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Dynamic Hedging Strategies in Clean and Dirty Cryptocurrency Markets: Analyzing Volatility and Portfolio Optimization with TVP-VAR

Stratégies de Couverture Dynamique sur les Marchés des Cryptomonnaies Propres et Polluantes : Analyse de la Volatilité et Optimisation de Portefeuille avec le Modèle TVP-VAR

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Abstract:
This study investigates connectivity, defined as the degree of interdependence and volatility spillovers among cryptocurrencies, in order to better understand their behavior during periods of financial stress. The methodological framework is based on the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model, which enables a flexible analysis of the evolving dynamic relationships among financial assets over time.
The main objective is to assess the role of three categories of cryptocurrencies so-called "dirty" cryptocurrencies (Bitcoin and Ethereum), "clean" cryptocurrencies (Algorand and Cardano), and stablecoins (USDT and USDC) in risk management and their effectiveness as hedging instruments in diversified portfolios, particularly during periods of heightened uncertainty such as the COVID-19 pandemic and the Russia–Ukraine conflict.
Using daily data from July 2019 to July 2024, the analysis reveals strong interconnectedness among volatile cryptocurrencies, especially between Bitcoin and Ethereum. In contrast, stablecoins exhibit greater stability and resilience to shocks. These findings highlight the relevance of accounting for dynamic interlinkages between assets when designing portfolios that are resilient to financial crises.
Keywords: Dirty and clean cryptocurrency; COVID-19; Russia-Ukraine war , TVP-VAR; minimum connectedness portfolio; hedging effectiveness.

Résumé :
Cette étude analyse la connectivité, définie comme le degré d’interdépendance et de transmission des chocs de volatilité entre différentes cryptomonnaies, afin de mieux comprendre leur comportement en période de crise. L’approche méthodologique repose sur le modèle TVP-VAR (modèle vectoriel autorégressif à paramètres variables dans le temps), qui permet de suivre de manière flexible l’évolution des relations dynamiques entre actifs financiers au fil du temps.
L’objectif principal est d’évaluer le rôle de trois catégories de cryptomonnaies les cryptomonnaies dites « polluantes » (Bitcoin et Ethereum), les cryptomonnaies « propres » (Algorand et Cardano), et les stablecoins (USDT et USDC) dans la gestion du risque et leur efficacité en tant qu’outils de couverture au sein de portefeuilles diversifiés, notamment durant des périodes de forte incertitude telles que la pandémie de COVID-19 et le conflit russo-ukrainien.
L’analyse, basée sur des données quotidiennes couvrant la période de juillet 2019 à juillet 2024, révèle une interconnexion marquée entre les cryptomonnaies volatiles, en particulier entre le Bitcoin et l’Ethereum. En revanche, les stablecoins se distinguent par une plus grande stabilité et une résilience accrue face aux chocs. Ces résultats soulignent l’importance d’intégrer les liens dynamiques entre actifs dans les stratégies de construction de portefeuilles robustes en contexte de crise.
Mots-clés : Cryptomonnaies polluantes et propres ; COVID-19 ; guerre Russie-Ukraine ; TVP-VAR ; portefeuille à connectivité minimale ; efficacité de la couverture.

Introduction

In recent years, cryptocurrencies have solidified their position as a distinct asset class, significantly impacting global financial markets (Ji et al., 2019). The rapid expansion of this sector is evidenced by the staggering increase in both the market capitalization and the number of digital currencies available. At the beginning of 2019, the total market capitalization of cryptocurrencies was approximately $133 billion, with Bitcoin commanding a dominant share of around $68.87 billion, followed by Ethereum at $14.64 billion. Today, the cryptocurrency market capitalization has surged to approximately $1.3 trillion, with Bitcoin still leading with nearly 50% of the market, valued at around $650 billion, while Ethereum has maintained its second position despite facing increased competition from emerging cryptocurrencies and stablecoins.

In light of these evolving market dynamics, this study aims to investigate the dynamic connectedness among three categories of cryptocurrencies: dirty (BTC, ETH), clean (ADA, ALGO), and stablecoins USDT, USDC). More specifically, the objective is to evaluate how these assets interact under different market conditions particularly during periods of crisis such as the COVID-19 pandemic and the Russia-Ukraine war and assess their implications for portfolio resilience and risk management.

Investing in cryptocurrencies can yield substantial returns; however, this potential comes with a significant degree of volatility, akin to many other financial markets. The cryptocurrency sector often exhibits herding behavior, where investors tend to mimic the actions of others, driven by either irrational tendencies or strategic calculations (Bikhchandani and Sharma, 2001). Numerous studies have examined this phenomenon within cryptocurrency markets, highlighting varying factors that influence herding behavior (Bouri et al., 2019; Poyser, 2018; Vidal-Tomás et al., 2019; Youssef, 2020; Amirat and Alwafi, 2020; Stavroyiannis and Babalos, 2019; Kallinterakis and Wang, 2019). However, findings across these studies often lack consistency, attributed to differences in portfolio construction methodologies, the specific cryptocurrencies analyzed, and the timeframes under consideration. For instance, Vidal-Tomás et al. (2019) identified herding behavior during market downturns within a sample of 65 cryptocurrencies from January 2015 to December 2017, revealing that an equal-weighted portfolio approach only aligned with a value-weighted approach when Bitcoin was excluded. Conversely, Kallinterakis and Wang (2019) found significant herding among the top 296 cryptocurrencies between December 2013 and July 2018, which dissipated under a value-weighted portfolio approach.

Moreover, previous research has often regarded all cryptocurrencies as homogeneous, neglecting their fundamental differences, particularly regarding sustainability (Corbet et al., 2021; Gallersdörfer et al., 2020). The substantial energy consumption associated with traditional cryptocurrencies, such as Bitcoin and Ethereum, has attracted considerable scrutiny. Studies have demonstrated that Bitcoin's energy use per transaction is approximately 707 kWh, while Ethereum's is also notably high, raising concerns among environmentally conscious investors. In contrast, newer cryptocurrencies like Cardano (ADA) and Algorand (ALGO) have emerged as more sustainable options, with energy consumption estimated at 0.548 kWh and 0.002 kWh per transaction, respectively. As global attention shifts toward sustainability, investors may increasingly favor these energy-efficient cryptocurrencies over traditional, energy-intensive ones, marking a significant trend toward eco-conscious investing in the cryptocurrency sector.

The burgeoning interest in cryptocurrencies has spurred numerous academic inquiries into their characteristics, including their market efficiency (Brauneis and Mestel, 2018; Tran and Leirvik, 2020), risk and return profiles (Moratis, 2020), and their potential for diversification and hedging (Bouri et al., 2017).

Disruptions to traditional financial markets due to the COVID-19 pandemic and the Russian-Ukrainian conflict, combined with regulatory changes and technological advances in the cryptocurrency sector, have heightened investment risks in these markets. By diversifying their portfolios to include investments in cryptocurrencies (BTC, ETH, ALGO, ADA, USDT, USDC), investors may potentially manage portfolio risk more effectively and enhance returns. Previous studies (e.g., Ji et al., 2019; Kumar et al., 2022) have explored the link between market volatility and cryptocurrency performance, showing that profits can vary significantly depending on volatility patterns (Elendner et al., 2016; Bouri et al., 2019).

Few researchers have examined the specific interconnections between clean and dirty cryptocurrencies, as well as the influence of stablecoins, particularly in times of crisis (Pham et al., 2021). Additionally, some studies (e.g., Sharif et al., 2023) argue that green investments may enhance portfolio resilience. Another strand of literature investigates the ability of stablecoins to hedge market risks effectively, such as those exacerbated by economic crises (Naeem et al., 2021).

However, a review of previous studies reveals limited exploration of dynamic connectivity between various types of cryptocurrencies, as well as a gap in examining the impacts of global crises like COVID-19 and the Russia-Ukraine conflict on cryptocurrency portfolios.

Furthermore, research on the inclusion of environmentally sustainable cryptocurrencies remains scarce, particularly regarding their influence on portfolio performance during crises. Existing literature primarily addresses risk hedging and diversification capabilities of high-volatility assets like Bitcoin, leaving room to examine and compare the risk diversification and hedging potential of various cryptocurrencies (both stable and volatile), especially during crisis periods.

Given these research gaps, the objective of this study is to examine the interconnection between clean and dirty cryptocurrencies, on the one hand, and stablecoins, on the other. Specifically, the study aims to assess their implications for portfolio resilience during the COVID-19 pandemic and the Russia-Ukraine war. We apply a Time-Varying Parameter Vector Autoregressive (TVP-VAR) model to capture the dynamic links among cryptocurrencies, considering the COVID-19 outbreak and the Russia-Ukraine war as key crisis periods. We then construct minimum variance (MVP), minimum correlation (MCP), and minimum connectedness (MCoP) portfolios to assess the performance of various portfolio compositions and the hedging potential of these assets throughout the entire sample period and during the crises.

The TVP-VAR methodology is a robust modeling tool for dynamic systems, offering significant advantages over other models like DCC-GARCH by capturing nonlinear dynamics through evolving coefficients. This allows for a realistic depiction of complex interactions and relationships, surpassing the limitations of linear models. The TVP-VAR model's adaptability, through Bayesian methods and sensitivity to structural changes, further enhances its effectiveness in modeling complex systems (Antonakakis et al., 2019; Adekoya and Oliyide, 2021).

Our research contributes to the fields of cryptocurrency and portfolio management in cryptocurrency investment, with a focus on portfolio management strategies during the COVID-19 pandemic and the Russia-Ukraine war. Studies have shown that green investments and cryptocurrencies can play a crucial role in portfolio hedging and diversification (Dias et al., 2023), yet little attention has been given to examining how these assets perform under crisis conditions. This study thus responds to an urgent need for research in the evolving field of sustainable investments in cryptocurrency portfolios.

