USDT	0.740	1.660	-0.100	0.830
STOXX50/DGX	0.020	0.020	0.000	0.810
STOXX50/GLC	0.000	0.010	0.020	0.950
STOXX50/SP500	0.650	0.170	0.410	0.120
STOXX50/Nikkei225	0.370	0.160	0.130**	0.010
STOXX50/CSI300	0.240	0.140	0.090	0.170
STOXX50/JKSE	0.320	0.140	0.080**	0.000
NIKKEI225/USDC	-0.560	1.730	-0.010	0.580
NIKKEI225/USDP	-0.430	0.330	0.000	0.800
NIKKEI225/USDT	-0.600	1.330	-0.020	0.830
NIKKEI225/DGX	0.000	0.010	0.000	0.810
NIKKEI225/GLC	0.000	0.000	0.000	0.950
NIKKEI225/SP500	0.260	0.080	0.080	0.120
NIKKEI225/STOXX50	0.370	0.100	0.160	0.180
NIKKEI225/CSI300	0.370	0.110	0.170	0.170
NIKKEI225/JKSE	0.460	0.110	0.150**	0.000
CSI300/USDC	-1.050	1.600	-0.010	0.580
CSI300/USDP	-0.180	0.290	0.000	0.800
CSI300/USDT	-0.090	0.940	-0.010	0.830
CSI300/DGX	0.020	0.010	0.000	0.810
CSI300/GLC	0.000	0.000	0.000	0.950
CSI300/SP500	0.260	0.130	0.050	0.120
CSI300/STOXX50	0.260	0.110	0.060	0.180
CSI300/Nikkei225	0.410	0.110	0.160**	0.010
CSI300/JKSE	0.380	0.120	0.080**	0.000
JKSE/USDC	-0.740	1.210	0.000	0.580
JKSE/USDP	0.020	0.180	-0.020	0.800
JKSE/USDT	-0.140	0.770	-0.050	0.830
JKSE/DGX	0.010	0.010	0.000	0.810
JKSE/GLC	0.000	0.000	0.000	0.950
JKSE/SP500	0.210	0.080	0.090	0.120
JKSE/STOXX50	0.200	0.070	0.090	0.180
JKSE/Nikkei225	0.290	0.100	0.160**	0.010
JKSE/CSI300	0.220	0.110	0.130	0.170

** indicates rejection of the null hypothesis at the 5 per cent significance level. βijt is the optimal hedge ratio for hedging a 1-dollar long position in variable i with a short βijt dollar position in variable j at time t. HE represents hedging effectiveness, and the HE value is the average dynamic hedging effectiveness. P-value is the lowest level of significance at which the null hypothesis is rejected: the two indices cannot effectively hedge each other's risk. St. dev. represents the standard deviation.
Source: Processed data, 2023

Table 3 shows the optimal hedge ratio between fiat and gold-based stablecoins with international stock indices. The βijt value in **Table 3** is the averaged median value of the dynamic hedging ratio for a 1-dollar long position on a stablecoin and international stock index and a dollar βijt short position on a stablecoin and other stock indices. The HE in **Table 3** shows the effectiveness of hedging, which is used to measure the risk reduction that investors can achieve based on hedging positions using either a dynamic portfolio weight strategy or a dynamic hedging ratio, compared to positions without hedging. The HE value is the average dynamic hedging effectiveness. P-value is the lowest level of significance at

Jurnal Manajemen e-JM
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which the null hypothesis is rejected: both variables cannot effectively hedge each other's risk.

