

On the Connectedness Between Bitcoin, Gold, Gold-Backed Cryptocurrencies and the G7 Banking Sector Stock Indices During Crises: Evidence from Quantile Vector Autoregression and Temporal-Frequency Connectivity approach

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Abstract

This study investigates the dynamic connectedness among conventional cryptocurrencies (Bitcoin), gold-backed currencies (PAXG and DGX), gold, and G7 banking sector indices (USA, Germany, Canada, France, UK, Italy, and Japan). Employing Quantile Vector Autoregression and Temporal-Frequency Connectivity methodologies, our analysis reveals nuanced relationships among these market blocks. France and Germany's banking indices exhibit the highest connectedness, emphasizing their central roles. Peaks in the Total Connectedness Index coincide with global events, underscoring the market's sensitivity to external shocks. G7 banking sectors

emerge as stable information transmitters, while Bitcoin, PAXG, DGX, and gold act as net receivers of shocks, reflecting their effectiveness as hedges during economic uncertainties. Our time-quantile space approach unveils a symmetrical pattern in dynamic connectivity, emphasizing robust interconnections between positively and negatively shifted assets. The time-frequency connectedness analysis highlights the market's short-term sensitivity, emphasizing the need for adaptive risk management. Decomposing net directional connectivity into short and long-term dynamics provides valuable insights for investors and risk managers. Ultimately, our findings contribute to a deeper understanding of dynamic connectedness in the cryptocurrency market, offering insights for effective risk management and decision-making in this evolving financial landscape.

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1. Introduction

Recently, the worldwide financial system has witnessed high vulnerability due to recent global crises. Initially, the COVID-19 health crisis resulted in a significant reduction in economic activities and created uncertainty on a global scale (Jeribi and Snene-Manzli, 2020; Jeribi et al., 2020; Ahadiat et al., 2021; Ghorbel et al., 2022). As the infection spread, strict lockdown measures and economic disruptions caused a significant drop in overall demand, production, and trading (Baker et al., 2020; Yarovaya et al., 2020; Jeribi et al., 2020; Jeribi and Snene_Manzli, 2020; Yousaf and Ali, 2021; Bounboua and Yatié, 2022). Following that, as the globe was still recuperating from the impactful consequences of the COVID-19 pandemic, the commencement of the Russian-Ukrainian conflict ensued. The ongoing conflict between Russia and Ukraine has resonated across the global financial system, significantly impacting several fronts (Boubaker et al., 2023). The upheavals generated by these two crises have considerably influenced and amplified unpredictability within the financial framework and led to fluctuations in financial markets worldwide, affecting currencies, commodities, and equities (Jeribi and Snene-Manzli, 2020; Ghorbel et al., 2022; Bounboua and Yatié, 2022; Fakhfekh et al., 2023; Béjaoui et al., 2023). Recently, the unexpected collapse of the SVB Bank, followed by the fall of Signature Bank, struck a crushing blow and had a notable impact on global financial markets, causing disruptions in the financial system and affecting investor confidence (Yousaf et

al., 2023). The SVB bank's downfall marked the second most significant banking failure in the United States, after the 2008 global financial crisis (Pandey et al., 2023; Aharon et al., 2023).

According to Demirgüç-Kunt et al. (2021), the pivotal function of the worldwide banking system involves absorbing shocks during periods of upheaval through the provision of credit to both the corporate sector and households. Nevertheless, the current global crises could pose significant challenges to the robustness of the banking system. In fact, understanding how the banking system responds to various crises remains a complex task and is rather scarce in the literature. For instance, Elnahass et al. (2021) explored the repercussions of the COVID-19 pandemic on the stability of 1090 banks across 116 diverse nations. Their findings present compelling proof that the financial health and stability of the worldwide banking sector have suffered detrimental consequences due to the onset of the COVID-19 outbreak.

Additionally, Demirgüç-Kunt et al. (2021) investigated the effects of the COVID-19 pandemic on the banking industry across 52 countries. Their outcomes underscore the heightened susceptibility of banks to shocks and the severe negative repercussions of the pandemic on banking systems. In an alternative setting, Boubaker et al. (2023) examine the effects of the conflict between Russia and Ukraine on the stocks of international banks. Their investigation indicates that, on the initial day of the war, global bank stocks experienced an average decline of 1.5%, highlighting the substantial impact of the conflict on the shares of banks. Manda (2023) examines the downfall of the Silicon Valley bank in the United States and its implications for the global banking system.

Their findings propose the presence of risk transmission due to the interconnectedness of financial services worldwide.

During times of instability, the susceptibility of the banking system to financial contagion significantly increases, underscoring the necessity of investigating approaches to mitigate the risks it poses. Special attention should be given to employing assets that exhibit low correlation to address these challenges effectively. In this regard, investors frequently regard gold and Bitcoin as favored tools for risk mitigation, portfolio diversification, and as safe-haven assets. Gold has traditionally been acknowledged for its resilience during periods of turmoil (Baur and Lucey, 2010), while Bitcoin has gained prominence owing to its decentralized characteristics (Bouri et al., 2020). On the other hand, significant focus has been given to the abilities of other types of assets, such as stablecoins. They are digital assets with the value pegged to relatively stable assets, such as gold and the US dollar. Moreover, stablecoins have proven to be safe haven assets during periods of turmoil (Baur and Hoang, 2020; Wang et al., 2020; Xie et al., 2021).

When examining the banking sector, there exists a conspicuous void in the existing body of literature regarding its reaction to various crises and the different measures adopted to shield against its associated risks in times of financial upheaval. Additionally, research on the efficacy of digital and financial assets in alleviating risks connected to the banking sector is scarce. Based on a combination of two distinct and complementary methodologies (Quantile Vector Autoregression (QVAR) and Temporal-Frequency Connectivity), our study fills this gap in the literature by examining the connectedness and spillover relationship between G7 banking sector stock indices,

Bitcoin, gold, and gold-backed currencies indices (PAX and DGX) during the COVID-19 pandemic, the Russian-Ukrainian military conflict and the Silicon Valley Bank (SVB) collapse.

The results reveal that, France and Germany's banking indices emerge as the most connected markets, emphasizing the interconnectedness among G7 economies, banking sectors, gold, and cryptocurrencies. The Total Connectedness Index (TCI) exhibits four distinct peaks, coinciding with significant global events, highlighting the market's sensitivity to external shocks and complex relationships between assets. G7 banking sector indices, particularly those of the USA, France, Germany, and Italy, function as stable sources of network information transmission. Bitcoin, PAXG, DGX, and gold play pivotal roles as major net receivers of shocks, reflecting their effectiveness as hedges during economic uncertainties. Our time-quantile space approach suggests a robust interconnection between positively and negatively shifted assets, emphasizing dynamic connectivity and net directional spillovers. Notable behaviors of individual assets, such as Bitcoin's risk-on role and gold's stability, enrich our understanding. The time-frequency connectedness analysis underscores the market's short-term sensitivity, necessitating adaptive risk management.

This paper makes a significant contribution to the existing literature in several ways. The first outstanding feature of our study is its pioneering examination of the G7 banking sector indices' performance during three pivotal recent events: the COVID-19 pandemic, the Russia-Ukraine military conflict, and the SVB collapse. In contrast to previous research that mostly concentrates on the connectedness between conventional assets (such as

Bitcoin and gold) and financial markets, our investigation introduces a fresh perspective by adding gold-backed cryptocurrencies. The recognition of G7 banking sectors as stable information transmitters and Bitcoin, PAXG, DGX, and gold as net receivers of shocks contributes valuable insights for investors and risk managers, showcasing the potential effectiveness of these assets as hedges during economic uncertainties.

The methodological contribution of our paper lies in the innovative combination of two distinct and complementary approaches: Quantile Vector Autoregression (QVAR) and Temporal-Frequency Connectivity. The utilization of QVAR, diverging from classical vector autoregressive models, explores nuanced relationships across various quantiles, forming a foundational framework for analyzing quantile-connectedness dynamics in financial time series data. This methodology unveils intricate nuances of extreme interactions and dependencies, offering insights into asymmetric responses to shocks during market disturbances. Simultaneously, the integration of Time-Frequency Connectivity provides a global perspective on connectivity evolution across diverse time scales in the digital and financial markets. This dual-method approach enriches our findings, offering comprehensive insights into both short- and long-term conclusions within these markets.

Overall, our findings contribute valuable insights for investors, risk managers, and policymakers, emphasizing the importance of adaptability and nuanced understanding for effective decision-making in the evolving financial landscape.

The rest of our paper is structured as follows: Section 2 reviews the literature, Section 3 presents the data and methodology,

Section 4 discusses the empirical results, Section 5 provides the discussion, and finally, Section 6 concludes.

2. Literature review

The susceptibility of the banking system to financial contagion becomes particularly elevated in times of financial crises, underscoring the crucial necessity to investigate efficient approaches for reducing the risks connected to it. In this regard, special attention should be given to different hedging assets to protect against the risks associated with the banking system.

Gold is one of the most discussed hedging and safe refuge assets in the literature. Baur and Lucey (2010) and Baur and McDermott (2010) state that gold is a safe haven against stocks during periods of crises. Shahzad et al. (2020) corroborate gold's role as a safe haven and hedge. Triki and Ben Maatoug (2021) discovered that gold is a perfect risk diversifier and a safe haven during times of turmoil. Ghorbel et al. (2022) discovered that gold serves as a safe haven for G7 stocks. Oosterlinck et al. (2022) support gold's diversification ability during periods of military tensions. Kang et al. (2023) discovered that gold is a perfect hedging instrument for the American financial market. Fakhfekh et al. (2023) stated that gold is a strong safe haven for G7 stocks during the Russian-Ukrainian conflict. Also, Azmi et al. (2023) support gold's safe haven feature during the Silicon Valley Bank collapse. Al-Nassar et al. (2023) explore the capacity of gold to serve as both a hedging tool and a safe haven for financial investors amid the COVID-19 pandemic. Their findings indicate that, during this health crisis, gold functions either as a robust hedge or a less robust safe haven for financial investors. Snene Manzli and Jeribi (2024c) state that

gold is a perfect diversifier and a safe haven against commodities during the COVID-19 pandemic, the Russia-Ukraine conflict, and the Silicon Valley Bank (SVB) collapse.

On the other hand, researchers have delved deeply into investigating the potential of cryptocurrencies, particularly Bitcoin, to serve as effective instruments for diversifying investment portfolios, hedging against market uncertainties, and providing a safe haven during turbulent economic conditions (Snene Manzli and Jeribi, 2024a,c). For instance, Guesmi et al. (2019) examine the legitimacy of Bitcoin within financial markets. They illustrate that Bitcoin can be employed to mitigate the investment risk associated with various financial assets. Kayral et al. (2023) examine the dynamic association between Bitcoin and the G7 stock market indices during the COVID-19 pandemic and the Russia-Ukraine military conflict. Their results reveal that before COVID-19, Bitcoin is an effective hedging asset and a diversifier throughout the outbreak and the Russian-Ukrainian war. Besides, their hedging effectiveness results reveal that Bitcoin acts as a safe haven for G7 stock markets. According to Tut (2022), Bitcoin enhances financial safety during periods of military conflicts. Corbet et al. (2020) and Hai Le et al. (2021) also assert that Bitcoin serves as a secure refuge amidst the COVID-19 pandemic. Abdelmalek and Benlagha (2023) investigate Bitcoin's capacity as a safe haven in comparison to conventional financial assets. They posit that it functions as a hedging tool before the onset of COVID-19 and as a refuge during the pandemic. Employing an innovative Quantile-VAR connectedness method, Snene Manzli, and Jeribi (2024a) explore the hedging and safe haven potential of gold and Bitcoin against the G7 stock market indices amidst the COVID-19 pandemic, the Russia-

Ukraine war, and the Silicon Valley Bank collapse. Their findings reveal that, at the median quantile, both gold and Bitcoin serve as efficient hedges during stable market conditions and as robust safe-haven assets during the three crises. They also state that gold is the most significant safe haven asset, surpassing Bitcoin, particularly during the war and the SVB collapse.