The findings suggest that cryptocurrencies play an increasingly complex and influential role across social, economic, and organizational domains. Environmental awareness is shaping cryptocurrency investment choices, with clean cryptocurrencies like Algorand (ALGO) and

Cardano (ADA) offering lower volatility and aligning with sustainable investment goals. Meanwhile, stablecoins, such as Tether (USDT) and USD Coin (USDC), act as stabilizers within portfolios, mitigating the high volatility associated with assets like Bitcoin (BTC) and Ethereum (ETH). This study highlights the importance of portfolio diversification in cryptocurrency investments, as different assets exhibit varied responses to market shocks, especially during crises like the COVID-19 pandemic and the Russia-Ukraine conflict. By applying the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model, the study captures these dynamic connections over time, emphasizing the value of combining volatile, stable, and sustainable assets for a balanced and adaptive investment strategy. These insights not only aid investors in assessing cryptocurrency risks but also encourage the development of more sustainable cryptocurrency options to support resilience in a rapidly evolving market.

The research problem addressed in this study is: **To what extent do clean, dirty, and stablecoin cryptocurrencies exhibit dynamic connectedness under varying market conditions, and how do these interlinkages impact portfolio diversification and risk management, particularly during periods of global crisis such as the COVID-19 pandemic and the Russia-Ukraine war?**

The rest of the study is as follows: Section 2 discusses the literature, Section 3 explains the data and methodology. Section 4 discusses the empirical results and Section 5 concludes the study.

1. Literature review

1.1. Environmental Considerations in Cryptocurrency Investments

The increasing focus on environmental issues has permeated financial markets, particularly in the realm of cryptocurrency investments. De Vries (2019) discussed the significant ecological consequences of cryptocurrencies such as Bitcoin (BTC), which relies on energy-intensive proof-of-work (PoW) systems. The energy consumption associated with Bitcoin mining is so substantial that it can exceed that of entire countries. This concerning environmental impact has motivated investors to seek more sustainable alternatives. Pham et al. (2021) investigated cryptocurrencies utilizing proof-of-stake (PoS) mechanisms, like Algorand (ALGO) and Cardano (ADA), which drastically lower energy consumption. Their findings indicated that PoS cryptocurrencies tend to exhibit reduced volatility, making them appealing for environmentally conscious investors and aligning with green investment strategies. Ren (2022) built upon this by assessing the performance differentials between environmentally friendly and conventional cryptocurrencies. The research concluded that sustainability increasingly sways investor choices, with assets like ADA and ALGO being perceived as more stable and integral to investment portfolios that balance both financial returns and ecological considerations. This paper extends this line of inquiry by analyzing the risk profiles of clean versus traditional cryptocurrencies, particularly their reactions to market dynamics and crises, thereby enhancing the discussion surrounding sustainability in the cryptocurrency sector.

1.2. The Function of Stablecoins in Portfolio Diversification and Risk Mitigation

The application of stablecoins, such as Tether (USDT) and USD Coin (USDC), as tools for hedging has been the focus of various studies. These stablecoins, often pegged to fiat currencies like the US dollar, provide a reliable alternative amid the volatility of the cryptocurrency markets. Naeem et al. (2021) found that stablecoins generally display low correlation with more volatile assets, which helps cushion against significant market fluctuations. Their analysis illustrated that incorporating stablecoins into portfolios with more volatile cryptocurrencies, such as BTC and ETH, can diminish overall portfolio volatility. Bouri et al. (2019) further examined the role of stablecoins within diversified investment portfolios, revealing that they function as shock absorbers and enhance liquidity during periods of market turbulence. Ji et al. (2019) also emphasized that the inclusion of stablecoins notably mitigates risk in cryptocurrency portfolios, particularly in times of crisis. These insights underline the idea that stablecoins enhance portfolio stability, especially when paired with more volatile assets. This study will explore how stablecoins alleviate volatility in cryptocurrency portfolios and their effectiveness as stabilizing forces during significant events like the COVID-19 pandemic and the Russia-Ukraine conflict.

1.3. Dynamic Modeling and Hedging Approaches in Cryptocurrency Portfolios

Conventional portfolio theories often struggle to address the extreme volatility inherent in cryptocurrency markets, necessitating dynamic models that can adapt to changing market conditions. The Time-Varying Parameter Vector Autoregressive (TVP-VAR) model has emerged as a useful tool for capturing the evolving relationships between assets over time. Ardia and Boudt (2018) showed that the TVP-VAR model excels at modeling the dynamic interrelations in cryptocurrency markets, as it accommodates fluctuating volatility and shifting asset dependencies. Broadstock et al. (2020) contributed to this field by presenting the Minimum Connectivity Portfolio (MCoP) strategy, which aims to minimize interconnections between assets during portfolio construction. Their research applied MCoP to green bonds and demonstrated that reducing asset interdependence can lower systemic risks and spillover effects. This method has since been adapted for application in other volatile markets, including cryptocurrencies, to evaluate its potential for enhancing portfolio resilience. This study will leverage the MCoP strategy in cryptocurrency portfolios, utilizing the TVP-VAR model to track real-time changes in asset relationships amid crises. Zhang et al. (2021) further emphasized the significance of dynamic management strategies for cryptocurrency investments, noting that static models fall short in capturing the abrupt market changes triggered by external shocks. This research contributes to existing literature by applying the TVP-VAR model to quantify the dynamic connectivity among various cryptocurrencies, testing the flexibility of MCoP strategies and validating the approach against historical crises such as the COVID-19 pandemic and the Russia-Ukraine war.

1.4. Market Responses to Crisis Events in Cryptocurrency

The reaction of the cryptocurrency market during crisis periods has been the subject of significant research, particularly in the context of the COVID-19 pandemic. Kumar et al. (2022) investigated how major cryptocurrencies behaved throughout the pandemic, discovering that traditional safe-haven assets lost their reliability while stablecoins emerged as key protective instruments. Their findings indicated that during turbulent times, the interconnectedness among cryptocurrencies tends to escalate, leading to amplified spillover effects and increased market volatility. In a similar vein, Demir et al. (2020) analyzed the relationship between cryptocurrencies and economic uncertainty during the pandemic, noting that Bitcoin (BTC) and Ethereum (ETH) displayed increased volatility, which exacerbated systemic risks. This body of work highlights that crises affect cryptocurrencies in diverse ways, with certain assets offering stability while others contribute to overall market stress. This study aims to further this discourse by investigating the interconnectedness and risk transmission among various cryptocurrency types during both the COVID-19 pandemic and the Russia-Ukraine conflict, providing a deeper understanding of their behavior amidst heightened uncertainty.

1.5. Considerations for Cryptocurrency Portfolio Management

Markowitz's (1952) Modern Portfolio Theory established diversification as a strategy for reducing portfolio risk. However, traditional models encounter challenges when applied to the cryptocurrency market, which is characterized by extreme volatility and the distinctive behaviors of digital assets. Ederington (1979) introduced the Minimum Variance Portfolio (MVP) strategy, which remains a widely used approach for managing risk. Despite this, static diversification techniques may not be effective for highly volatile cryptocurrencies that demonstrate time-varying interdependencies.

Traditional hedging approaches such as constant correlation-based models and fixed-parameter VAR techniques often assume stable relationships among assets and rely on historical averages. These models tend to lag in response to structural market shifts, particularly during periods of heightened uncertainty or crisis. As a result, they may misrepresent the true risk exposure and lead to suboptimal allocation decisions. In the fast-evolving cryptocurrency space, where correlations and volatilities fluctuate sharply over time, these static frameworks prove inadequate for capturing real-time market dynamics.

Recent studies (e.g., Corbet et al., 2018; Bouri et al., 2019) suggest that employing dynamic models, such as the Time-Varying Parameter Vector Autoregressive (TVP-VAR) approach, can significantly improve risk management in cryptocurrency portfolios. These models take into account the changing correlations and volatility among assets, allowing for more accurate and responsive hedging strategies. This research builds on these insights by integrating the MVP, Minimum Correlation Portfolio (MCP), and Minimum Connectedness Portfolio (MCoP) strategies with the TVP-VAR model to evaluate portfolio performance across various market scenarios, underscoring the necessity for adaptive strategies in response to market shocks induced by crises.

2. Data and methodology

2.1. Data

This study utilizes daily data from July 1, 2019, to July 1, 2024, covering six key cryptocurrencies: Bitcoin (BTC) and Ethereum (ETH) representing "dirty" cryptocurrencies, Algorand (ALGO) and Cardano (ADA) representing "clean" cryptocurrencies, and Tether (USDT) and USD Coin (USDC) representing stablecoins. These cryptocurrencies were selected to capture a broad spectrum of the market, from highly volatile assets to more stable alternatives. The data, sourced from CoinMarketCap, includes daily price and market data, providing a comprehensive view of their performance across various market conditions. This dataset allows us to analyze the behavior of these cryptocurrencies over a five-year period, offering insights into their volatility, interconnections, and suitability for inclusion in diversified portfolios.