Table 4. Dynamic Optimal Portfolio Weights and Hedging Effectiveness

Long position/Short position	Wijt	Std.Dev.	HE	p-value
USDC/USDP	0.760	0.310	0.250**	0.000
USDC/USDT	0.570	0.270	0.240**	0.000
USDC/DGX	0.990	0.030	0.030	0.590
USDC/GLC	1.000	0.000	-0.070	0.270
USDC/SP500	0.930	0.110	0.100	0.110
USDC/STOXX50	0.940	0.110	0.110	0.080
USDC/NIKKEI225	0.940	0.100	0.040	0.560
USDC/CSI300	0.950	0.100	0.200**	0.000
USDC/JKSE	0.920	0.120	0.130**	0.020
USDP/USDC	0.240	0.310	0.330**	0.000
USDP/USDT	0.280	0.330	0.290**	0.000
USDP/DGX	0.990	0.030	0.020	0.740
USDP/GLC	1.000	0.000	-0.060	0.390
USDP/SP500	0.930	0.080	0.130**	0.030
USDP/STOXX50	0.930	0.070	0.080	0.210
USDP/Nikkei225	0.920	0.080	0.000	0.950
USDP/CSI300	0.930	0.080	0.170**	0.000
USDP/JKSE	0.900	0.090	0.040	0.570
USDT/USDC	0.430	0.270	0.290**	0.000
USDT/USDP	0.720	0.330	0.260**	0.000
USDT/DGX	1.000	0.030	0.010	0.820
USDT/GLC	1.000	0.000	-0.020	0.700
USDT/S&P500	0.940	0.110	0.170**	0.000
USDT/STOXX50	0.940	0.100	0.140**	0.020
USDT/Nikkei225	0.940	0.100	0.020	0.730
USDT/CSI300	0.950	0.100	0.180**	0.000
USDT/JKSE	0.920	0.130	0.110	0.080
DGX/USDC	0.010	0.030	1**	0.000
DGX/USDP	0.010	0.030	1**	0.000
DGX/USDT	0.000	0.030	1**	0.000
DGX/GLC	0.830	0.240	0.620**	0.000
DGX/S&P500	0.050	0.110	0.990**	0.000
DGX/STOXX50	0.070	0.100	0.990**	0.000
DGX/Nikkei225	0.070	0.050	0.990**	0.000
DGX/CSI300	0.060	0.060	0.990**	0.000
DGX/JKSE	0.040	0.060	0.990**	0.000
GLC/USDC	0.000	0.000	1**	0.000
GLC/USDP	0.000	0.000	1**	0.000
GLC/USDT	0.000	0.000	1**	0.000
GLC/DGX	0.170	0.240	0.880**	0.000
GLC/S&P500	0.000	0.010	0.990**	0.000
GLC/STOXX50	0.010	0.010	0.990**	0.000
GLC/Nikkei225	0.010	0.010	1**	0.000
GLC/CSI300	0.010	0.010	1**	0.000
GLC/JKSE	0.010	0.000	1**	0.000
S&P500/USDC	0.070	0.110	0.940**	0.000
S&P500/USDP	0.070	0.080	0.940**	0.000
S&P500/USDT	0.060	0.110	0.940**	0.000
S&P500/DGX	0.950	0.110	0.270**	0.000
S&P500/GLC	1.000	0.010	-0.020	0.780