Apart from Bitcoin and traditional cryptocurrencies, substantial focus has been directed toward assessing the capabilities of alternative cryptocurrency variants that integrate the dependability of precious metals with digital advancements, specifically stablecoins. Among these assets, we can mention gold-backed stablecoins. Aloui et al. (2021) endorse the diversifying potential of cryptocurrencies backed by gold in times characterized by geopolitical risk. Xie et al. (2021) corroborate the safe-haven feature of gold-backed cryptocurrencies during the COVID-19 pandemic. Yousaf and Yarovaya (2022) assert that engaging in gold-supported cryptocurrencies diminishes the risk associated with stock portfolios amid the COVID-19 outbreak. Díaz et al. (2023) support stablecoins' hedging ability. More recently, Maouchi et al. (2024) examine the diversification, hedging, and safe-haven properties of gold-backed cryptocurrencies against different crypto assets during the COVID-19 pandemic and the Russia-Ukraine war. Their findings suggest that the studied cryptocurrencies backed by gold serve as effective diversification tools, exhibiting diverse hedging capabilities and acting as safe havens depending on the type of crises considered. Using a quantile vector autoregression approach, Snene Manzli, and Jeribi (2024b) examine the diversification, hedging, and safe haven abilities of gold-

backed cryptocurrencies against the G7 stock market indices during the COVID-19 pandemic, the Russia-Ukraine conflict, and the SVB collapse. Their findings underscore these digital gold assets' strong safe haven ability during crises. Utilizing the threshold GARCH (T-GARCH)-asymmetric dynamic conditional correlation (ADCC) model, Snene Manzli, and Jeribi (2024c) examine the safe haven characteristics of Bitcoin, gold, and two gold-backed cryptocurrencies (DGX and PAXG) against commodities during the COVID-19 pandemic, the Russia-Ukraine conflict, and the Silicon Valley Bank (SVB) collapse. Their findings indicate that PAXG functions as a robust hedging tool, while gold, Bitcoin, and DGX act as effective diversifiers during stable periods. During times of crises, gold-backed cryptocurrencies also demonstrate strong performance as both diversifiers and safe havens.

Gökgöz et al. (2024) investigate the protective qualities of gold, Bitcoin, and gold-backed cryptocurrencies in relation to the stock and banking indices of G7 nations during periods of economic distress. Their results underscore the defensive and safe-haven characteristics of these various asset types against stock market fluctuations. Employing the time-varying Student's copula, Belguith et al. (2024) explore the hedging and safe-haven capabilities of gold-backed cryptocurrencies in relation to DeFi and NFT assets. Their findings reveal that gold-backed cryptocurrencies function as effective hedging or diversifying assets during stable periods and serve as reliable safe havens during times of crisis. Fakhfekh et al. (2024) examine the interrelationships among eighteen cryptocurrency assets, including NFTs, DeFi tokens, gold-backed cryptocurrencies, and conventional cryptocurrencies. Their analysis

highlights the diversification advantages gained from incorporating gold-backed cryptocurrencies into NFT/DeFi portfolios, especially during periods of extraordinary events.

3. Data and Methodology

3.1. Data

The paper examines the connectedness and spillover relationships between G7 banking sector stock indices, Bitcoin, gold, PAX, and DGX as Gold-backed currency indices. The data span from September 26, 2019, to October 31, 2023. The timeframe is marked by major events such as the global COVID-19 pandemic, the war between Ukraine and Russia, and the Silicon Valley Bank collapse. The returns of the different variables are calculated by employing the formula $R_t = \ln(P_t/P_{t-1})$, with P_t denoting the price for the current day.

The selection of PAXG and DGX as the gold-backed cryptocurrencies for this study was driven by several key factors. Firstly, PAXG and DGX are among the most prominent and widely traded gold-backed cryptocurrencies in the market. Their substantial market capitalization and liquidity make them representative of this asset class, ensuring that our analysis is both robust and reliable.

In addition to these gold-backed cryptocurrencies, the inclusion of gold and Bitcoin in our study was guided by their established roles and significance in the financial markets. Gold is a well-known traditional asset with a long history of serving as a safe haven during periods of market turbulence and economic uncertainty. Its inclusion allows us to examine its comparative performance and stability relative to newer

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financial instruments like gold-backed cryptocurrencies and Bitcoin.

Bitcoin, as a leading cryptocurrency, represents a widely recognized and influential digital asset. Its significant market capitalization, widespread adoption, and growing role as an alternative investment make it a crucial component of our analysis. By including Bitcoin, we can assess its dynamic interactions with traditional assets like gold and emerging assets such as gold-backed cryptocurrencies.

Furthermore, the availability of historical data for gold and Bitcoin was also a key consideration. Both assets have extensive and well-documented price histories, enabling a comprehensive analysis of their time-varying connectedness with other financial assets.

In summary, the selection of PAXG, DGX, gold, and Bitcoin was guided by their market prominence, historical significance, and data availability. This approach provides a robust and comprehensive foundation for our study, allowing us to offer valuable insights into the dynamic connectedness of traditional and digital assets within the broader financial landscape.

3.2. Methodology

To develop our methodological approach, we combine two distinct and complementary methodologies: Quantile Vector Autoregression (QVAR) and Temporal-Frequency Connectivity. The QVAR, notably developed by Ando et al. (2018), differs from classical vector autoregressive models by exploring the field of quantiles. This methodology serves as a fundamental framework for exploring nuanced relationships across various quantiles, laying the groundwork for the analysis of quantile-connectedness dynamics within financial time series data. The use of this innovative

approach reveals complex nuances of extreme interactions and dependencies within financial time series data. Finally, we assess whether there is an asymmetric response to shocks during various types of market disturbances.

At the same time, Time-Frequency Connectivity operates in the time-frequency domain, providing a global view of the evolution of connectivity across different time scales. Thus, to extend our results, we discuss the implications of the time-frequency domain for analyzing short- and long-term conclusions. We use the framework developed, notably by Barunik et al. (2016), and Baruník and Křehlík (2018), in which the spectral decomposition is based on the Fourier transform, a representation of quantiles using moving averages.

To sum it up and to make our methodology more replicable, we further detail the key steps of our approach. We first use the Vector Auto-Regression by Quantiles (QVAR) model, developed by Ando et al. (2018), to explore relationships between different quantiles of financial data. This method allows to analyze the connectivity dynamics by quantiles, highlighting the extreme interactions and dependencies within financial time series. Then, we apply the analysis of Temporal-Frequency Connectivity, which allows us to examine dynamic interactions at different time horizons. This approach captures short-term fluctuations as well as longer-term variations, providing a thorough understanding of market responses to various disruptions. By combining these two methodologies, we are able to reveal complex interactions and determine whether responses to shocks differ depending on the types of market disturbances.

To measure the connectedness indices, we estimate a quantile VAR denoted as QVAR(p).

Initially, we consider the following VAR model, which expresses the i^{th} cryptocurrency index as a function of the lagged cryptocurrency index in the dataset.

$$y_{it} = \mu_i + \sum_{j=1}^p \Phi_{ij} y_{t-j} + \varepsilon_{it} \quad (1)$$

Haut du formulaire

For the entire set of observed cryptocurrencies, the subsequent quantile vector autoregression system, denoted as QVAR(p), for the variable y_i is expressed as:

$$y_t = \mu(\tau) + \Phi_1(\tau)y_{t-1} + \Phi_2(\tau)y_{t-2} + \dots + \Phi_p(\tau)y_{t-p} + \mu_t(\tau) \quad (2)$$

$$y_t = \mu(\tau) + \sum_{j=1}^p \Phi_j(\tau)y_{t-j} + \mu_t(\tau) \quad (3)$$

Where:

y_i and $y_{(t-1)}$ are vectors, are $k \times 1$ -dimensional vectors that present the endogenous variables.

τ signifies a conditional quantile within the range of (0,1). In addition, p specifies the lag length for the QVAR model. $\mu(\tau)$ represents a vector with dimensions $k \times 1$, consisting of constants.

$\Phi_j(\tau)$ denotes a $k \times k$ matrix encompassing QVAR parameters, while $\mu_t(\tau)$ indicates a $k \times 1$ error vector characterized by a $k \times k$ variance-covariance matrix, denoted as $\Sigma(\tau)$.

Following the methodology described by Koop et al. (1996) and Pearson and Shin (1998) (as referenced in Yousaf and Yarovaya, 2022), we compute the Generalized Forecast Error Variance Decomposition (GFEVD) with a forecast horizon of H . Through this analysis, we are able to evaluate how a shock in variable j affects the variance of the prediction error for variable i . The idiosyncratic innovation approach of Ando et al. (2018) is followed when measuring the portion of the forecast error variance for the j^{th} variable at a specific

time point (y_t). The equation is presented as follows:

$$\theta_{ij}(H) = \frac{(\Sigma(\tau))_{jj}^{-1} \sum_{h=0}^H ((\Psi_h(\tau) \Sigma(\tau))_{ij})^2}{\sum_{h=0}^H ((\Psi_h(\tau) \Sigma(\tau) \Psi_h'(\tau))_{ii})} \quad (4)$$

These two equalities represent the outcomes:

$$\sum_{i=1}^k \tilde{\theta}_{ij}(H) = 1 \text{ and } \sum_{j=1}^k \sum_{i=1}^k \tilde{\theta}_{ij}(H) = k$$

The total connectedness index (TCI), designed to assess the level of interconnections within the network, is used to start calculating measures of connectedness. The following formula is used to derive this index:

$$TCI_t(H) = \frac{1}{k} \sum_{i,j=1, i \neq j}^k \tilde{\theta}_{ij,t}(H) \quad (5)$$

Then, we move on to calculate the directional spillover indexes, which allows us to measure the impact of variable i on all variables j , quantifying the extent to which a disturbance in series i affects all other series j . This is represented by the **Total Directional Connectedness (TDC) TO** other variables.

$$TO_i(H) = \sum_{i=1, i \neq j}^k \tilde{\theta}_{ji}(H) \quad (6)$$

In the next step, the calculation of Total Directional Connectedness FROM Others, which determines the extent to which series i receives from series j , is carried out as follows:

$$FROM_i(H) = \sum_{i=1, i \neq j}^k \tilde{\theta}_{ij}(H) \quad (7)$$

Finally, the difference between TDC TO others and TDC FROM others elucidates the overall impact that series i wields on the examined network.

$$NET_i(H) = TO_i(H) - FROM_i(H) \quad (8)$$

Our focus has been on the time domain connectedness assessment, and now we

are moving on to the frequency domain. We can explore the connection between connectedness and frequency using Stiasny (1996)'s spectral decomposition method. Initially, we inspect the frequency response function, represented as $(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h} \Psi_h$, where $i = \sqrt{-1}$ and ω is the frequency.

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x_{t-h}) e^{-i\omega h} = (e^{-i\omega h})_t \Psi'(e^{i\omega h}) \quad (9)$$

Similarly, the frequency-based Generalized Forecast Error Variance Decomposition (GFEVD) is a fusion of the spectral density and the GFEVD. In fact, normalizing the frequency GFEVD is key, and is presented as follows:

$$\theta_{ij}(H) = \frac{(\Sigma(\tau)_{jj}^{-1} \sum_{h=0}^{\infty} ((\Psi(\tau) e^{-i\omega h} \Sigma(\tau))_{ij})^2)}{\sum_{h=0}^H (\Psi e^{-i\omega h} \Sigma(\tau) \Psi(\tau) (e^{i\omega h})_{ii})} \quad (10)$$

$$\tilde{\theta}_{ij}(\omega) = \theta_{ij}(\omega) \sum_{k=1}^N \theta_{ij}(\omega) \quad (11)$$

The term $\tilde{\theta}_{ij}(\omega)$ signifies the proportion of the spectrum of the i^{th} series at a given frequency ω that can be attributed to a shock in the j^{th} series. This measure is devoted to as a within-frequency sign, as it aids in assessing the interconnectedness between the two series at that particular frequency. To assess connectedness through both short-term and long-term time frames, instead of focusing on a single frequency, we aggregate all frequencies within a stated range, denoted as: $d = (a, b)$: $a, b \in (-\pi, \pi)$, $a < b$:

$$\tilde{\theta}_{ij}(d) = \int_a^b \tilde{\theta}_{ij}(\omega) d\omega \quad (12)$$

Consequently, we have the ability to compute similar connectedness measures

as those introduced by Diebold and Yilmaz (2012, 2014). Nevertheless, in this case, these measures are recognized as frequency connectedness measures. They allow us to assess the transmission of effects within specific frequency ranges (represented by d), which can be interpreted in a comparable manner:

$$TO_i(d) = \sum_{j=1, j \neq i}^N \tilde{\theta}_{ji}(d) \quad (13)$$

$$FROM_i(d) = \sum_{i=1, i \neq j}^N \tilde{\theta}_{ij}(d) \quad (14)$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \quad (15)$$

$$TCI(d) = N - 1 \sum_{i=1}^N TO_i(d) = N - 1 \sum_{i=1}^N FROM_i(d) \quad (16)$$

Here, we consider two frequency bands that capture short-term and long-term dynamics. The first band, $d1 = (\pi/5, \pi)$, covers a range of 1 to 5 days, while the second band, $d2 = (0, \pi/5]$, encompasses time frames from 6 days to an infinite horizon. Therefore, $TO(d1)$, $FROM_i(d1)$, $NET_i(d1)$, and $TCI(d1)$ represent short-term total directional connectedness towards others, short-term total directional connectedness from others, short-term net total directional connectedness, and short-term total connectedness index, respectively. Alternatively, $TO(d2)$, $FROM_i(d2)$, $NET_i(d2)$, and $TCI(d2)$ depict long-term total directional connectedness towards others, long-term total directional connectedness from others, long-term net total directional connectedness, and long-term total connectedness index, respectively.