2.2. Methodology

In the first part of this study, we employ the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model, as proposed by Antonakakis et al. (2020), to analyze the evolving dynamics of interconnections among assets. This methodology, built upon a multivariate Kalman filter, allows model parameters to vary over time and incorporates exponential moving averages to adapt both the error variances and coefficient variances, making it particularly well-suited for capturing unstable financial dynamics. Unlike traditional models that assume stable relationships between assets, the TVP-VAR provides a more intuitive, real-time understanding of financial markets functioning more like a continuous video stream of asset interactions rather than a static snapshot. This dynamic framework enables the model to detect structural breaks and periods of market stress by allowing the parameters to adjust instantaneously. Traditional risk-hedging approaches such as Markowitz's Modern Portfolio Theory, fixed multivariate GARCH models, or static correlation measures often fall short in the cryptocurrency market context, where extreme volatility, regime shifts, and crisis events are prevalent. These conventional methods assume temporal stability in asset relationships and thus may underestimate contagion risk or overestimate an asset's hedging ability, especially during turbulent periods. For instance, a pair of assets might exhibit a stable negative correlation in normal times, only for that relationship to turn positive during a crisis undermining the effectiveness of diversification strategies. Moreover, such static approaches are unable to identify when an asset transitions from being a net transmitter to a net receiver of shocks. By contrast, the TVP-VAR model offers a flexible and dynamic framework that captures the shifting systemic roles of assets, enabling the identification of periods when an asset acts as a stabilizer or, conversely, a source of systemic risk. This insight is invaluable for portfolio management, dynamic risk hedging, and asset allocation in uncertain market environments. The TVP-VAR model is formulated as follows:

$$\mathcal{Y}_t = \Phi_t \mathcal{Y}_{t-1} + e_t, \qquad e_t|F_{t-1} \sim \mathrm{N}(0,H_t) \tag{1}$$

$$vec\,(\Phi_t) = vec(\Phi_{t-1}) + \zeta_t, \qquad \zeta_t|F_{t-1} \sim \mathrm{N}(0,\Xi_t) \tag{2}$$

The term F_{t-1} represents all the information available up to t-1, while $\mathcal{Y}_t$ and e_t are vectors of dimension m ×1 , and Φ_t and $H_t$are matrices of dimension m×m. Additionally, $\zeta_t$and vec (Φ_t) are vectors of dimension m^2 ×1 and Ξ_t is a matrix of dimension $m^2 \times m^2$. As a result, the transition equation of the time-varying parameters adopts a random walk structure, which has proven very effective in accurately capturing parameters. Financial time series, especially for daily or higher frequency data, are widely recognized for containing time-varying conditional heteroscedasticity. The matrices H_t and Ξ_t play a crucial role in dealing with this heteroscedasticity by allowing variable variance terms in the model. The time-varying parameters and error variances are fundamental elements in the generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD), developed by Koop et al. (1996) and Pesaran and Shin (1998), which form the basis of the connectivity approach of Diebold and Yilmaz (2012, 2014).

To obtain the GIRF and GFEVD, it is necessary to convert the TVP-VAR into its TVP-VMA representation by applying Wold's representation theorem. This theorem states that:

$$z_t = \sum_{i=1}^{p} \Phi_{it} z_{t-i} + e_t = \sum_{j=1}^{\infty} \Lambda_{jt}\, e_{t-j} + e_t. \tag{3}$$

The GIRFs ($\Psi_{\mathrm{ij,t}}$ (K)), where K is the forecast horizon, do not assume or depend on the structure or order of the errors, thus providing a more robust approach for interpreting VAR models than standard IRFs, which are known to be sensitive to the order of variables in the econometric system. The GIRF approach captures the dynamics between all variables j. Mathematically, this can be formalized as follows:

$$\mathrm{GIRF}_{\,t}(K, \sqrt{H_{jj,t}}, F_{t-1}) = \mathrm{E}(\mathcal{Y}_{t+k} | \epsilon_{j,t} = \sqrt{H_{jj,t}}, F_{t-1}) - \mathrm{E}(\mathcal{Y}_{t+j} | F_{t-1}) \tag{4}$$

$$\Psi_{\mathrm{ij,t}}(K) = H_{jj,t}^{-\frac{1}{2}} \Lambda_{k,t} H_t \epsilon_{j,t} \tag{5}$$

Next, the GFEVD ($\Psi_{\mathrm{ij,t}}(K)$) demonstrates the specific contribution of each variable to the forecast error variance of variable i. This reflects the percentage of influence one variable exerts on the forecast error variance of another variable in the system. In other words, it measures the relative impact of one variable on the forecast error variance of another. Mathematically, this can be expressed as follows:

$$\Psi_{\mathrm{ij,t}}(K) = \frac{\sum_{t=1}^{K-1} \Psi_{\mathrm{ij,t}}^2}{\sum_{j=1}^{m} \sum_{t=1}^{K-1} \Psi_{\mathrm{ij,t}}^2}, \qquad \sum_{j=1}^{m} \Psi_{\mathrm{ij,t}}(K) = 1, \qquad \sum_{i,j=1}^{m} \Psi_{\mathrm{ij,t}}(K) = \mathrm{m}. \tag{6}$$

With these GIRF and GFEVD measures, we can precisely describe the extent to which variable i is influenced by other variables, as well as its influence on them. This allows us to determine whether variable i has a greater impact on the others than it receives. To achieve this, we use the following three measures:

First, we want to assess the influence of all other variables in the system on variable i. To do so, we sum the forecast error variance contributions of i attributed to all other variables j. This measure is called the total directional connectivity FROM other variables and is calculated as follows:

$$\Gamma_{i\leftarrow j,t}(K) = \frac{\sum_{j=1,i\neq j}^{m} \Psi_{\text{ij,t}}(K)}{\sum_{i=1}^{m} \Psi_{\text{ij,t}}(K)} * 100 \tag{7}$$

The influence of all other variables on variable i must be strictly less than 100% since the influence of i on itself is excluded.

Secondly, we change our perspective and calculate the influence of variable i on all other variables j in the system. This measure is called the total directional connectivity TO toward other variables. It is obtained by summing the effects (forecast error variances) that variable j has on the forecast error variance of each of the other variables:

$$\Gamma_{i\rightarrow j,t}(K) = \frac{\sum_{j=1,i\neq j}^{m} \Psi_{\text{ji,t}}(K)}{\sum_{j=1}^{m} \Psi_{\text{ji,t}}(K)} * 100 \tag{8}$$

This measure can take values less than, equal to, or greater than 100%.

Finally, we combine the two previous measures to obtain what is called the total net directional connectivity (NET). This measure indicates whether the influence of variable i on others is greater than the influence of others on i . It is simply obtained by taking the difference between the two equations (7) and (8).

$$\Gamma_{i,t}(K) = \Gamma_{i\rightarrow j,t}(K) - \Gamma_{i\leftarrow j,t}(K) \tag{9}$$

This helps determine whether variable i exerts more influence on other variables than it receives from them.

A positive (negative) value indicates that variable i influences others more (less) than it is influenced by them.

It is important to note that if a variable is considered a "net transmitter," it does not mean that it dominates each of the other variables individually, but rather that it has, on average, a greater influence on other variables in the network. In addition to the three aggregate measures mentioned above, we are also interested in more detailed pairwise summaries. This helps to better understand which variables j variable i is a transmitter to and which ones it is a receiver from.

We decompose the information contained in the GFEVD to obtain pairwise net directional connectivity (NPDC) measures, defined as follows:

$$NPDC_{ij}(K) = (\frac{\Psi_{\mathrm{ji,t}}(K) - \Psi_{\mathrm{ij,t}}(K)}{k})*100 \tag{10}$$

Finally, it is common to examine indicators of the total system connectivity. Although these measures do not provide the same depth of information as those described earlier, they offer a single measure that can describe whether the overall connectivity patterns within the system are weak or strong. The Total Connectivity Index (TCI) is used for this purpose. Based on Monte Carlo simulations presented by Chatziantoniou and Gabauer (2020) and Antonakakis et al. (2020), it is demonstrated that the own variance shares are always, by construction, greater than or equal to all cross-variance shares. This means that the TCI ranges between 0 and $\frac{k-1}{k}$ .To obtain the average network co-movement measure as a percentage, which should be between [0,1], we must slightly adjust this calculation.

$$TCI_t^g(K) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\Psi}_{ij,t}^g(K)}{\mathrm{k}-1}, \qquad 0 \leq TCI_t^g(K) \leq 1. \tag{11}$$

Finally, the definition of the TCI can be modified to obtain Pairwise Connectivity Index (PCI) scores between variables i and j as follows:

$$PCI_{ijt}(K) = 2(\frac{\tilde{\Psi}_{ij,t}^g(K) + \tilde{\Psi}_{ji,t}^g(K)}{\tilde{\Psi}_{ii,t}^g(K) + \tilde{\Psi}_{ij,t}^g(K) + \tilde{\Psi}_{0ij,t}^g(K) + \tilde{\Psi}_{jj,t}^g(K)}), \quad 0 \leq PCI_{ijt}(K) \leq 1. \tag{12}$$

The set of measures described above helps illustrate the extent and severity of connectivity between the different cryptocurrency markets we are examining, from an econometric perspective. To bridge the gap between statistical significance and economic relevance, and to more concretely illustrate the financial significance of our results, it is crucial to address the following question: Does taking into account the environmental characteristics of cryptocurrencies influence their ability to hedge risks within an investment portfolio, and does this result in a financial premium for investors?

2.2.1 Portfolio Backtesting

To assess the financial significance of our results during crises, we will examine the historical performance of cryptocurrency investments by testing various portfolios. The underlying assumptions are that the investor can directly buy cryptocurrencies (assuming that investable derivatives or equivalent investment vehicles exist), that the investor wants to invest in different types of cryptocurrencies, including clean, dirty, and stablecoins, and that they are open to international investments. These are relatively narrow assumptions, but sufficient for our illustration. We consider several portfolio construction approaches, including traditional methods as well as newer, connectivity-focused portfolios. We provide brief summaries of the approaches we use.