Jurnal Manajemen
e-JM
E-ISSN: 2549-8797
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Long position/Short position	Wijt	Std.Dev.	HE	p-value
S&P500/STOXX50	0.540	0.270	0.200**	0.000
S&P500/Nikkei225	0.530	0.190	0.490**	0.000
S&P500/CSI300	0.560	0.220	0.580**	0.000
S&P500/JKSE	0.390	0.190	0.550**	0.000
STOXX50/USDC	0.060	0.110	0.940**	0.000
STOXX50/USDP	0.070	0.070	0.930**	0.000
STOXX50/USDT	0.060	0.100	0.940**	0.000
STOXX50/DGX	0.930	0.100	0.130**	0.030
STOXX50/GLC	0.990	0.010	0.000	0.970
STOXX50/S&P500	0.460	0.270	0.150**	0.010
STOXX50/Nikkei225	0.510	0.200	0.400**	0.000
STOXX50/CSI300	0.540	0.220	0.520**	0.000
STOXX50/JKSE	0.370	0.160	0.520**	0.000
Nikkei225/USDC	0.060	0.100	0.920**	0.000
Nikkei225/USDP	0.080	0.080	0.900**	0.000
Nikkei225/USDT	0.060	0.100	0.910**	0.000
Nikkei225/DGX	0.930	0.050	0.030	0.600
Nikkei225/GLC	0.990	0.010	0.010	0.840
Nikkei225/S&P500	0.470	0.190	0.310**	0.000
Nikkei225/STOXX50	0.490	0.200	0.230**	0.000
Nikkei225/CSI300	0.540	0.170	0.320**	0.000
Nikkei225/JKSE	0.330	0.160	0.430**	0.000
CSI300/USDC	0.050	0.100	0.940**	0.000
CSI300/USDP	0.070	0.080	0.930**	0.000
CSI300/USDT	0.050	0.100	0.930**	0.000
CSI300/DGX	0.940	0.060	0.050	0.380
CSI300/GLC	0.990	0.010	0.010	0.840
CSI300/S&P500	0.440	0.220	0.480**	0.000
CSI300/STOXX50	0.460	0.220	0.440**	0.000
CSI300/Nikkei225	0.460	0.170	0.380**	0.000
CSI300/JKSE	0.320	0.170	0.570**	0.000
JKSE/USDC	0.080	0.120	0.900**	0.000
JKSE/USDP	0.100	0.090	0.870**	0.000
JKSE/USDT	0.080	0.130	0.890**	0.000
JKSE/DGX	0.960	0.060	0.120**	0.040
JKSE/GLC	0.990	0.000	0.000	0.990
JKSE/S&P500	0.610	0.190	0.180**	0.000
JKSE/STOXX50	0.630	0.160	0.170**	0.000
JKSE/Nikkei225	0.670	0.160	0.240**	0.000
JKSE/CSI300	0.680	0.170	0.370**	0.000

** indicates rejection of the null hypothesis at the 5 per cent significance level. Wijt is the weight of variable i in a 1-dollar portfolio of two variables i and j at time t. HE represents hedging effectiveness, and the HE value is the average dynamic hedging effectiveness. P-value is the lowest level of significance at which the null hypothesis is rejected: the two indices cannot effectively hedge each other's risk. St. dev. represents the standard deviation
Source: Processed data, 2023

Table 4 shows the results of dynamic portfolio weights and hedging effectiveness. The Wijt value in **Table 4** is the median value of the average dynamic portfolio weight of variable i in the 1-dollar portfolio for both variables i and j at time t. The portfolio weight value ranges from 0 to 1. However, if you look at the HE results, this value is insignificant if the portfolio weight is 1.

DISCUSSIONS

Table 2 shows that the Total Connectedness Index (TCI) of the connectedness volatility series is 41.290 per cent, which shows a connection between several stablecoin returns and several international stock index returns. Regarding pairwise connectedness, the most considerable spillover effect comes from GLC to USDP, which is 43.800 per cent. Meanwhile, the most miniature spillover effect is USDC to DGX, USDC to GLC, USDP to DGX, USDP to GLC, USDT to DGX, USDT to GLC at 0 per cent, or we can conclude that there is no spillover effect between fiat-based stablecoins and gold-based stablecoin.

For TO value, GLC has the largest TO value of 180.820 per cent, and USDC has the smallest TO value of 9.280 per cent. For the FROM value results, JKSE has the largest OF value, namely 60.610 per cent, and GLC has the smallest OF value, 0.41 per cent. Even though the FROM value of GLC has the smallest value, the net directional connectedness of GLC is the most significant value, 180.420 per cent, which illustrates that GLC is a transmitter of absolute volatility connectivity. Meanwhile, JKSE has the most significant negative net directional connectedness value is negative 48.340 per cent, which shows that JKSE is the recipient of complete volatility connectivity, among other variables.