4. Empirical results:

4.1. Descriptive Statistics

Table 1 presents the descriptive statistics for the daily return series. All the returns exhibit stationarity at the 1% significance level, as indicated by the ERS unit root test. Most variables display negative skewness and high kurtosis, indicating the presence of extreme negative observations. In contrast, DGX shows positive skewness and excess kurtosis, suggesting an asymmetric and fat-tailed nature of the asset. The analysis is in

line with the Jarque-Bera test, confirming the non-normality of the returns. Moreover, $Q(20)$ and $Q^2(20)$ values indicate autocorrelation in the percentage changes of the variables and their squared returns. Furthermore, based on Kendall's coefficients, the analysis reveals significant dependencies among various assets. The highest dependence is observed between PAXG and gold, followed by the Canadian and US banking sector stock indices. Whereas, the lowest dependence is observed between gold and the UK banking sector stock index.

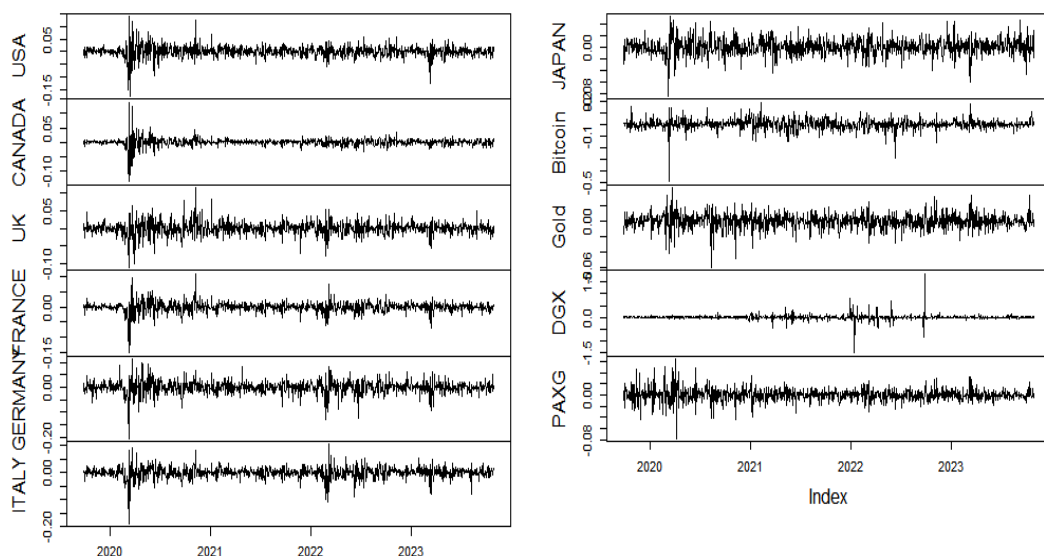


Figure 1. Returns

Table 1. Descriptive statistics

	US.BAKNING	CANADA	UK	FRANCE	GERMANY	ITALY	JAPAN	Bitcoin	Gold	DGX	PAXG
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
	(0.692)	(0.946)	(0.887)	(0.925)	(0.566)	(0.525)	(0.276)	(0.297)	(0.379)	(0.982)	(0.500)
Variance	0.001***	0.000***	0.000***	0.000***	0.001***	0.000***	0.000***	0.002***	0.000***	0.012***	0.000***
Skewness	-0.455***	-0.570***	-0.193***	-0.894***	-0.806***	-1.248***	-0.296***	-1.686***	-0.427***	2.400***	0.015
	(0.000)	(0.000)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.838)
Ex.Kurtosis	8.784***	32.254***	5.295***	12.423***	7.041***	10.600***	2.352***	20.345***	3.431***	120.835***	5.552***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	3444.564***	46006.050***	1244.668***	6957.349***	2304.340***	5237.795***	259.777***	18783.310***	552.046***	645901.922***	1361.700***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-12.535***	-12.788***	-7.744***	-11.390***	-7.213***	-9.389***	-3.004***	-11.930***	-7.782***	-16.859***	-7.873***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	93.368***	119.200***	22.704***	43.708***	22.552***	33.426***	11.343	21.849***	13.870	51.396***	21.334***
	(0.000)	(0.000)	(0.005)	(0.000)	(0.006)	(0.000)	(0.368)	(0.008)	(0.177)	(0.000)	(0.010)
Q2(20)	818.221***	1149.926***	153.083***	406.150***	168.499***	278.081***	253.235***	13.341	100.962***	28.079***	188.407***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.209)	(0.000)	(0.000)	(0.000)
Kendall Analysis											
US.BAKNING	1.000***										
CANADA	0.575***	1.000***									
UK	0.390***	0.369***	1.000***								
FRANCE	0.417***	0.430***	0.570***	1.000***							
GERMANY	0.400***	0.385***	0.523***	0.607***	1.000***						
ITALY	0.361***	0.369***	0.465***	0.634***	0.566***	1.000***					
JAPAN	0.098***	0.133***	0.128***	0.133***	0.121***	0.087***	1.000***				
Bitcoin	0.152***	0.146***	0.077***	0.116***	0.118***	0.129***	0.013	1.000***			
Gold	-0.022	-0.006	-0.049**	-0.026	-0.039	-0.022	0.008	0.081***	1.000***		
DGX	0.053***	0.049**	0.020	0.030	0.033	0.051***	-0.003	0.223***	0.065***	1.000***	
PAXG	0.031	0.024	-0.036	-0.017	-0.013	-0.005	-0.011	0.103***	0.582***	0.085***	1.000***

Notes: JB denotes the Jarque and Bera (1980) normality test; ERS is Stock et al. (1996) unit-root test with constant; Q(20) and Q²(20) represent Fisher and Gallagher (2012) weighted portmanteau tests. Kendall measures the linear correlation between the variables. Finally, *, **, and *** show significance at 1%, 5% and 10%, respectively.

4.2. Total Dynamic Connectedness

The connectedness indices within the cryptocurrency market exhibit considerable variation, revealing diverse influence dynamics among different digital assets. The FROM connectedness values span a range of 58.81 percentage points, fluctuating between 19.46% (DGX) and 74.05% (France). On the other hand, the TO connectedness values range from 12.95% (DGX) to 94.97% (France), showcasing significant variation. Notably, France and Germany's banking indices are the most connected markets, demonstrating

the highest pairwise connectedness index. The NET values provide a net measure of each asset's connectedness, considering both its influence on others and its influence on it. Precisely, the USA, France, Germany, Canada, Italy, and England are shock contributors to the network's total connectedness, while Japan, Bitcoin, Gold, PAXG, and DGX are the main net receivers of shocks from other indices. Our findings emphasize the existence of distinct, influential linkages among the banking sectors of G7 economies, gold, and cryptocurrencies.

Table 2. Average dynamic connectedness

	USA	CANADA	UK	FRANCE	GERMANY	ITALY	JAPAN	Bitcoin	Gold	DGX	PAXG	FROM
USA	31.94	16.90	10.37	11.01	9.82	9.17	1.81	3.27	2.59	0.63	2.49	68.06
CANADA	16.97	32.36	9.35	11.75	9.46	9.60	2.15	3.52	2.20	0.70	1.95	67.64
UK	9.58	8.67	29.76	16.62	14.77	12.77	1.76	1.73	1.81	0.79	1.74	70.24
FRANCE	9.43	9.64	14.54	25.95	15.62	17.20	1.58	2.18	1.75	0.65	1.45	74.05
GERMANY	8.83	8.43	14.32	17.17	28.54	15.44	1.72	2.21	1.40	0.70	1.25	71.46
ITALY	8.36	8.62	12.44	18.92	15.40	28.58	1.55	2.40	1.68	0.65	1.40	71.42
JAPAN	11.44	7.57	7.46	7.97	6.75	8.05	43.27	2.11	2.20	1.06	2.13	56.73
Bitcoin	5.81	5.68	3.08	4.17	4.07	4.06	1.90	59.71	4.09	3.08	4.36	40.29
Gold	3.44	3.09	2.60	3.23	2.54	2.71	1.25	3.52	44.97	2.57	30.09	55.03
DGX	1.59	1.59	1.27	1.45	1.39	1.37	1.28	3.91	3.05	80.54	2.56	19.46
PAXG	3.23	2.92	2.66	2.70	2.19	2.41	1.06	3.34	29.89	2.13	47.47	52.53
TO	78.68	73.10	78.10	94.97	82.00	82.79	16.07	28.18	50.67	12.95	49.41	646.91
NET	10.62	5.46	7.86	20.92	10.54	11.37	-40.66	-12.11	-4.36	-6.52	-3.12	TCI :58.81

In Figure 1, we examine the evolution of the TCI over the sample period to better assess dynamic market risk. The analysis reveals four distinct peaks in the cryptocurrency market. Firstly, a substantial peak occurred in the first half of 2020, coinciding with the onset of the COVID-19 pandemic (Giudici et al., 2020). Following this, a significant increase was observed in late 2021. The third peak occurred at the beginning of 2022,

aligning with the commencement of the Russian-Ukrainian military conflict (Appiah-Otoo, 2023). A deeper examination of the graph shows a fourth peak where overall connectedness strengthened in Q2 and Q3 of 2023. This high point underscores the Silicon Valley Bank collapse that directly influences cryptocurrency prices (Yousaf et al., 2023; Galati and Capalbo, 2023).

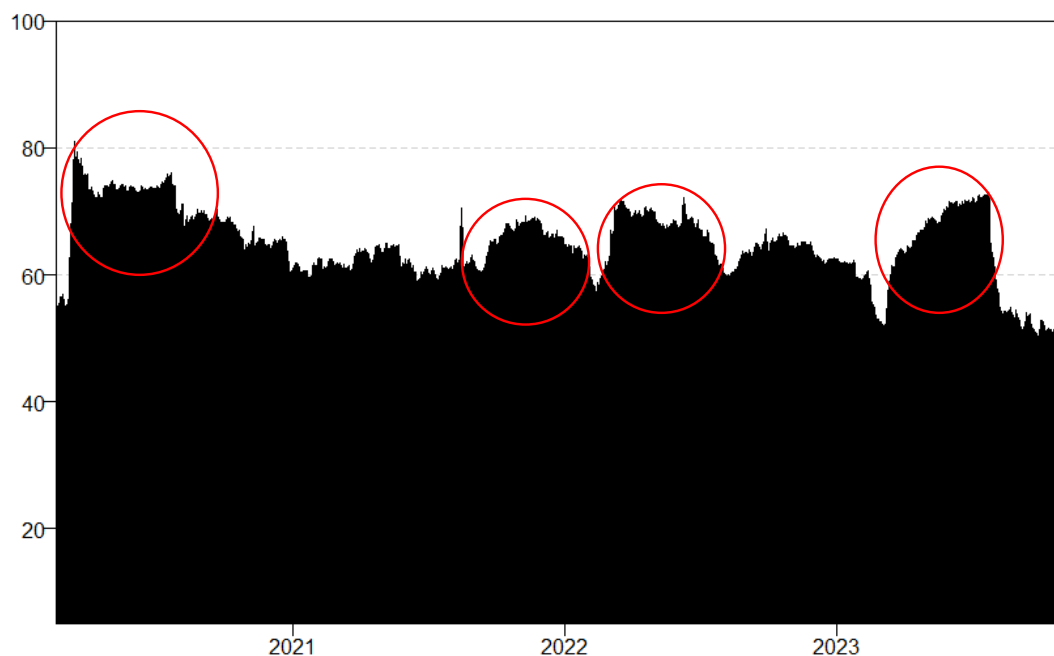


Figure 2. Total Dynamic Connectedness between 2020 and 2023

4.3. Net total and pairwise directional connectedness

Figure 3 portrays the net total directional connectedness for each studied index. It is important to note that when an asset has a positive value, it means it is a shock transmitter within the network, while a negative value means it is a receiver within the network. The influence it has on all the system's remaining variables is greater than it has on itself. Our results show several significant peaks at various points in time, suggesting significant

changes in network dynamics. Specifically, the USA, France, Germany, and Italy banking markets emerge as stable sources of network information transmission, while the gold-backed DGX, Bitcoin, and Japan banking index emerge as stable network information receivers. Moreover, several indices demonstrate varying patterns in net spillovers over the study period, such as Canada, UK, PAXG, and gold. They display phases of being a net shock transmitter at various points in time, switching to be net shock receivers after.