2.2.2. Minimum Variance Portfolio

One of the most common portfolio construction methods is the Minimum Variance Portfolio (MVP), developed by Harry Markowitz in 1959. This method aims to create a portfolio that minimizes volatility while including multiple assets. The Minimum Variance Portfolio is particularly valued for its ability to reduce risk without necessarily sacrificing returns. The asset weights in this portfolio can be calculated using the following formula:

$$w_{Ht} = \frac{H_t^{-1}I}{IH_t^{-1}I} \qquad (13)$$

Where $w_{Ht}$is a portfolio weight vector of dimension m ×1 is a vector of dimension m filled with 1s, and H_t is the conditional variance-covariance matrix of dimension m×m at period t.

2.2.3. Minimum Correlation Portfolio

Another more recent approach to portfolio construction, proposed by Christoffersen et al. (2014), involves obtaining the portfolio weights using the conditional correlation matrix rather than the conditional covariance matrix. Before constructing this multivariate portfolio, it is essential to describe the conditional correlations. This can be done as follows:

$$R_t = \, diag(H_t)^{-0.5} H_t diag(H_t)^{-0.5} \tag{14}$$

Where $R_t$is a matrix of dimension $m \times m$. The weights of the minimum correlation portfolio (MCP) are then given by:

$$w_{Rt} = \frac{R_t^{-1} I}{I R_t^{-1} I} \tag{15}$$

2.2.4. Minimum Connectedness Portfolio

As part of our analysis of cryptocurrency portfolios during times of crisis, we adopt an approach similar to the two previously mentioned portfolio techniques by creating a minimum connectivity portfolio (MCoP). Instead of using the variance or the correlation matrix, we rely on all pairwise connectivity indices. This minimization of interconnection between variables, and consequently their spillovers, allows for the creation of a portfolio that is less sensitive to network shocks or more resilient to them. As a result, investment instruments that neither influence nor are influenced by others will be assigned a higher weight in the portfolio. This can be formulated as follows

$$w_{Rt} = \frac{PCI_t^{-1} I}{I PCI_t^{-1} I} \tag{16}$$

Where PCI_t is the pairwise connectivity index at time t, and I is the unit vector.

2.2.5. Hedging Effectiveness

Finally, to evaluate the portfolio's performance, we utilize the hedge effectiveness (HE) score. In accordance with Ederington's (1979) approach, hedge effectiveness is defined as follows:

$$\text{HE} = 1 - \frac{Var(y_{p)}}{Var(y \, unhedged)} \tag{17}$$

Where $Var(y_{p)}$ represents the variance of the portfolio returns, and $Var(y \, unhedged)$ represents the variance of the unhedged asset. HE indicates the percentage reduction in the variance of the unhedged position. The higher the HE score, the greater the risk reduction, and vice versa. According to Antonakakis et al. (2020), this method provides a precise and rigorous way to quantify hedge effectiveness

3. Empirical Analysis and Discussion of Findings

The following table provides summary statistics for the returns of selected cryptocurrencies, highlighting key aspects such as average returns, volatility, skewness, kurtosis, and correlations, alongside tests that assess distributional properties, stationarity, and volatility patterns insights critical for understanding performance, diversification potential, and risk dynamics in financial analysis.

Table N° 1: Descriptive Statistics: Time-Varying Variables.

	BTC	ETH	ALGO	ADA	USDT	USDC
Mean	0.000	0.001	- 0.001	0.000	0.000	0.000
	(0.236)	(0.193)	(0.380)	(0.467)	(0.958)	(0.979)
Variance	0.000***	0.000***	0.001***	0.000***	0.000***	0.000***
Skewness	-1.333***	-1.305***	-0.603**	-0.247***	0.405***	1.059***
	(0.000)	(0.000)	(0.034)	(0.733)	(0.000)	(0.000)
Kurtosis	19.999***	16.824***	11.496***	8.177***	138.461***	70.235***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	31003.347***	22078.230***	10176.628***	5110.981***	1460281.926***	376066.844***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-9.744***	-16.880***	-6.938***	-13.665***	-3.575***	-6.121***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	20.206**	32.345***	29.164***	31.758***	486.712***	436.698***
	(0.016)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(20)$	32.856***	62.513***	45.507***	124.446***	501.182***	628.511***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unconditional Correlation						
BTC	1.000***	0.833***	0.626***	0.694***	-0.111***	-0.083***
ETH	0.833***	1.000***	0.682***	0.750***	-0.127***	-0.095***

ALGO	0.626***	0.682***	1.000***	0.664***	-0.074***	-0.067***
ADA	0.694***	0.750***	0.664***	1.000***	-0.093***	-0.059**
USDT	-0.111***	-0.127***	-0.074***	-0.093***	1.000***	0.712***
USDC	-0.083***	-0.095***	-0.067***	-0.059**	0.712***	1.000***

Source: Authors' calculations based on the TVP-VAR methodology.

Table 1 provides a series of summary statistics on the returns of various cryptocurrencies, including BTC, ETH, ALGO, ADA, USDT, and USDC. The average returns are generally close to zero, suggesting that price fluctuations are neutral on average, although the variance is significant at the 1% level for all series. This indicates significant price fluctuations, particularly for volatile cryptocurrencies like BTC and ETH, while stablecoins (USDT, USDC) exhibit lower volatility, confirming their role as stabilizers. Skewness reveals a pronounced tendency towards extreme losses for BTC (-1.333) and ETH (-1.305), with significantly negative skewness values, whereas stablecoins, USDT (0.405) and USDC (1.059), show positive skewness, indicating rare but significant positive returns. ALGO and ADA have moderate negative skewness (-0.603) and (-0.247) respectively. The kurtosis values reveal that all cryptocurrencies have significant leptokurtosis, indicating thicker tails than a normal distribution. USDT (138.461) and USDC (70.235) display particularly high kurtosis, suggesting a strong concentration around the mean with more likely extreme events. The Jarque-Bera test rejects the normality hypothesis for all series with very low significance ($p < 0.01$), confirming their non-normality. Contrary to an initial interpretation of the results, the Elliott, Rothenberg, and Stock (ERS) unit root test shows that the series are stationary, meaning that the data does not need to be transformed for use in econometric models such as TVP-VAR or ARCH/GARCH models. These models, however, remain relevant for capturing the temporal dynamics and conditional variance variability. Furthermore, the Portmanteau Q(20) and $Q^2(20)$ tests reveal significant autocorrelation in returns and their squares. This suggests that cryptocurrency returns are not entirely independent over time, and that volatility exhibits dependence on past volatility. These results indicate ARCH/GARCH effects, where volatility varies conditionally, with periods of calm followed by periods of high volatility. Regarding unconditional correlations, BTC and ETH are highly correlated (0.833***), reflecting significant interdependence between these two major cryptocurrencies. BTC also shows positive correlations with ALGO (0.626***) and ADA (0.694***), but negative correlations with stablecoins USDT (-0.111***) and USDC (-0.083***), highlighting divergent behavior of these assets during periods of volatility. ETH displays similar correlations, particularly with ALGO (0.682***) and ADA (0.750***), revealing significant interactions between "dirty" and "clean" cryptocurrencies. The stablecoins USDT and USDC are highly correlated with each other (0.712***), illustrating similar behavior as stabilizing assets. These weak or negative correlations between stablecoins and other cryptocurrencies suggest that they can be used to diversify and reduce overall risk exposure in portfolios. In summary, despite the interconnection between volatile cryptocurrencies like BTC and ETH, stablecoins offer unique hedging and diversification opportunities, which could be advantageous for balanced portfolio management strategies.

3.1. Total connectedness Index (TCI)

The total connectedness index (TCI) is derived from Monte Carlo simulations, as demonstrated in the works of Chatziantoniou and Gabauer (2020) and Antonakakis et al. (2020), which show that the own variance shares are inherently greater than or equal to all cross variance shares. The initial results we present focus on averaged connectedness measures, which are detailed in Table (2). It is important to note that the diagonal elements of Table (2) represent idiosyncratic shocks specific to each variable, while the off-diagonal elements indicate the interactions among different types of cryptocurrencies.

Table N°2: Average Dynamic Connectedness Table: The results are based on a TVP-VAR(0.99, 0.99) with a lag.

	BTC	ETH	ALGO	ADA	USDT	USDC	FROM
BTC	37.14	26.15	14.78	19.03	1.86	1.03	62.86
ETH	25.09	35.35	16.63	20.73	1.37	0.83	64.65
ALGO	16.44	19.63	42.39	19.53	1.18	0.83	57.61
ADA	19.63	22.34	17.73	38.19	1.26	0.85	61.81
USDT	4.42	3.40	2.71	3.04	64.03	22.40	35.97
USDC	2.43	2.08	1.53	2.12	21.42	70.43	29.57
contribution **TO** others	68.01	73.59	53.38	64.46	27.08	25.95	312.47
NET directional connectedness	5.15	8.94	-4.23	2.65	-8.89	-3.63	TCI
NPDC transmitter	4.00	5.00	2.00	3.00	0.00	1.00	52.08

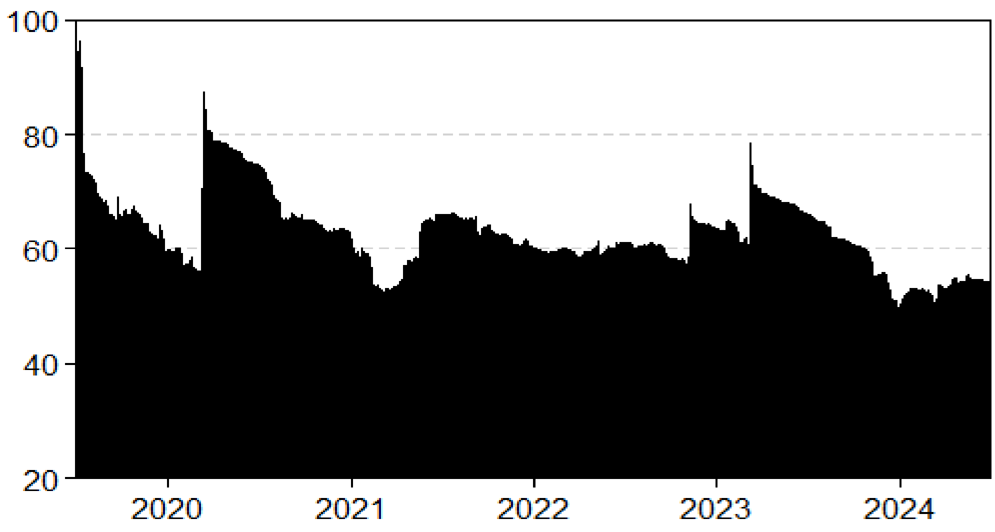
Source: Authors' calculations based on the TVP-VAR methodology.