Figure 1 uses node size, arrow direction, and node labels to convey information about estimated network characteristics that can help this research better show the structure of dynamic connectivity. The node size represents the TO value; the larger the TO value, the larger the node size. The direction of the arrow indicates the direction of transmission of the pairwise connectedness between the two variables. The size of the arrow represents the degree of pairwise connectedness value transferred between two variables, and the number shown above the arrow represents the specific value of pairwise connectedness; the larger the value, the thicker the arrow. The variable displayed by the node label next to the number is the receiver, and the variable that does not display any other node label is the transmitter. In the figure, it can be seen that the GLC node is the largest while the minor node is on the USDC asset; this shows that GLC makes the most significant contribution to the impact of volatility-volatility linkages on other variables while USDC makes the minor contribution, which is consistent with the results in the linkage **Table 1**. The thickness of the arrow and the numbers on the arrow show that GLC contributes the highest volatility linkage to USDP (43.799 per cent).

Regarding the spikes depicted in **Figure 2**, this research tries to link the spikes with economic events that affected the crypto market and international stock indices. To explain the turmoil that occurred, we can see that there was a first spike at the beginning of 2020, which was closely linked to the COVID-19 crisis, which was declared by the World Health Organization (WHO) as a global pandemic on March 11, 2020, which had an impact on the global economy, causing it to worsen. Disparities within and between countries, and the impact is very severe, especially in developing countries, where COVID-19 will continue to occur and develop through new variants until 2021. Then, there was quite a spike in early 2022 when The Russian invasion of Ukraine occurred, which impacted the global economy, causing a significant slowdown in global growth and a spike in commodity prices in countries around the world. Moreover, finally, the spike that occurred at the end of 2022 was linked to the issue of a recession that will hit the world economy in 2023, which was indicated by the aggressive increase in benchmark interest rates carried out by the central banks of various countries to reduce the rate of inflation. The findings from this study differ from research conducted by (Wang et al., 2020), which stated that gold-pegged stablecoins performed worse as a haven than USD-pegged ones. However, these findings support research conducted by (Kolodziejczyk, 2023), which found evidence of a contagion effect between stablecoin and underlying asset markets such as stock indices.

Next, investment diversification and risk management strategies are calculated using hedging ratios and portfolio weights to estimate the hedging ability of an asset and also taking into account hedging effectiveness or effective hedging, which is a measure of the extent to which a hedging strategy can protect or reduce the risks associated with fluctuations in the value of assets or liabilities between stablecoins and international stock indices. **Table 3** shows the optimal hedge ratio between fiat- and gold-based stablecoins and international stock indices. The βijt value in **Table 3** is the average median value of the dynamic hedging ratio for a 1-dollar long position on a stablecoin and an international stock index and a dollar βijt short position on a stablecoin and other stock indices. HE in Table 4.3 shows the effectiveness of hedging, which is used to measure the risk reduction that investors can achieve based on hedging positions using either a dynamic portfolio weight strategy or a dynamic hedging ratio, compared to positions without hedging. The HE value is the average dynamic hedging effectiveness. P-value is the lowest level of significance at which the null hypothesis is rejected: both variables cannot effectively hedge each other's risk. However, the p-value of HE, where the null hypothesis is rejected from **Table 3**, shows that only a few assets can effectively hedge each other's risks.

From the conclusion of the results of the optimal hedging ratio for each asset, we can see from the statistical values that each asset can effectively hedge against risks to the Nikkei225 and JKSE stock index assets. These results also support the research conducted by (Gao & Mei, 2019), which investigated the correlation structure between US and Asian markets during the financial crisis that there was dependence between all major stock markets in Asia except the Chinese stock market index. The same thing also supports research conducted by (Garcia-Jorcano & Benito, 2020), who conducted research between bitcoin and international stock indices. The research results stated that Bitcoin strongly depends on the Asian market as a hedging asset.