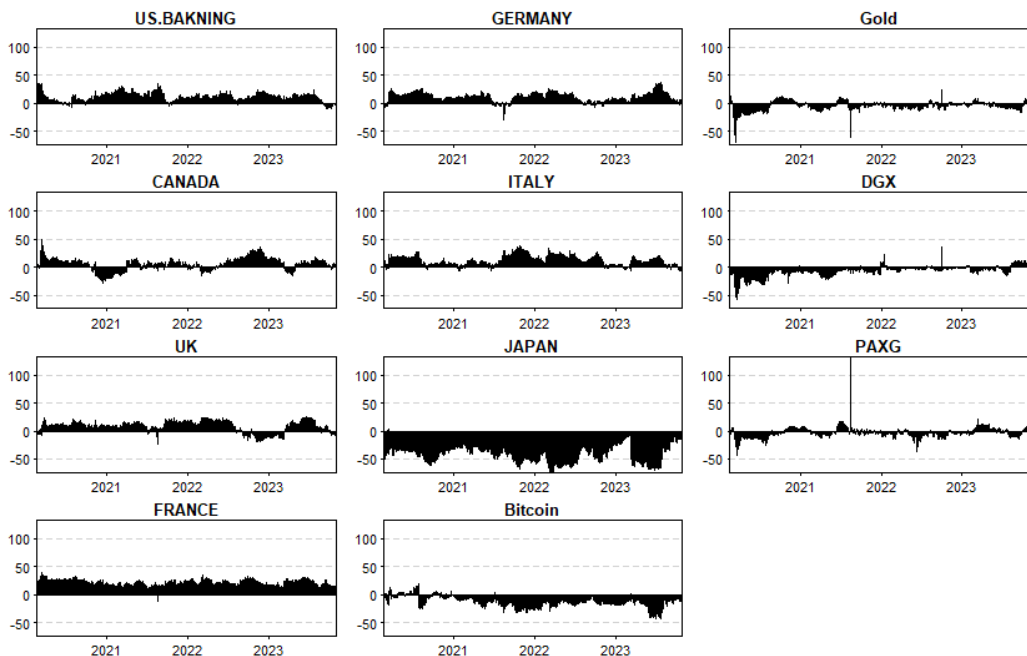


Figure 3. Net total directional connectedness. between 2020 and 2023

The network graph in Fig. 4 demonstrates the pairwise directional connection between the eleven variables in the network and provides a comprehensive view of their interconnections and relationships. The net reception effect of shocks is indicated by the size of the nodes marked in blue, while those marked in yellow represent the role of the asset as a net transmitter of shocks. Lastly, the arrows on the lines indicate the direction of net spillover between the different assets.

As shown in Figure 4, conventional assets, i.e., G7 banking sector indices except the Japan index, are the main drivers of fluctuations across various assets in the system. The high connection between these assets is evident in our findings and has been largely documented by many previous studies (Kim and In, 2007; Kirkulak Uludag, 2019; Matos et al., 2021). Moreover, the US Banking index emerges as a pivotal shock

transmitter, connecting significantly with the Japan index. This strong link can be attributed to global economic interdependence and financial market integrations between the two countries (Kanamura, 2023). Other significant interconnections between all G7 indices and Japan are interesting, indicating a complex web of financial relationships (Agyei et al., 2022). When it comes to Bitcoin, it is a net receiver from the US Banking asset, and such a result is explained by its role as a sought-after alternative investment during times of economic uncertainty (Guesmi et al., 2019; Tut, 2022; Kayral et al., 2023). PAXG, DGX, and Gold stand out as major receivers of shocks from the network but have no pairwise connections with each of the studied indices. Interestingly, Gold and backed-gold cryptocurrencies appear to be the least receivers from the network, suggesting their potential role as more stable assets and

hedges in times of market turbulence (Baur and Lucey, 2010; Baur and McDermott, 2010;

Shahzad et al., 2020; Baur and Hoang, 2020; Wang et al., 2020; Xie et al., 2021).

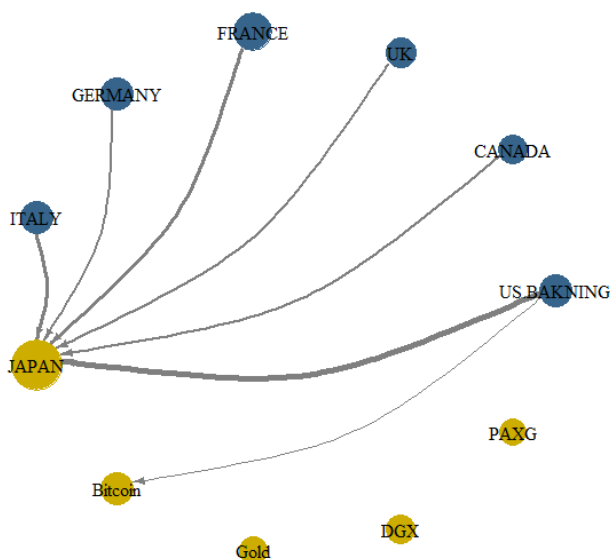


Figure 4. Net-Pairwise Directional Connectedness

4.4. Total and Net Connectedness using quantile connectedness approach

To better understand market dynamics, we present the total connectivity (Figure 5) and the net directional connectivity (Figure 6 - 16) of the indices studied in the time-quantile space. Specifically, the heat map shown in Figure 6 was generated using a 100-day moving window and a 20-day forecast using the QVAR model (1). The x-axis shows the chronology, while the quantiles, ranging from 0.05 to 0.95 in 1% increments, are represented on the y-axis. Warmer segments indicate higher levels of connectivity, while lighter regions have lower levels. According to Figure 6, dynamic shocks from both significantly positive (above 75% quantile) and negatively shifted (below 25% quantile) assets demonstrate solid interconnections over the

entire study period. It is also important to note that this dynamic connectivity has a symmetrical pattern. In addition, fluctuations in the 50% quantile, representing the average total connectivity index (TCI) of the network, present a cyclical pattern. The fallout was particularly intensified in the first half of 2020, coinciding with the spread of the COVID-19 epidemic. Remarkably, in late 2022 and early 2023, there was a high degree of linkage but of lesser magnitude compared to the COVID period. This period corresponds to a period of global economic recovery and renewed investor confidence. Finally, another episode of strong connectivity is observed in the middle of 2023, corresponding to heightened geopolitical tensions and uncertainties in the global financial landscape due to the collapse of the Silicon Valley Bank.

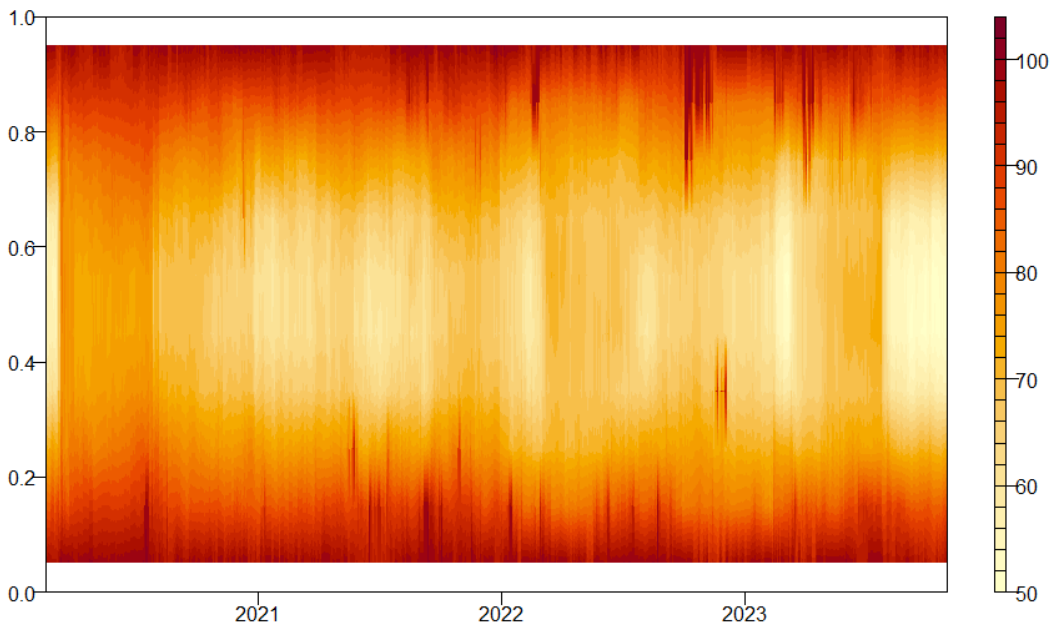


Figure 5. Total dynamic connectedness through quantiles

As previously mentioned, Fig. 6-16 presents the quantile net directional spillovers. The objective is to comprehend how investors react to diverse market conditions, whether bearish (low quantile), stable (middle quantile), or bullish (high quantile). In each heatmap diagram, warmer shades reveal a net contributing asset, while colder shades reveal a net receiving asset. Our findings show that time-varying attributes identify numerous economic events that shape dynamic spillovers at various quantiles.

Precisely, starting with cryptocurrencies, PAXG appears to be a weak net receiver during 2020 across almost all quantiles, while it turns out to be a net transmitter of shocks to the network during specific periods, precisely in upper and lower quantiles. On the other hand, the role of Bitcoin in the network appears to shift between a net receiver and a net transmitter during the period and in extreme

quantiles. Particularly, during COVID-19, Bitcoin does not interact with other markets except in mid-2020 where it shifts between a weak net reception and transmission of shocks. It exhibits low reception to the system in the middle quantiles, being a net receiver on average. A remarkable behavior is Bitcoin being a strong net contributor in the middle of 2021 and the beginning of 2023 in the lower quantile. This could be explained by increased investor confidence and adoption of Bitcoin as a risk-on asset during these specific periods (Guesmi et al., 2019; Kayral et al., 2023; Abdelmalek and Benlagha, 2023).

Regarding gold-backed currencies, DGX exhibits a net reception effect during almost the entire studied period, as indicated by its cooler shade across both positive and negative price changes in comparison to other markets. However, around 2021, DGX showed a strong transmission function in the

upper and lower quantiles. This implies that positive and negative price changes in DGX led to significant shocks transmitted to other markets. Referring to gold returns, the asset generally acted as a weak recipient of shocks with some episodes of shock transmission. We also observe periods with no interaction between Gold and other markets. The timeframe under consideration mainly spans from 2021 to mid-2023.

The G7 banking sector indices, except for the Japanese index, stand out as prominent actors within the system, exhibiting a consistent net transmitter effect between the 15th and 85th quantiles throughout the entire sample period. This observation is consistent with the conclusions drawn from Figure 3, highlighting their status as the primary net transmitters within the network. Looking at the extremes of the data, both show a general trend toward shifting between net recipients and net transmitters. Notably, the France index is the strongest transmitter during 2020, and the US Banking index during 2021. Moreover, an almost absence of interaction is witnessed for Germany in mid-2021 and for Canada in

the first half of 2022. Notably, the UK index is almost a weak net transmitter, except during the end of 2022 and the beginning of 2023, where it shifts to be a weak net receiver of shocks. Similarly, the Canada index is a prominent weak net transmitter of shocks but turns out to be a net receiver at the end of 2021 and the beginning of 2022, and it loses interactions with other markets at the beginning of 2023 temporarily.