The first set of results presented concerns the average connectedness measures, illustrated in Table 2. The elements on the main diagonal correspond to idiosyncratic shocks specific to each cryptocurrency, while the other values reflect interactions between different assets. The percentages of own volatility are high for USDT (64.03%) and USDC (70.43%), highlighting the importance of internal factors. However, these assets are not isolated from market dynamics: for example, 29.57% of USDC's variance is due to external connections, of which 21.42% comes from interactions with USDT, indicating the interdependence between these two stablecoins. This relationship, although partial, has implications for portfolio diversification, as it can increase exposure to systemic risk. Additionally, ADA shows notable interconnection with other cryptocurrencies, with 61.81% of its variations influenced by external factors, particularly 22.34% coming from ETH. This highlights the influence of "dirty" cryptocurrencies on "cleaner" markets, pointing to a complex interdependence within the ecosystem. In terms of net directional connectedness, ETH (8.94%) and BTC (5.15%) emerge as significant net contributors, while USDT (-8.89%) and ALGO (-4.23%) are more receivers than influencers. Moreover, the net bilateral transmission index reveals particularly intense relationships between certain cryptocurrencies, such as those between BTC (4.00) and ETH (5.00). Finally, the Total Connectedness Index (TCI) of 52.08% shows that more than half of the system's volatility is attributable to interactions between different assets, underscoring the high interconnection of the cryptocurrency market. Although opportunities for diversification exist, these assets remain influenced by common factors. It is also important to note that these results represent an average over the entire sample, potentially masking the effects of specific events. A more detailed analysis, such as the one based on the temporal evolution of total connectedness (TCI) presented in Figure 4, allows for a better capture of the impact of economic or political events, offering a more dynamic and nuanced view of the interconnection between cryptocurrencies.

3.2. Net Total Directional Connectedness

In our analysis, high TCI values signify strong co-movements across the network, suggesting that perceived risks among the cryptocurrency types of interest are becoming more comparable, reflecting similar levels of market confidence. Figure (1) shows that total connectedness within our network fluctuates significantly over time, ranging from below 50% to nearly 100%. This variation indicates that the connectedness among different cryptocurrency types not only responds quickly to relevant bond market events but also does so with substantial intensity.

Figure N°1 : Dynamic Total Connectedness: Results are based on a TVP-VAR(0.99,0.99) model with lag length of order1 (BIC) and a 20-step-ahead forecast.



Source: Authors' calculations based on the TVP-VAR methodology.

Figure N°2 : NET Total Directional Connectedness: Results are based on a TVP-VAR(0.99,0.99) with one lag.

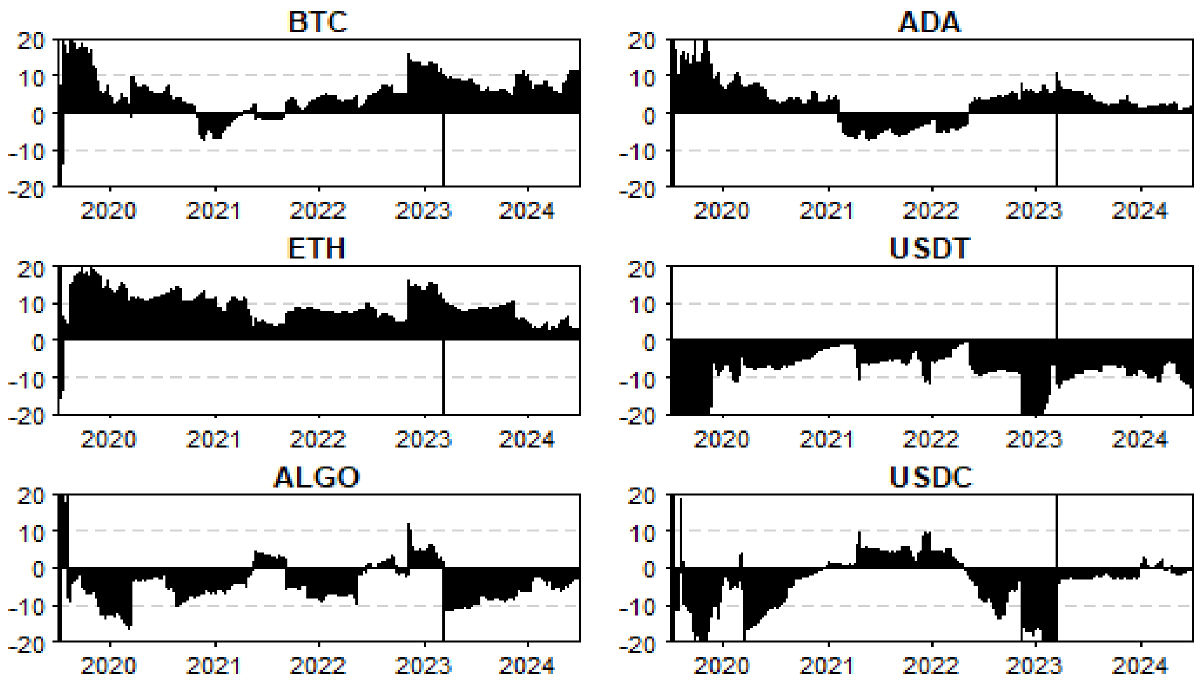
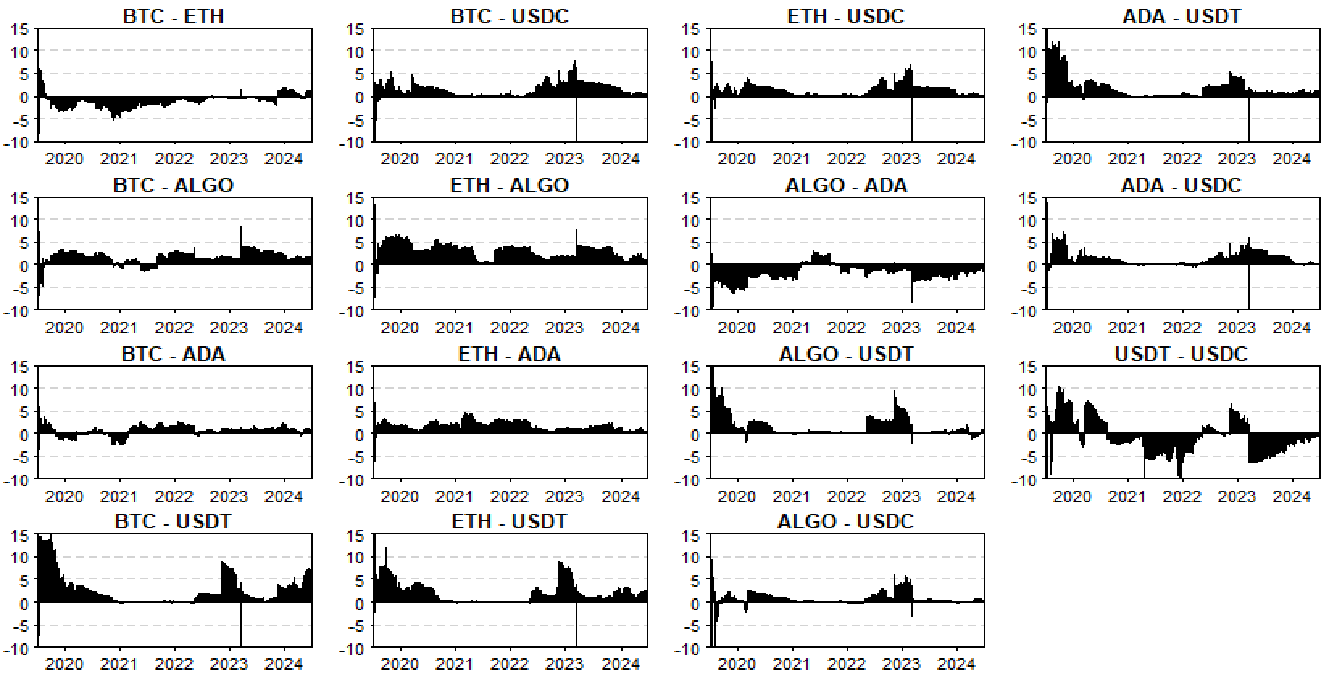


Figure N°3 : Net Pairwise Directional Connectedness: Results are based on a TVP-VAR(0.99,0.99) with one lag



Source: Authors' calculations based on the TVP-VAR methodology.