Table 4 shows the results of dynamic portfolio weights and hedging effectiveness. The Wijt value in **Table 4** is the median value of the average dynamic portfolio weight of variable I in the 1-dollar portfolio for both variables i and j at time t. The portfolio weight value ranges from 0 to 1. However, if you look at the HE results, this value is insignificant if the portfolio weight is 1. More precisely, only DGX and GLC are entered into a 1-dollar position, where the HE value of both assets is significant when combined with all assets used in this research. This conclusion further suggests that DGX and GLC are suitable for long positions. In addition, the HE statistical value is relatively high for fiat-based stablecoin portfolios (USDC, USDP, and USDT) with fiat-based stablecoin portfolios. Meanwhile, the HE statistical value is relatively high for the gold-based stablecoin portfolio (DGX and GLC) with fiat-based stablecoins and international stock indices. Meanwhile, international stock indices (S&P500, STOXX50, Nikkei225, CSI300, and JKSE) have relatively high HE statistical values against fiat-based stablecoins (USDC, USDP, and USDT) but have low HE statistical values against gold-based stablecoins (DGX and GLC).

CONCLUSION

This research investigates the dynamic connectedness between fiat-based stablecoins and gold-based stablecoins with international stock indices using a new method, namely the

DCC GARCH-based dynamic, connected approach proposed by (Gabauer, 2020) to investigate spillover effects that vary over time and using networks. To visualize the level and direction of dynamic connectivity between stablecoin assets and the international stock index used. In addition, this research estimates the DCC GARCH t-copula model proposed by (Antonakakis et al., 2020) to calculate effective hedging ratios and portfolio weights and possible financial rewards that can be generated using time-series data from October 10 2018 to June 27 2023. Based on the results of quantitative testing carried out in Chapter 4, the conclusions of the research results are as follows: First, in the dynamic connectedness analysis for all samples used, this study found that the total dynamic connectedness of stablecoins and the international stock index used in this study was 41.290 per cent, which shows that there is a conditional correlation between stablecoin assets and the international stock index used in this research. More precisely, among the samples used, the most considerable spillover effect came from GLC on USDC, namely 43.800 per cent, but on the contrary, the smallest spillover effect was 0.000 per cent. These findings suggest that GLC has apparent one-way risk contagion to other assets. In addition, GLC contributed the most to other spillover effects (180.820 per cent), and USDC contributed the least (9.280 per cent). In contrast, the JKSE stock index received the largest spillover effect compared to other indices (60.610 per cent), and the GLC received the least (0.41 per cent). This shows that GLC is the transmitter of the spillover effect, and the JKSE stock index is the recipient of the spillover effect.

Second, by using the network refers to (Bilgin & Yilmaz, 2018) to visualize dynamic connectedness, this research examines the intensity of the spillover effect transmission direction. The network graph shows that gold-based stablecoins, especially GLC, are the assets that provide the largest transmitter of spillover effects compared to other assets. In contrast, JKSE assets are the recipients of the largest spillover effects compared to other assets.

Third, total dynamic linkage for gold and fiat-based stablecoins with international stock indices ranges between 30 per cent and 80 per cent of total dynamic linkage. This conclusion shows that the linkage between stablecoins and stock indices varies over time, and major economic, political, and financial events from 2018 to 2023 influence sharp fluctuations in total linkage.

Fourth, this research finds evidence to suggest that portfolio construction can significantly reduce investment risk in several assets. The results of the hedging effectiveness of the optimal hedging ratio show that hedging for all assets used in this study is suitable for taking long positions to hedge future risks effectively on the Nikkei225 and JKSE stock indices. The two stock indices have almost the same market characteristics. According to research conducted by (Gao & Mei, 2019), who examined the correlation structure between US and Asian markets, except for the Chinese market index, there is a dependency between all major Asian stock markets

Last, based on portfolio construction from the effectiveness results for hedging and portfolio weights from the total sample of assets used in this research, only DGX and GLC assets are suitable for long positions against all assets used.

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