Another noteworthy behavior is the Japanese index's net receiving function at the median quantile, with a stronger position in mid-2022 and mid-2023, coinciding with periods of increased economic stability and positive market sentiment (BIS, 2022). During instances of extreme market conditions, however, it exhibits a dynamic interplay as it swings between being a net receiver and a net transmitter. The impact of spillovers has been highlighted by quantiles due to the various events that took place during this period, such as the resolution of trade disputes and improved economic indicators, illustrating the dynamic responsiveness to changing market scenarios.

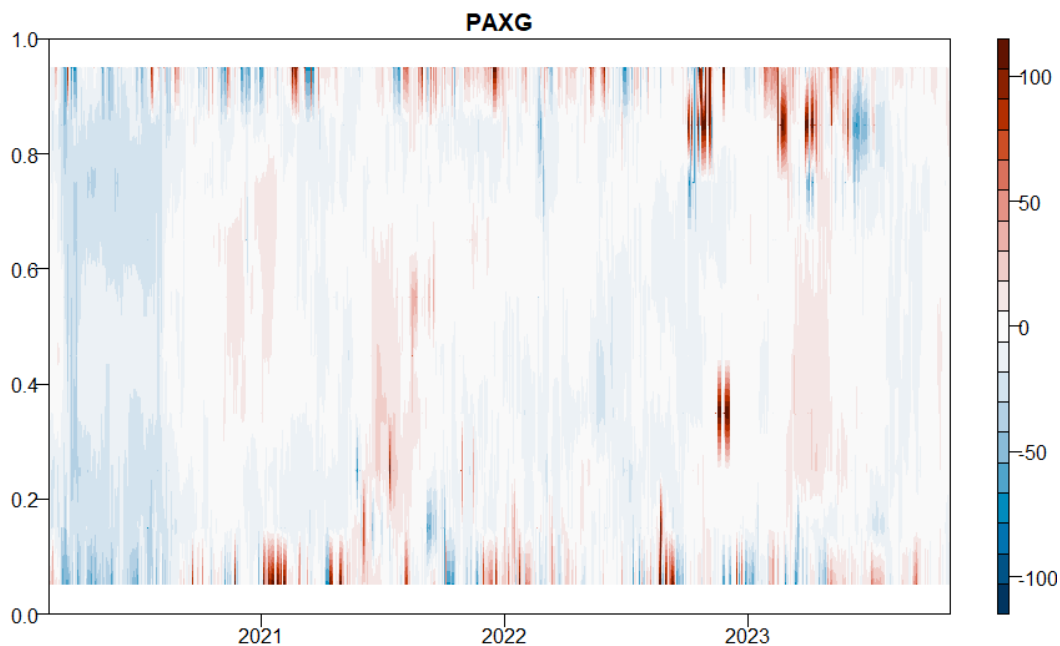


Figure 6. Net total dynamic connectedness through quantiles for PAXG

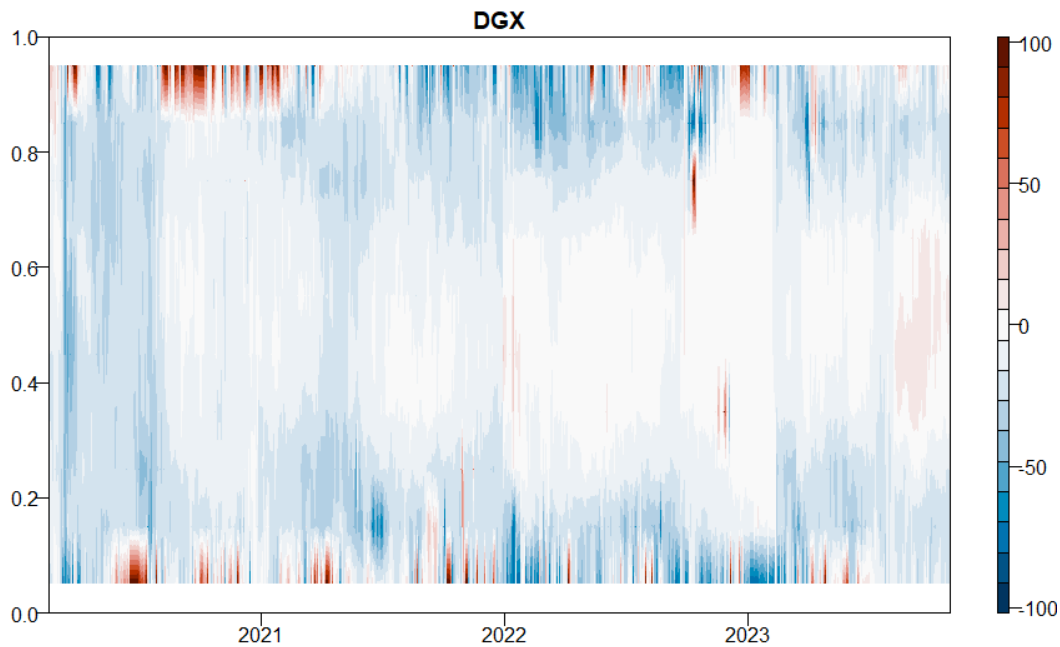


Figure 7. Net total dynamic connectedness through quantiles for DGX

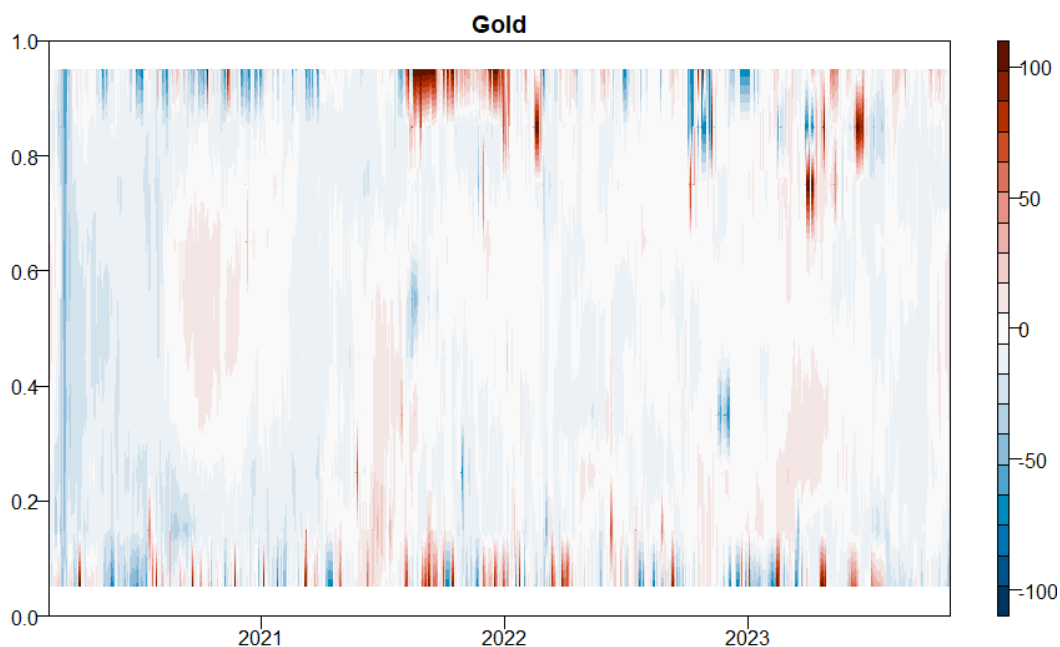


Figure 8. Net total dynamic connectedness through quantiles for Gold

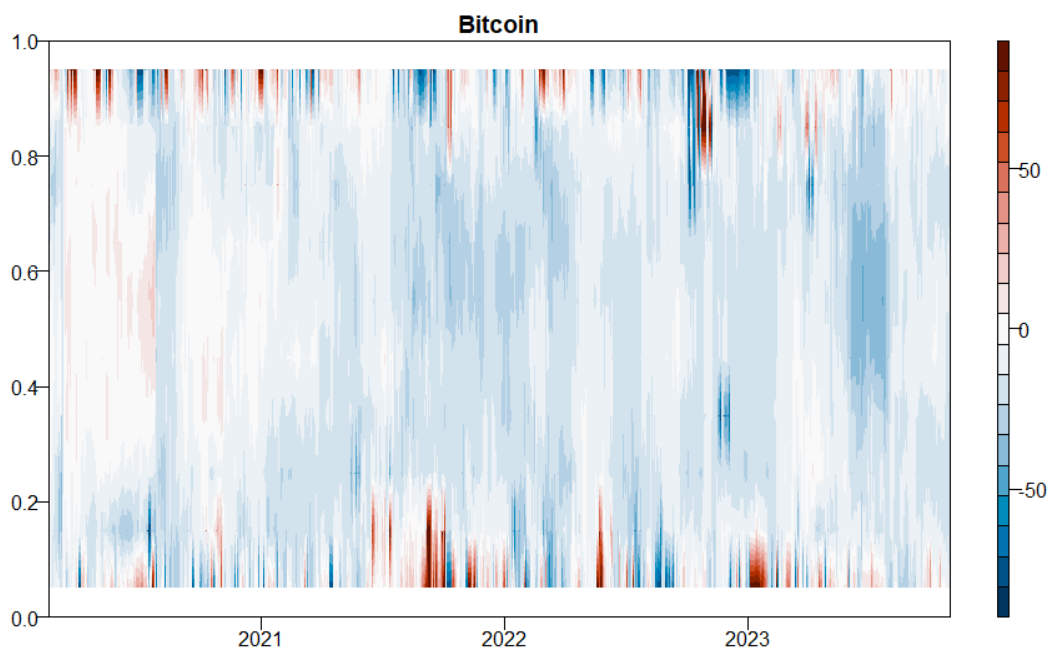


Figure 9. Net total dynamic connectedness through quantiles for Bitcoin

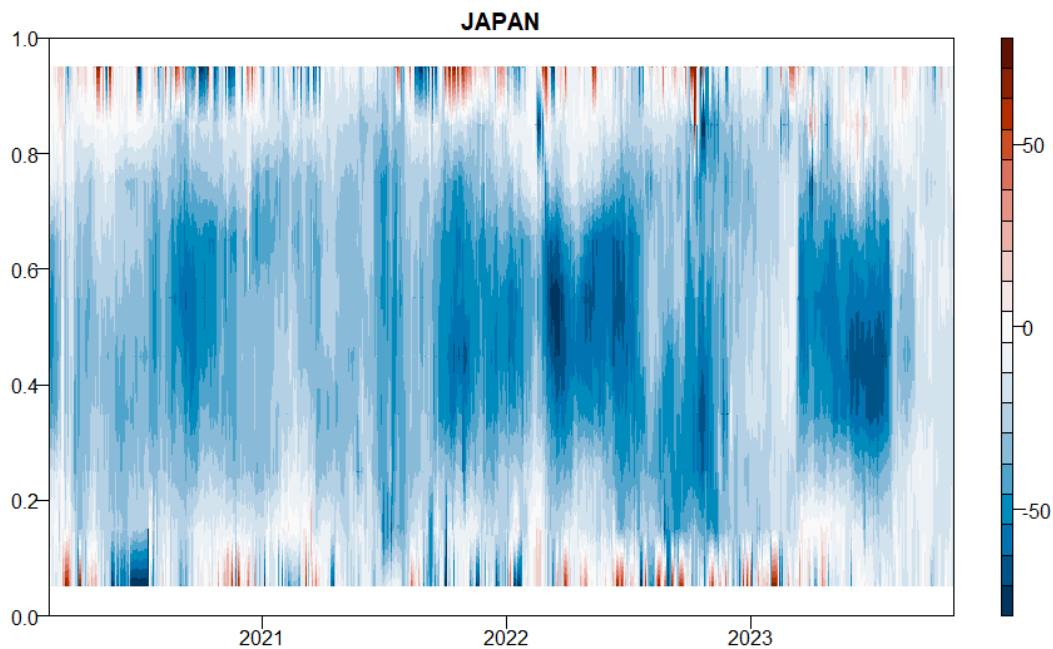


Figure 10. Net total dynamic connectedness through quantiles for Japan

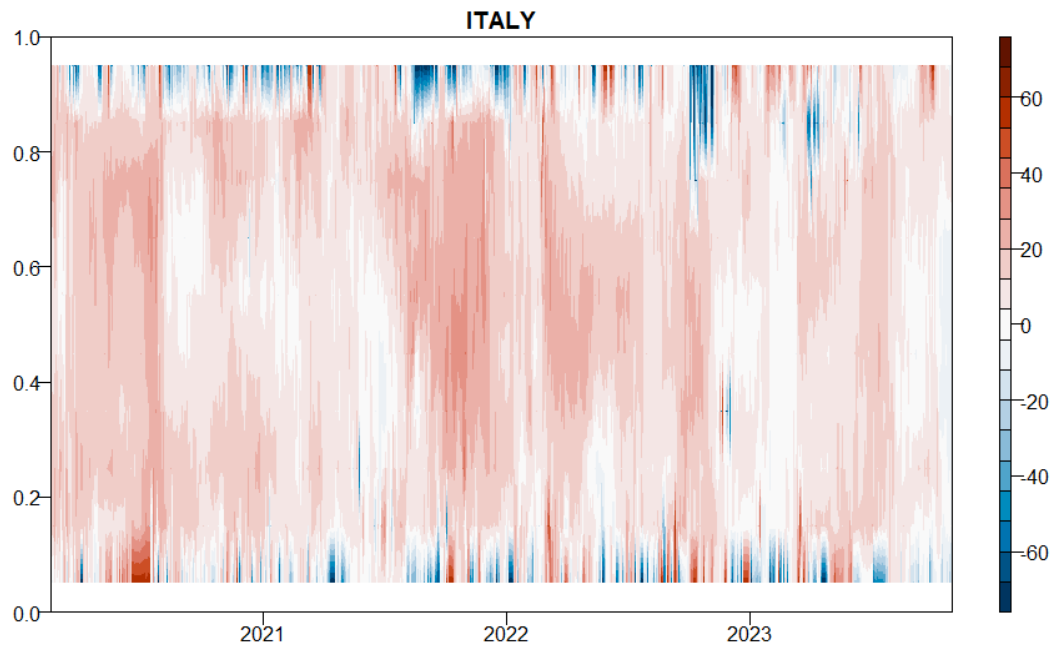


Figure 11. Net total dynamic connectedness through quantiles for Italy

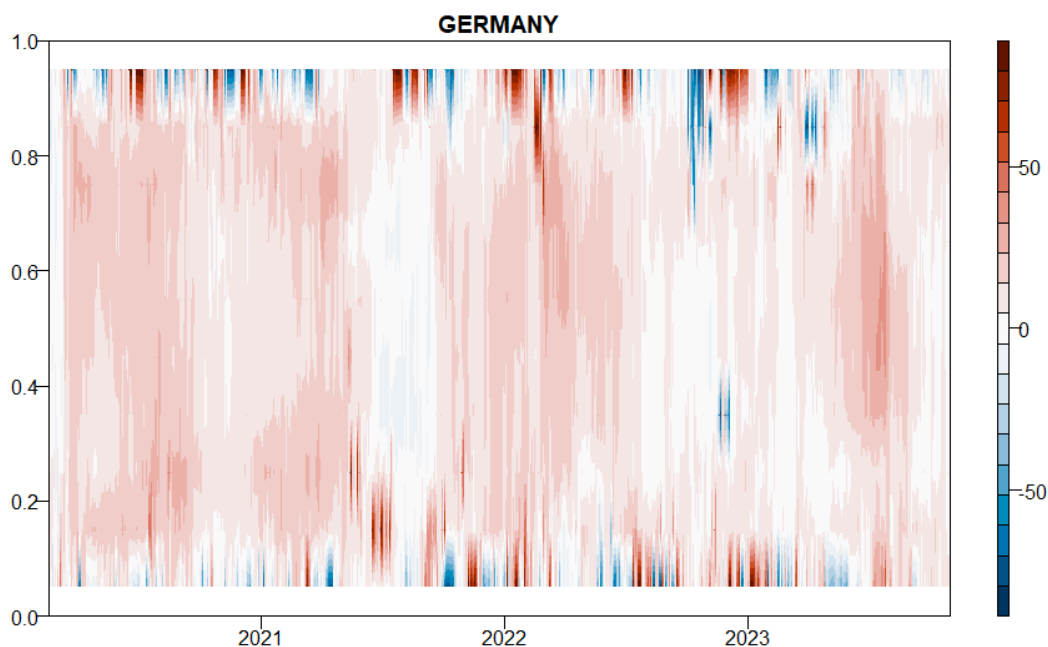


Figure 12. Net total dynamic connectedness through quantiles for Germany

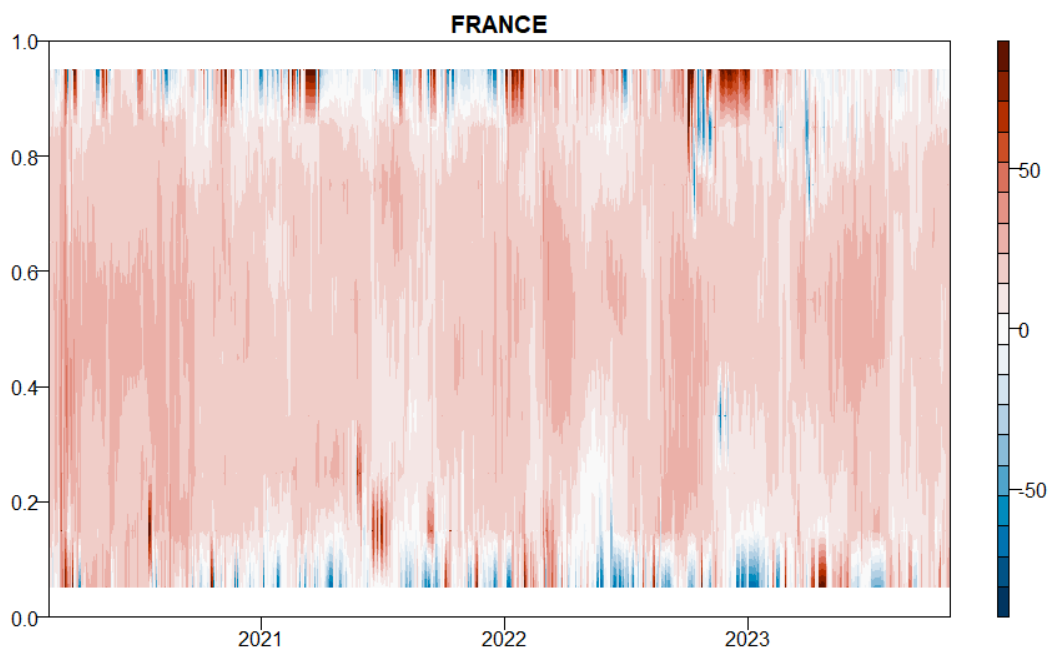


Figure 13. Net total dynamic connectedness through quantiles for France

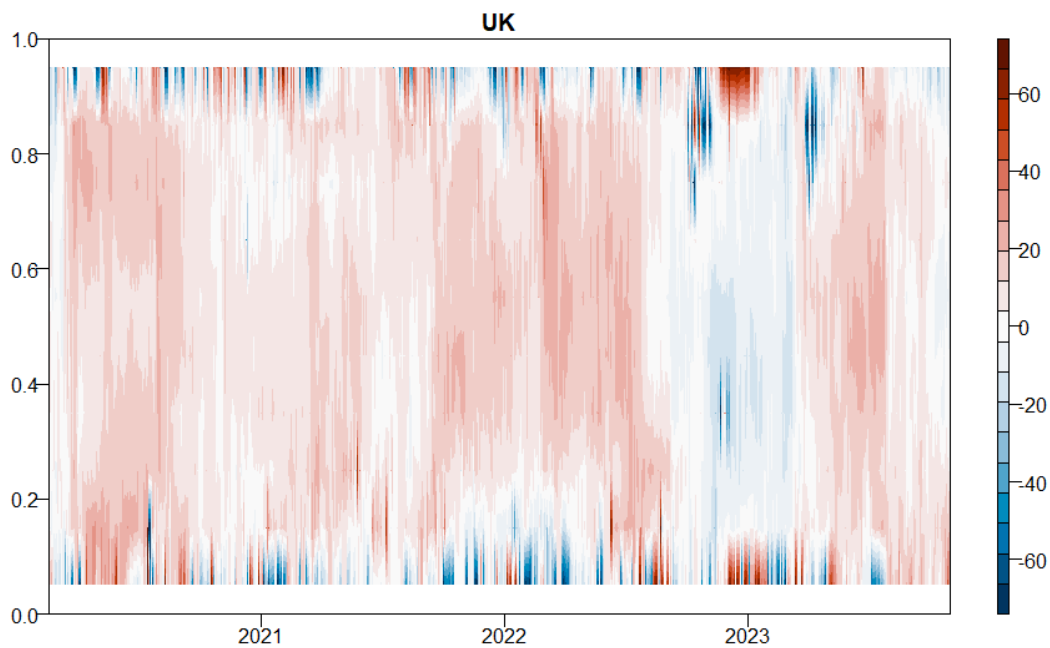


Figure 14. Net total dynamic connectedness through quantiles for UK

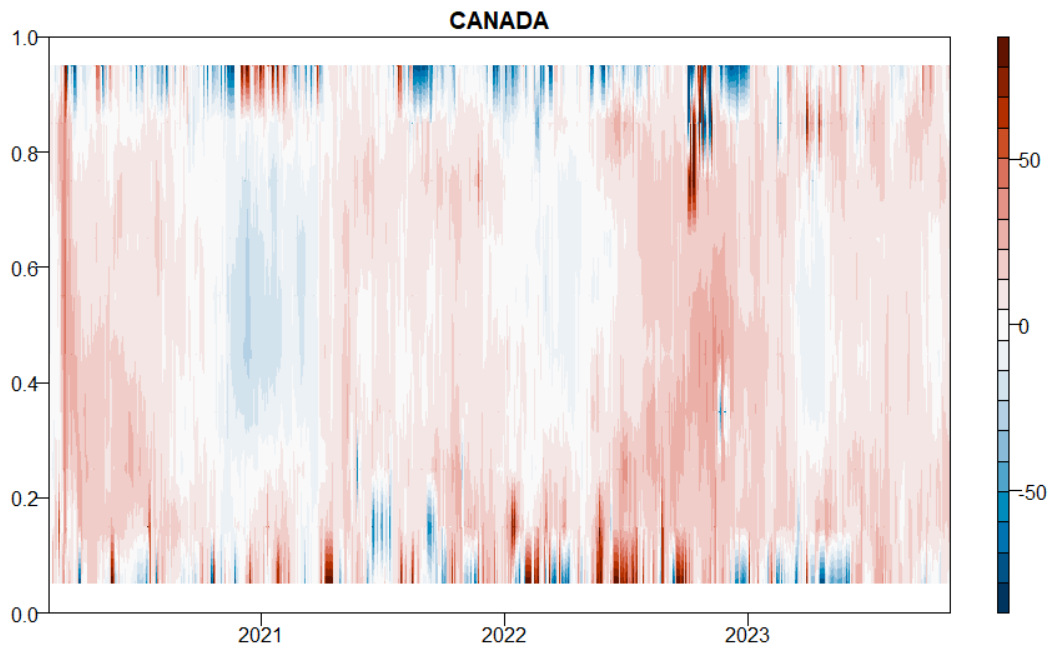


Figure 15. Net total dynamic connectedness through quantiles for Canada

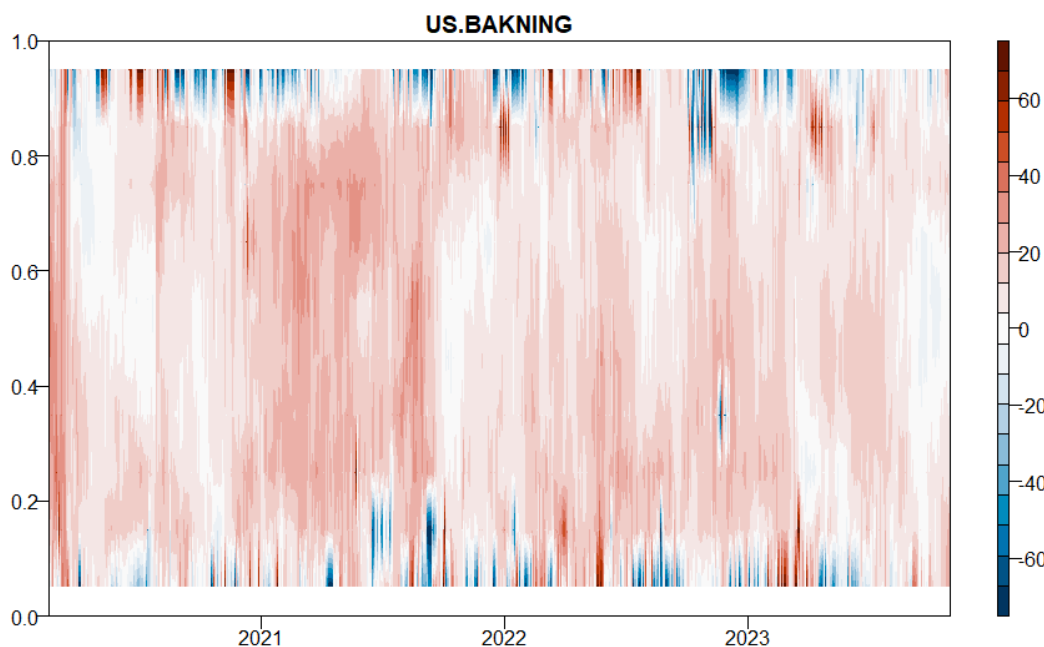


Figure 16. Net total dynamic connectedness through quantiles for Canada

4.5. Total and Net Connectedness using the time frequency connectedness approach

Analyzing through time-frequency connectedness offers a complete understanding of how interconnections evolve and fluctuate across varying time frames. This approach enables a nuanced examination of how market dynamics unfold over time, unveiling the intricate relationships and dependencies between different indices. By dissecting these connections across different frequencies or time intervals, we can identify patterns, trends, and shifts in interconnectedness. This detailed analysis sheds light on how shocks, events, or changes in one market reverberate across different time scales, providing invaluable insights into the evolving nature of financial linkages and their impacts.

Such an approach is more flexible than the initial connectedness approach proposed by Diebold and Yilmaz (2012, 2014). The frequency-connectedness analysis reveals a notable prominence of short-term dynamics over long-term trends in the financial markets. This observation underscores the market's sharp sensitivity to immediate events and temporary factors. The domination of short-term interconnectedness suggests that rapid adjustments to novel information and swift responses to short-lived market drivers play a significant role in shaping the behavior of the analyzed variables. This result has implications for risk management strategies, signaling the importance of adapting to the quick and pronounced fluctuations associated with short-term dynamics. Investors and other actors would find value in strategies that capitalize on short-term trends or