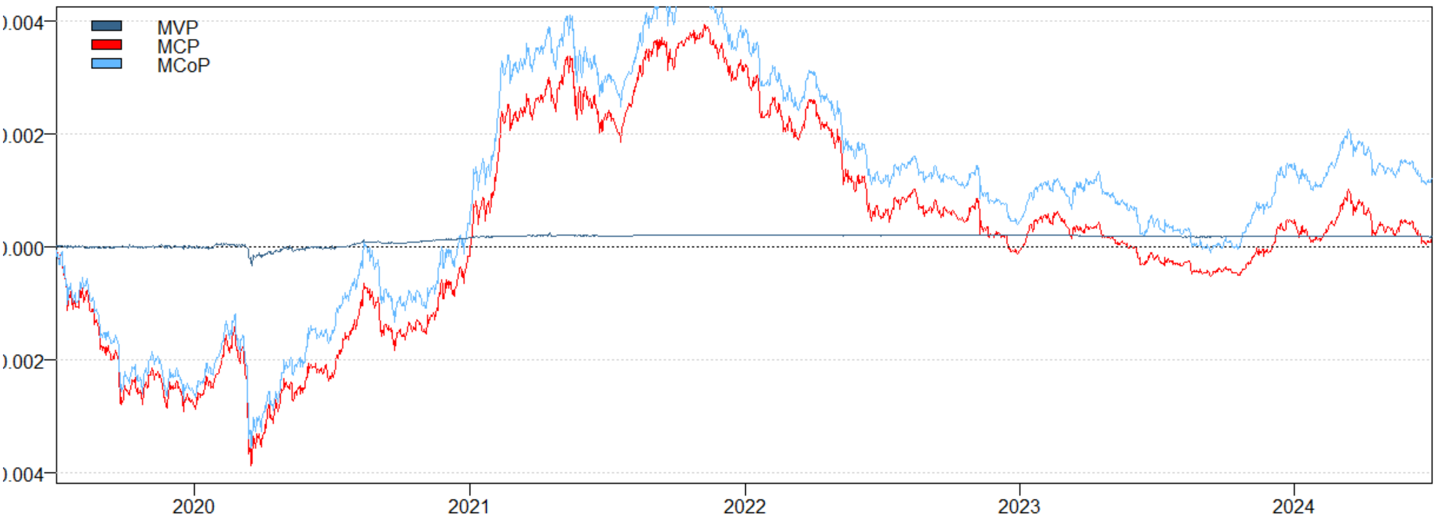
Figure 1 illustrates the evolution of total net directional connectedness of cryptocurrencies from 2019 to 2024, calculated using a TVP-VAR (0.99, 0.99) model with a lag length of order 1 and a 20-step-ahead forecast. This figure highlights significant fluctuations in the interconnectedness of cryptocurrencies over time, with marked peaks and significant declines, reflecting changing perceptions of risk by investors. At the beginning of the period, around 2019, net directional connectedness reaches nearly 100%, suggesting an almost complete synchronization between assets, possibly in response to speculative events or global shocks affecting the market uniformly. This high interconnectedness gradually decreases in 2020, falling to around 60%, which may indicate some desynchronization and reduced correlations between cryptocurrencies. However, new peaks appear in 2021 and 2023, where connectedness again exceeds 80%, possibly linked to global crises such as the COVID-19 pandemic and the Russia-Ukraine war, which exacerbated market volatility and reinforced co-movements among cryptocurrencies. The fluctuations in the TCI, with values oscillating between peaks near 95% and lows around 50%, reveal that investor confidence in these assets is not constant. A high TCI reflects a homogeneous market perception of risk, where investors react uniformly to external events, while periods of low TCI, more frequent in 2024, suggest a slight decoupling of assets and, therefore, potential diversification opportunities. This decrease towards the end of the period may indicate the maturing of the cryptocurrency market, with more differentiated risk management by investors, although this requires further analysis. Thus, the figure reveals a fluctuating but persistent interdependence between cryptocurrencies, where shocks affecting one asset quickly spread to others, reducing diversification opportunities. However, during phases of low connectedness, such as those observed in 2021 and 2024, more effective risk management opportunities emerge, offering investors greater flexibility to adjust their portfolios. This dynamic, closely tied to global economic and geopolitical events, underscores the importance for investors of understanding the changing correlations between cryptocurrencies to optimize their investment strategy based on market conditions and overall risk perception. **Figure 2** presents the total net directional connections of cryptocurrencies. This analysis helps distinguish and classify different types of cryptocurrencies as either net emitters or net receivers of shocks in the system studied. When the shaded area in the graphs is positive, it indicates that the corresponding cryptocurrency is acting as a net emitter of shocks; if it is negative, the cryptocurrency is classified as a net receiver. The examination of the figure reveals that most of the cryptocurrencies studied primarily act as either emitters or receivers of shocks, although the intensity of this role varies over time. For instance, USDT appears as a net receiver of shocks throughout the analysis period, with ALGO also sharing this characteristic, though with a few minor exceptions. For the so-called "dirty" cryptocurrencies, such as BTC and ETH, they primarily act as net emitters of shocks to other markets. However, BTC shows an interesting dynamic, briefly transitioning to a net receiver role at the end of 2020 before resuming its net emitter role from 2021 onward. ADA, which initially acts as a net emitter, starts receiving shocks during 2021 after being a persistent emitter. USDC stands out with more ambiguous behavior among the cryptocurrencies studied. It begins as a net recipient of shocks but between early 2021 and mid-2022 assumes a more net transmission role before returning to being a recipient for the remainder of the sample period. This variability indicates a flexibility or response to changing market conditions. In summary, this analysis shows that the roles of cryptocurrencies as either emitters or receivers of shocks are not fixed and can evolve in response to market dynamics, external shocks, or changes in investor perceptions.

The results relating to total net connectedness are useful for identifying net emitters and receivers in the cryptocurrency network, but they do not capture pairwise dynamics that can offer additional insights and clarify the exact role of each cryptocurrency relative to others over time. **Figure 3** shows the bilateral directional connections between different pairs of cryptocurrencies, providing a more detailed view of specific interactions. Examining BTC, it primarily appears as a net receiver of shocks from ETH throughout the analyzed period. Although BTC sometimes acts as a net emitter, particularly at the beginning and end of the sample, the magnitude of these effects is generally small. This suggests that BTC is significantly influenced by ETH but does not transmit as many shocks to other cryptocurrencies. Conversely, the roles of shock emitter and receiver alternate between stablecoins USDT and USDC. Initially, USDT is a net emitter of shocks influencing USDC, but this dynamic reverses around 2021-2022, where USDT becomes a net receiver, absorbing market fluctuations. Subsequently, USDT reverts to being a net emitter before taking on a slight receiver role again towards the end of the period. This alternation in directional connections reflects a complex interaction between the two stablecoins, underscoring that even assets perceived as stable can exhibit varied dynamics, influencing each other's volatility and impacting investors' diversification and risk management strategies. Furthermore, **Figure 3** shows that stablecoins are mostly net receivers of shocks from other cryptocurrencies studied, particularly in pairs involving more volatile cryptocurrencies like BTC, ETH, and ADA. Similarly, ALGO primarily transmits shocks to USDT and USDC. However, the magnitude of the observed effects is generally low, indicating that although these stablecoins absorb some shocks, their role in the network remains relatively passive in terms of shock transmission.

3.3. Net Pairwise Connections

The next figure examines three alternative portfolio methods, each displaying distinct performance levels.

Figure N°4 : Dynamic Multivariate Portfolio Weights



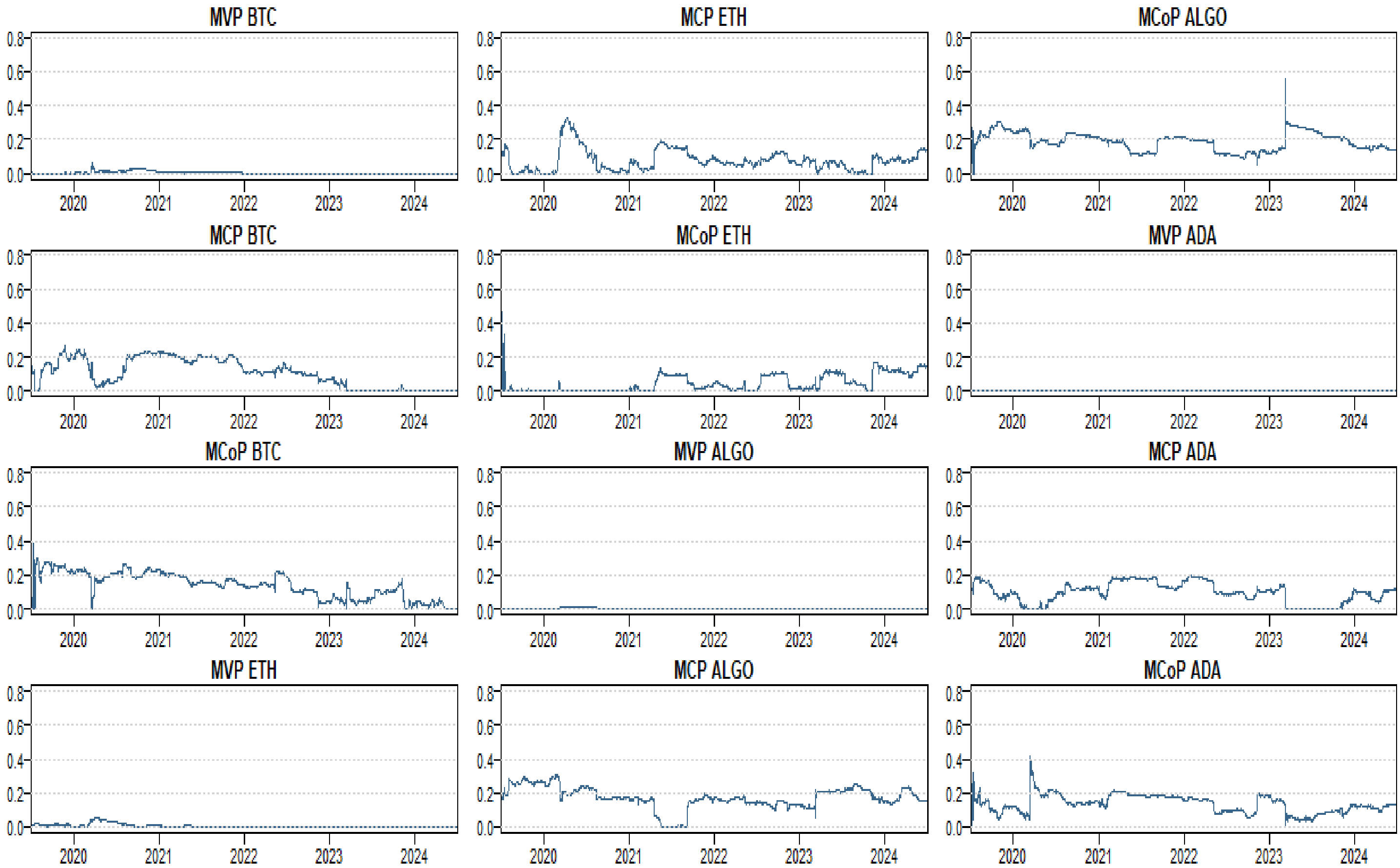
Source: Authors' calculations based on the TVP-VAR methodology.