respond swiftly to market shifts, aligning their approaches with the observed prevalence of short-term interconnectedness.

In the connectivity literature, discovering the net transmission power of each series is significant and provides crucial insights for investors and risk managers. In particular, our analysis involves the decomposition of total net directional connectivity into short and long-term dynamics at a fixed quantile ($Q=0.5$ in our case), revealing essential information on the factors influencing the role of each series as a net transmitter or receiver of shocks. Notably, we observe that both short-term

and long-term dynamics play distinct roles in determining the heterogeneous nature of how a series acts as a net receiver or transmitter. What stands out significantly is the supremacy of short-term dynamics to explain the dynamic status of net reception or transmission. This highlights the importance of instantaneous market conditions and transient factors in inducing directional connectivity of the studied series. This nuanced understanding provides investors and risk managers with a valuable framework to anticipate and navigate the complexities of market dynamics across different time horizons.

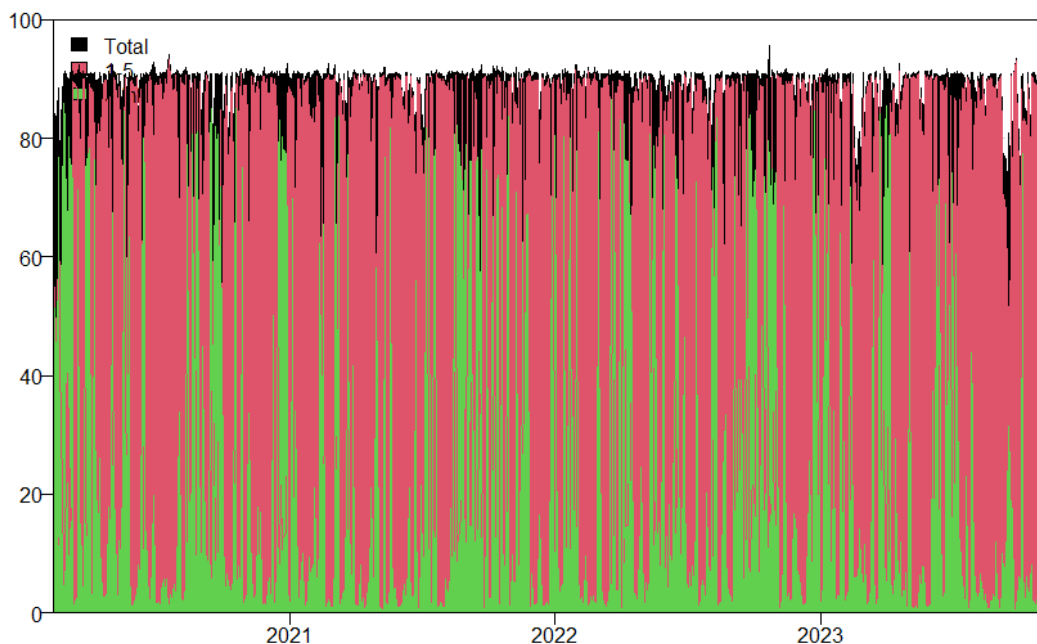


Figure 17. Dynamic total connectedness

Notes: Results are based on a QVAR model with a 100 days rolling-window size, a lag length of order one (BIC), and a 20-step-ahead generalized forecast error variance decomposition. The black area represents the time dynamic connectedness values while the green and blue areas demonstrate the long and short-term results. The corresponding lines illustrate the results of the standard VAR time and frequency domain connectedness approach.

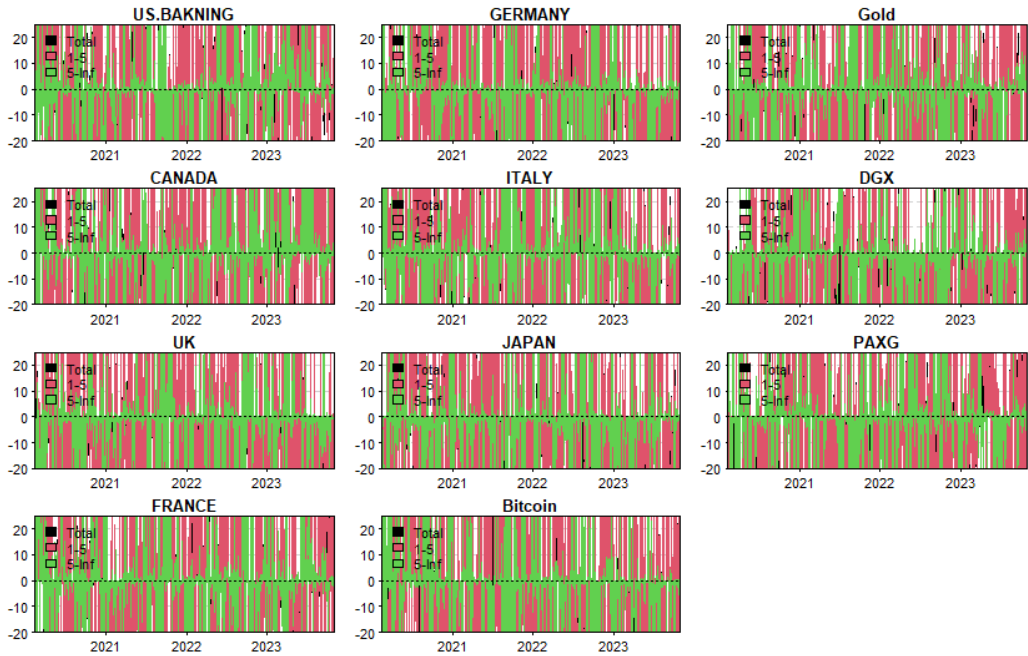


Figure 18. Dynamic net total connectedness



Figure 19. Dynamic net pairwise connectedness

5. Discussion

Our study reveals significant variations in the connectedness indices within the cryptocurrency market, indicating diverse influence dynamics among different digital assets. The FROM connectedness values exhibit a range of 58.81 percentage points, fluctuating between 19.46% (DGX) and 74.05% (France). Similarly, the TO connectedness values range from 12.95% (DGX) to 94.97% (France), showcasing substantial variation. Notably, the banking indices of France and Germany exhibit the highest pairwise connectedness, indicating their strong interconnectedness.

The NET values, which provide a net measure of each asset's connectedness, highlight that the USA, France, Germany, Canada, Italy, and England are primary shock contributors to the network's total connectedness. Conversely, Japan, Bitcoin, Gold, PAXG, and DGX are the main net receivers of shocks from other indices. These findings underscore the presence of distinct and influential linkages among the banking sectors of the G7 economies, gold, and cryptocurrencies.

The evolution of the Total Connectedness Index (TCI) over the sample period reveals four distinct peaks in the cryptocurrency market. The first substantial peak occurred in the first half of 2020, coinciding with the onset of the COVID-19 pandemic. A significant increase followed in late 2021, and another peak was observed at the beginning of 2022, aligning with the commencement of the Russian-Ukrainian military conflict. The fourth peak, occurring in Q2 and Q3 of 2023, underscores the Silicon Valley Bank collapse that directly influenced cryptocurrency prices.