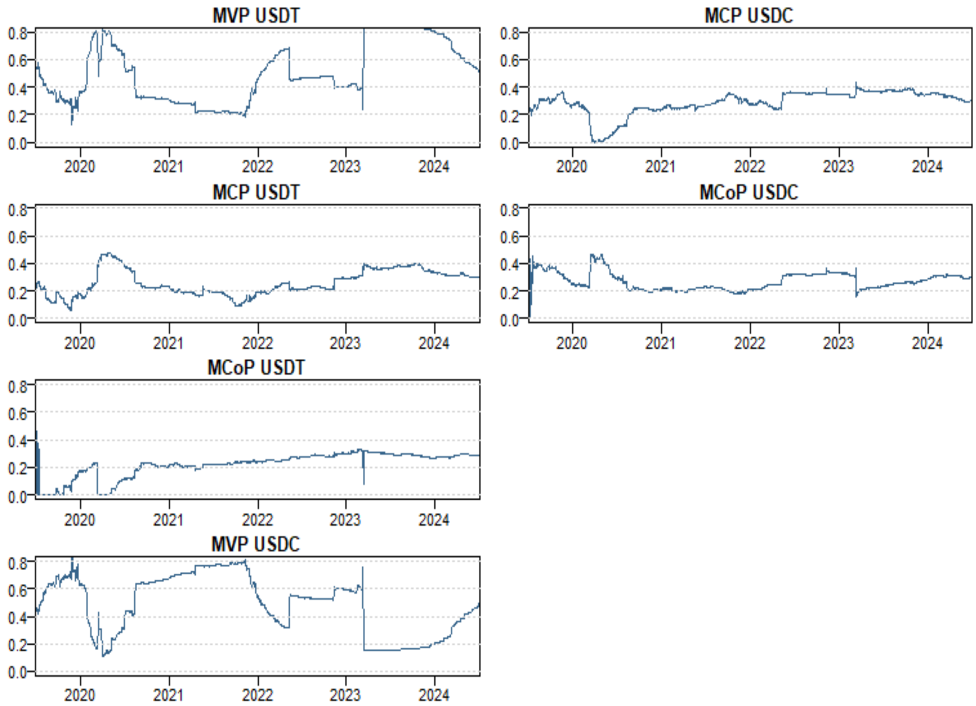
Figure 4 shows varying levels of equivalence between the three portfolios. The MVP (Minimum Variance Portfolio) exhibits a stable, low-risk profile, with few major fluctuations, remaining close to the zero line, indicating a conservative approach with minimized risk. In contrast, the MCP (Minimum Correlation Portfolio) and MCoP (Minimum Connectivity Portfolio) display similar equivalence levels, sharing an underlying dynamic, particularly with a modest increase in index values around 2021 and early 2022, followed by a gradual decline until 2024.

3.4. Dynamic Portfolios

To provide a clearer view of each portfolio's composition, we illustrate the dynamic portfolio weights in Figure (5). A quick look reveals that the MVP composition differs significantly from that of MCP and MCoP, which are more closely aligned. The resemblance between MCP and MCoP portfolios is understandable from a technical perspective, as both are derived from the same time-varying variance-covariance matrix. However, the processes used to obtain the final inputs for portfolio calculations diverge considerably. For MCP, the variance-covariance matrix is simply transformed into a correlation matrix, while MCoP requires a more complex set of calculations, including the computation of GIRFs and GFEVDs, along with subsequent pairwise connectedness adjustments. Thus, despite having the same foundational components, the transformation differences in MCP and MCoP lead to similar but not necessarily expected portfolio weight correlations.

Figure N°5 : Dynamic Multivariate Portfolio Weights





Source: Authors' calculations based on the TVP-VAR methodology.

The results in **Figures 5** show the dynamic portfolio weights based on time-varying variance-covariance matrices. At first glance, it is clear that the composition of the MVP (Minimum Variance Portfolio) differs significantly from that of the MCP (Minimum Correlation Portfolio) and MCoP (Minimum Connectivity Portfolio), while the MCP and MCoP have relatively similar compositions. This similarity can be explained by their common origin in the time-varying variance-covariance matrix. However, the transformations required to obtain the final portfolio weights differ considerably between the MCP and MCoP. The MCP simply converts variance-covariance into a correlation matrix, whereas the MCoP uses more complex calculations involving GIRF and GFEVD, as well as pairwise connectedness. Examining the weights of BTC, for example, an increase is observed for both series at the beginning of 2020. However, for the MCP, the weight gradually decreases thereafter, while for the MCoP, it fluctuates, increasing again from mid-2022. The MVP shows generally low weights for assets such as BTC, ETH, ALGO, ADA, USDT, and USDC, reflecting a cautious approach to minimizing total variance. The weights of USDT and USDC show more marked variations, especially around 2020 and 2021, indicating adjustments in response to volatility changes. In contrast, the MCP shows greater weight variability, particularly for ETH and ADA, in response to changing correlations between assets. Stablecoins, with relatively stable weights, play a stabilizing role. The MCoP, on the other hand, presents notable fluctuations in the weights of BTC, ETH, and ADA, particularly between 2021 and 2022, suggesting a strategy focused on minimizing directional connectedness between assets. The higher weight of USDT in this portfolio compared to the others indicates a distinct role in this strategy.

Observing empirical similarities between MCP and MCoP, we delve further into their implications for portfolio and risk management. To achieve this, we compare the MCoP approach with traditional portfolio methods, MVP and MCP, focusing on hedging effectiveness scores. The outcomes of this comparison are presented in Table (3).

Table N°3: Dynamic Multivariate Portfolio Weights:

MINIMUM VARIANCE PORTFOLIO						
	Mean	**Std.Dev**	**5%**	**95%**	**HE**	**p-value**
BTC	0.00	0.01	0.00	0.02	1.00	0.00
ETH	0.01	0.01	0.00	0.03	1.00	0.00
ALGO	0.00	0.00	0.00	0.01	1.00	0.00
ADA	0.00	0.00	0.00	0.00	1.00	0.00
USDT	0.51	0.21	0.22	0.84	0.32	0.00
USDC	0.48	0.22	0.15	0.77	0.33	0.00
MINIMUM CORRELATION PORTFOLIO						
	Mean	**Std.Dev**	**5%**	**95%**	**HE**	**p-value**
BTC	0.11	0.08	0.00	0.23	0.61	0.00
ETH	0.08	0.06	0.00	0.19	0.76	0.00
ALGO	0.17	0.06	0.00	0.27	0.87	0.00
ADA	0.10	0.06	0.00	0.19	0.82	0.00
USDT	0.26	0.09	0.12	0.42	-55.92	0.00
USDC	0.29	0.09	0.07	0.38	-55.19	0.00
MINIMUM CONNECTEDNESS PORTFOLIO						
	Mean	**Std.Dev**	**5%**	**95%**	**HE**	**p-value**
BTC	0.14	0.08	0.00	0.25	0.56	0.00
ETH	0.05	0.05	0.00	0.14	0.73	0.00
ALGO	0.19	0.05	0.11	0.28	0.86	0.00

ADA	0.14	0.05	0.05	0.21	0.80	0.00
USDT	0.22	0.09	0.00	0.31	-63.19	0.00
USDC	0.27	0.06	0.19	0.39	-62.36	0.00

Source: Authors' calculations based on the TVP-VAR methodology.