Figure 3 illustrates the net total directional connectedness for each studied index.

Positive values indicate that an asset is a shock transmitter within the network, while negative values indicate it is a shock receiver. The analysis shows several significant peaks at various points in time, suggesting notable changes in network dynamics. The USA, France, Germany, and Italy banking markets consistently emerge as stable sources of network information transmission, while the gold-backed DGX, Bitcoin, and the Japan banking index consistently appear as stable network information receivers. Various indices, such as those of Canada, the UK, PAXG, and gold, demonstrate varying patterns in net spillovers over the study period, switching between being net shock transmitters and net shock receivers at different points in time.

The network graph in Figure 4 demonstrates the pairwise directional connection between the eleven variables in the network, providing a comprehensive view of their interconnections and relationships. Conventional assets, specifically the G7 banking sector indices excluding the Japan index, are the main drivers of fluctuations across various assets in the system. The high connection between these assets is evident in our findings and has been documented in numerous previous studies. The US Banking index emerges as a pivotal shock transmitter, significantly connecting with the Japan index, highlighting the global economic interdependence and financial market integrations between the two countries. Other significant interconnections among all G7 indices and Japan indicate a complex web of financial relationships.

Bitcoin is identified as a net receiver from the US Banking asset, a result explained by its role as a sought-after alternative investment during times of economic uncertainty. PAXG, DGX, and Gold stand out as major receivers of shocks from the network but have no

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pairwise connections with any of the studied indices. Interestingly, gold and gold-backed cryptocurrencies appear to be the least receivers from the network, suggesting their potential role as more stable assets and hedges in times of market turbulence.

The quantile connectedness approach, depicted in Figure 6-16, provides further insights into market dynamics. The heat map generated using a 100-day moving window and a 20-day forecast using the QVAR model reveals that dynamic shocks from both significantly positive and negatively shifted assets demonstrate strong interconnections over the entire study period. The connectivity exhibits a symmetrical pattern, with fluctuations in the 50% quantile presenting a cyclical pattern. The fallout was particularly intensified in the first half of 2020, coinciding with the spread of the COVID-19 epidemic. In late 2022 and early 2023, a high degree of linkage is observed, corresponding to a period of global economic recovery and renewed investor confidence. Another episode of strong connectivity is noted in mid-2023, corresponding to heightened geopolitical tensions and uncertainties due to the Silicon Valley Bank collapse.