Table 3 briefly examines the average portfolio allocations. There are certain specific characteristics, with USDT and USDC generally having the largest weights across the three indices, which holds true for the MVP (Minimum Variance Portfolio), MCP (Minimum Correlation Portfolio), and MCoP (Minimum Connectivity Portfolio). The average portfolio weights indicate that stable assets play a significant role in a fixed-income investment portfolio. For example, portfolio weights for USDT range from around 22% of the portfolio allocation in the MCoP to 51% for the MVP. This is especially true in the MVP approach, where only stable cryptocurrencies have a notable weight, with a combined weight of 99% for USDT and USDC in the portfolio. For the MCP, the average weights are as follows: BTC = 11%, ETH = 8%, ALGO = 17%, ADA = 10%, USDT = 26%, and USDC = 29%, giving stablecoins a combined average weight (over time) of 55%. Lastly, for the Minimum Connectivity Portfolio, the average weights are: BTC = 14%, ETH = 5%, ALGO = 19%, ADA = 14%, USDT = 22%, and USDC = 27%, giving stablecoins a combined average weight (over time) of 49%.

Regarding hedge effectiveness (HE) ratios, the results from the MVP approach suggest that if, on average, we invest 0% in BTC, 1% in ETH, 0% in ALGO, 0% in ADA, 51% in USDT, and 48% in USDC, the volatility of each asset in this portfolio would be statistically significantly reduced by 100%, 100%, 100%, 100%, 32%, and 33%, respectively. These volatility reductions are both financially and statistically significant at a 0.1% significance level. For the MCP approach, if we invest, on average, 11% in BTC, 8% in ETH, 17% in ALGO, 10% in ADA, 26% in USDT, and 29% in USDC, the volatility of the portfolio assets is mostly statistically significantly lower compared to their initial value. Specifically, the capital allocation chosen by the MCP would lead to a reduction in the volatility of BTC and ETH by around 61% and 76%, respectively. The only exception concerns the stablecoins, USDT and USDC, for which the portfolio volatility significantly increases, with HE values of -55.92% for USDT and -55.19% for USDC. The negative values of the HE indicator for stablecoins (USDT and USDC) indicate that they do not act as effective hedging assets in the two portfolios tested. Although they are designed for stability, their high connectivity or correlation with other assets and their low yield can exacerbate overall risk, making their inclusion in the portfolio counterproductive in terms of risk management. However, it is worth noting that although these figures seem high, the raw values of the stablecoin index (USDT and USDC) are considerably smoother than those of the other series, meaning the initial volatility conditions for this index are already much lower compared to its counterparts. Finally, the MCoP approach suggests that if we invest, on average, 14% in BTC, 5% in ETH, 19% in ALGO, 14% in ADA, 22% in USDT, and 27% in USDC, we can reduce the volatility of each asset by 56%, 73%, 86%, 80%, -63.19%, and -62.36%, respectively. All volatility reductions are statistically significant at the 0.1% significance level. One noteworthy result is that the volatility of dynamic portfolio weights is lower when using the MCoP approach compared to the MVP or MCP approaches. Overall, the portfolio analysis results seem to indicate the presence of a dynamic network offering diversification opportunities. However, we do not have sufficient evidence from this single application of the technique to draw definitive conclusions or to assert that this would be the case in other applications. This is a point that future research may want to consider the possibility that minimum connectivity portfolios could result in lower volatility, with equal returns, compared to minimum correlation portfolios.

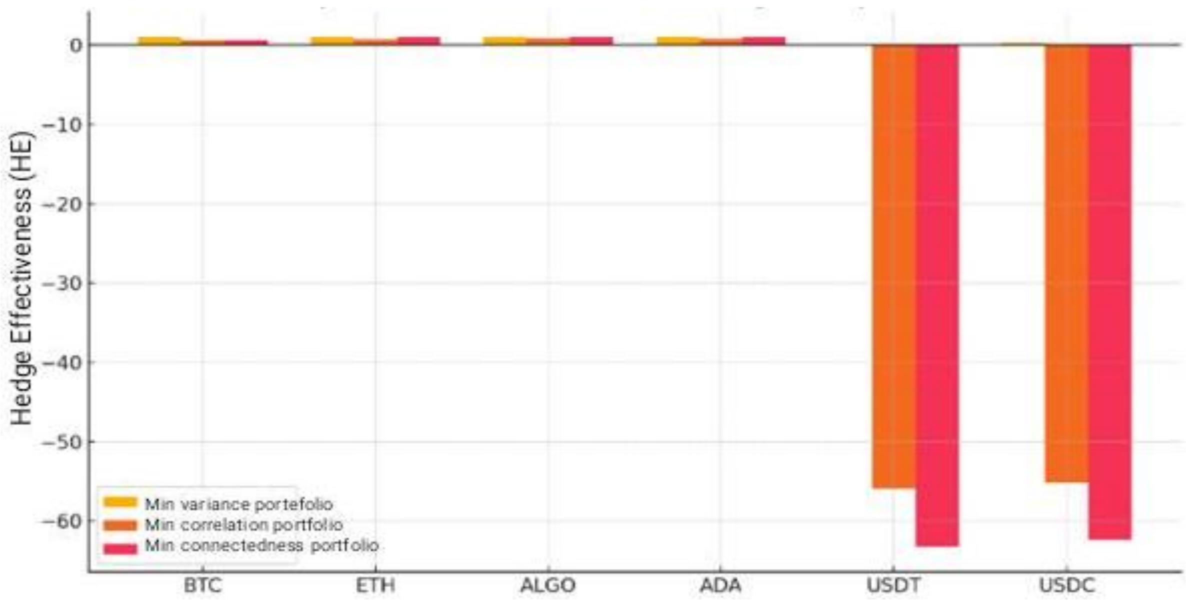
Table N°4: Portfolio Performance Comparison

CRYPTO	MINIMUM VARIANCE PORTFOLIO			MINIMUM CORRELATION PORTFOLIO			MINIMUM CONNECTEDNESS PORTFOLIO		
	Mean	**Std.Dev**	**HE**	**Mean**	**Std.Dev**	**HE**	**Mean**	**Std.Dev**	**HE**
BTC	0.00	0.01	1.00	0.11	0.08	0.61	0.14	0.08	0.56
ETH	0.01	0.01	1.00	0.08	0.06	0.76	0.05	0.05	1.00
ALGO	0.01	0.01	1.00	0.17	0.06	0.87	0.10	0.06	1.00
ADA	0.01	0.01	1.00	0.15	0.06	0.82	0.09	0.06	1.00
USDT	0.51	0.21	0.00	0.26	0.09	-55.92	0.22	0.09	-63.19
USDC	0.48	0.22	0.33	0.29	0.09	-55.19	0.27	0.09	-62.36

Source : Authors

The comparative analysis of the three portfolio strategies minimum variance Minimum Correlation, and Minimum Connectedness reveals distinct performance characteristics. The Equally Weighted portfolio shows uniform weight distribution and maximum heterogeneous effects (HE = 1) for all cryptocurrencies, except stablecoins, which display reduced diversification benefits. In contrast, the Minimum Correlation Portfolio offers moderate average returns and lower volatility, yet stablecoins exhibit highly negative HE values, suggesting their limited contribution to risk diversification. Similarly, the Minimum Connectedness Portfolio achieves the lowest volatility levels for high-connected assets, while reinforcing the marginal or even adverse role of stablecoins within the portfolio. Stable wedges do not contribute to diversification or are perceived as sources of stress transmission in the TVP-VAR model. They can therefore have a low weighting in an optimal portfolio and a high negative HE. Overall, the results highlight the effectiveness of connectedness-based portfolio construction in reducing systemic risk, while also underlining the heterogeneity in asset contributions, particularly the destabilizing influence of stablecoins in dynamic market conditions.

Figure N°6: A comparative graph of HE



Source : Authors

Despite their low volatility, stablecoins such as USDT and USDC exhibit significantly negative heterogeneous effects (HE), particularly in the minimum correlation and minimum connectedness portfolios. This indicates that these assets do not contribute effectively to diversification and may even act as channels for risk transmission within the TVP-VAR model. In other words, their strong interconnectedness with other cryptocurrencies can amplify systemic risk rather than mitigate it. Thus, a hedging strategy that includes such assets might inadvertently increase overall portfolio risk, especially when the initial volatility is low but the connectedness to the system is high. This highlights the importance of evaluating both volatility and interdependence when constructing optimal portfolios.

Conclusion

The analysis of cryptocurrencies through hedging strategies highlights complex dynamics influenced by inherent volatility, the speculative nature of the market, and interactions between digital assets. The results show significant correlations, particularly between Bitcoin (BTC) and Ethereum (ETH), which exhibit similar reactions to market fluctuations. The high volatility of these two assets contrasts sharply with the relative stability of stablecoins, such as USDT and USDC, which serve as net shock absorbers, confirming their role as stabilizers in portfolios. Descriptive statistics reveal significant leptokurtosis and negative skewness for most cryptocurrencies, indicating their non-normal distributions and extreme fluctuations. These findings support the use of dynamic models, such as the TVP-VAR, to capture time-varying conditional volatility and correlations. In terms of portfolio management, dynamic strategies based on variance, correlation, or minimal connectivity offer different approaches to mitigate risks. Minimum Connectivity Portfolios (MCoP) prove effective in managing market shocks by minimizing spillovers between assets, while stablecoins play a key role in reducing volatility. Hence, volatile cryptocurrencies like BTC and ETH pose major challenges to traditional hedging strategies, requiring innovative tools like the TVP-VAR to model dynamic interactions. Additionally, stablecoins present a unique opportunity for diversification and stabilization.

This study demonstrates that effective risk management in the cryptocurrency sector relies on a deep understanding of directional connections and shocks, allowing for portfolio optimization despite high volatility. However, the study has limitations, notably the focus on a limited number of cryptocurrencies and a specific time period, which may not capture the full range of market dynamics. Future research could extend the analysis to a broader set of assets and include different market conditions to validate the robustness of these findings.

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