The quantile net directional spillovers highlight how investors react to diverse market conditions. PAXG is a weak net receiver during 2020 across almost all quantiles but turns out to be a net transmitter of shocks during specific periods. The Bitcoin's role shifts between a net receiver and a net transmitter during extreme quantiles. During COVID-19, Bitcoin's interaction with other markets is limited, except in mid-2020, where it shifts between weak net reception and transmission of shocks. Bitcoin exhibits low reception to the system in the middle quantiles, acting as a net receiver on average. Notably, Bitcoin

becomes a strong net contributor in mid-2021 and early 2023 in the lower quantile, likely due to increased investor confidence and adoption of Bitcoin as a risk-on asset during these periods.

DGX exhibits a net reception effect during almost the entire studied period, with significant transmission function in the upper and lower quantiles around 2021. Gold generally acts as a weak recipient of shocks, with some episodes of shock transmission, particularly from 2021 to mid-2023.

The G7 banking sector indices, except for the Japanese index, consistently act as net transmitters within the network. The French index is the strongest transmitter during 2020, and the US Banking index during 2021. There are periods of almost no interaction for the German index in mid-2021 and for the Canadian index in the first half of 2022. The UK index shifts to a weak net receiver at the end of 2022 and the beginning of 2023, while the Canadian index becomes a net receiver at the end of 2021 and the beginning of 2022, temporarily losing interactions with other markets at the beginning of 2023.

The Japanese index shows a net receiving function at the median quantile, with stronger reception in mid-2022 and mid-2023, coinciding with periods of increased economic stability and positive market sentiment. During extreme market conditions, the Japanese index swings between being a net receiver and a net transmitter, reflecting the dynamic responsiveness to changing market scenarios.

Time-frequency connectedness analysis reveals the prominence of short-term dynamics over long-term trends in financial markets, emphasizing the market's sensitivity to immediate events and temporary factors. This dominance suggests that rapid adjustments to new information and swift

responses to short-lived market drivers play a significant role in shaping the behavior of the analyzed variables. The decomposition of total net directional connectivity into short and long-term dynamics highlights the importance of instantaneous market conditions in determining whether a series acts as a net receiver or transmitter. This nuanced understanding provides investors and risk managers with a valuable framework to anticipate and navigate the complexities of market dynamics across different time horizons.

6. Conclusion

This study enhances existing literature on Bitcoin, gold-backed cryptocurrencies, gold, and G7 banking sector indices by exploring the time-varying connectedness among these market blocks. Specifically, it focuses on conventional cryptocurrencies (Bitcoin), gold-backed currencies (PAXG and DGX), Gold, and G7 indices (USA, Germany, Canada, France, UK, Italy, and Japan). The objective is to comprehend dynamic linkages through diverse market scenarios and identify potential hedging opportunities by combining two methodologies: Quantile Vector Autoregression (QVAR) and Temporal-Frequency Connectivity.

Our findings delve into the total dynamic connectedness within the cryptocurrency market, revealing a nuanced landscape of influence dynamics among digital assets. The analysis of FROM and TO connectedness values highlights a substantial range, with France and Germany's banking indices emerging as the most connected markets. NET values underscore specific assets' roles as shock contributors or receivers, emphasizing interconnectedness among G7 economies' banking sectors, gold, and cryptocurrencies.

The evolution of the Total Connectedness Index (TCI) unveils four distinct peaks coinciding with significant global events, indicating the market's sensitivity to external shocks and complex relationships between assets. Analysis of net total and pairwise directional connectedness elucidates the intricate web of financial relationships. G7 banking sector indices, particularly the USA, France, Germany, and Italy, emerge as stable sources of network information transmission. Bitcoin, PAXG, DGX, and Gold stand out as major net receivers of shocks, reflecting their hedging roles during economic uncertainties and market turbulence.

Using a time-quantile space approach, our results provide insights into the market's dynamic connectivity and net directional spillovers, suggesting a robust interconnection between positively and negatively shifted assets. Notable behaviors of individual assets, such as Bitcoin's role as a risk-on asset and Gold's stability during market turbulence, enrich our understanding.

The time-frequency connectedness analysis comprehensively examines interconnectedness across varying time frames, emphasizing the market's sensitivity to immediate events and the need for adaptive risk management strategies. The decomposition of net directional connectivity into short and long-term dynamics offers valuable insights for investors and risk managers, providing a nuanced understanding of market dynamics across different time horizons.

In essence, our findings contribute to a deeper understanding of the cryptocurrency market's dynamic connectedness, offering valuable insights for investors, risk managers, and policymakers navigating this evolving financial landscape. The complex and evolving nature of financial linkages

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highlighted underscores the importance of adaptability and a nuanced understanding of interconnectedness for effective risk management and decision-making.

Despite its comprehensive analysis, this study has several limitations. Firstly, the study period, though extensive, might not capture all possible market scenarios and their impacts on connectedness. Secondly, the reliance on specific methodologies like QVAR and Temporal-Frequency Connectivity may limit the scope of analysis to certain types of relationships and dynamics, potentially overlooking other significant aspects. Thirdly, the study focuses on a select group of assets and indices, which may not fully represent the broader market. Additionally, external factors such as regulatory changes, technological advancements, and macroeconomic shifts were not explicitly accounted for, which could influence the market dynamics in unpredictable ways.

Future research could address these limitations by extending the analysis to a broader range of assets and including more diverse market scenarios. Incorporating additional methodologies could provide a more comprehensive understanding of market dynamics. Furthermore, exploring the impact of external factors such as regulatory changes, technological advancements, and macroeconomic shifts on connectedness could offer deeper insights. Longitudinal studies capturing longer time periods and more global events would also enhance the robustness of the findings. Additionally, investigating the role of emerging cryptocurrencies and new financial instruments in market connectedness would be valuable, given the rapidly evolving nature of the financial landscape.

References

- Ando, T., Greenwood-Nimmo, M., and Shin, Y. (2018) Quantile Connectedness: Modelling Tail Behaviour in the Topology of Financial Networks. *Management Science*, 68(4), 2401-2431. <https://doi.org/10.1287/mnsc.2021.3984>.
- Ahadiat, A., & Kesumah, F.S.D. (2021). Risk Measurement and Stock Prices during the COVID-19 Pandemic: An Empirical Study of State-Owned Banks in Indonesia. *The Journal of Asian Finance, Economics and Business*, 8(6), 819-828. <https://doi.org/10.13106/JAFEB.2021.VOL8.NO6.0819>.
- Aloui, C., Hamida, H.B., & Yarovaya, L. (2021). Are Islamic gold-backed cryptocurrencies different?. *Finance Research Letters*, 39, 101615. <https://doi.org/10.1016/j.frl.2020.101615>.
- Agyei, S. K., Owusu Junior, P., Bossman, A., Asafo-Adjei, E., Asiamah, O., & Adam, A. M. (2022). Spillovers and contagion between BRIC and G7 markets: New evidence from time-frequency analysis. *PLoS One*, 17(7), e0271088.
- Azmi, W., Anwer, Z., Azmi, S.N., & Nobanee, H. (2023). How did major global asset classes respond to Silicon Valley Bank failure?. *Finance Research Letters*, 56, 104123. <https://doi.org/10.1016/j.frl.2023.104123>.
- Al-Nassar, N. S., Boubaker, S., Chaibi, A., & Makram, B. (2023). In search of hedges and safe havens during the COVID-19 pandemic: Gold versus Bitcoin, oil, and oil uncertainty. *The Quarterly Review of Economics and Finance*, 90, 318-332. <https://doi.org/10.1016/j.qref.2022.10.010>.
- Appiah-Otoo, I. (2023). The Impact of the Russia-Ukraine War on the Cryptocurrency

- Market. *Asian Economics Letters*, 4(1). <https://doi.org/10.46557/001c.53110>.
- Aharon, D.Y., Ali, S., & Naved, M. (2023). Too big to fail: The aftermath of Silicon Valley Bank (SVB) collapse and its impact on financial markets. *Research in International Business and Finance*, 66, 102036. <https://doi.org/10.1016/j.ribaf.2023.102036>.
- Abdelmalek, W., & Benlagha, N. (2023). On the safe-haven and hedging properties of Bitcoin: new evidence from COVID-19 pandemic. *Journal of Risk Finance*, 24(2), 145-168. <https://doi.org/10.1108/JRF-06-2022-0153>.
- Baur, D.G., & Lucey, B.M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *The Financial Review*, 45 (2), 217–229. <https://doi.org/10.1111/j.1540-6288.2010.00244.x>.
- Baur, D.G., & McDermott, T.K. (2010). Is gold a safe-haven? International evidence. *Journal of Banking & Finance*, 34, 1886–1898. <https://doi.org/10.1016/j.jbankfin.2009.12.008>.
- Baruník, J., Křehlík, T., & Vacha, L. (2016). Modeling and forecasting exchange rate volatility in time-frequency domain. *European Journal of Operational Research*, 251(1), 329-340. <https://doi.org/10.1016/j.ejor.2015.12.010>.
- Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, 16(2), 271-296. <https://doi.org/10.1093/jfinec/nby001>.
- Baur, D.G., & Hoang, L.T., (2020). A crypto safe haven against Bitcoin. *Finance Research Letters*, 101431. <https://doi.org/10.1016/j.frl.2020.101431>.
- Bouri, E., Shahzad, S.J.H., & Roubaud, D. (2020). Cryptocurrencies as hedges and safe-havens for US equity sectors. *The Quarterly Review of Economics and Finance*, 75, 194-307. <https://doi.org/10.1016/j.qref.2019.05.001>.
- Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The Unprecedented Stock Market Reaction to COVID-19. *The Review of Asset Pricing Studies*, 10(4), 742-758. <https://doi.org/10.1093/rapstu/raaa008>.
- Bank for International Settlements (BIS). (2022). Japan. Retrieved from https://www.bis.org/mc/currency_areas/jp.htm.
- Boungou, W., & Yatié, A. (2022). The impact of the Ukraine-Russia war on world stock market returns. *Economics Letters*, 215(C). <https://doi.org/10.1016/j.econlet.2022.110516>.
- Boubaker, S., Nguyen, N., Trinh, V.Q. & Vu, T. (2023). Market reaction to the Russian Ukrainian war: a global analysis of the banking industry. *Review of Accounting and Finance*, 22 (1), 123-153. <https://doi.org/10.1108/RAF-10-2022-0294>.
- Béjaoui, A., Frikha, W., Jeribi, A., Bariviera, A.F. (2023). Connectedness between emerging stock markets, gold, cryptocurrencies, DeFi and NFT: Some new evidence from wavelet analysis. *Physica A: Statistical Mechanics and its Applications*, 619, 128720. <https://doi.org/10.1016/j.physa.2023.128720>.
- Belguith, R., Manzli, Y. S., Bejaoui, A., & Jeribi, A. (2024). Can gold-backed cryptocurrencies have dynamic hedging and safe-haven abilities against DeFi and NFT assets?. *Digital Business*, 4(2), 100077. <https://doi.org/10.1016/j.digbus.2024.100077>.
- Corbet, S., (Greg) Hou, Y., Hu, Y., Larkin, C., & Oxley, L. (2020). Any port in a storm:

Articles

- Cryptocurrency safe-havens during the COVID-19 pandemic. *Economics Letters*, 194, 109377.
- Diebold, F.X., and Yilmaz, K. (2012). Better to give than to receive: predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28, 57-66. <https://doi.org/10.1016/j.ijforecast.2011.02.006>.
- Diebold, F.X., and Yilmaz, K. (2014). On the network topology of variance decompositions: measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1) 119-134. <https://doi.org/10.1016/j.jeconom.2014.04.012>.
- Demirgüç-Kunt, A., Pedraza, A., & Ruiz-Ortega, C. (2021). Banking sector performance during the COVID-19 crisis. *Journal of Banking & Finance* 133, 106305. <https://doi.org/10.1016/j.jbankfin.2021.106305>.
- Díaz, A., Esparcia, C., & Huélamo, D. (2023). Stablecoins as a tool to mitigate the downside risk of cryptocurrency portfolios. *The North American Journal of Economics and Finance*, 64, 101838. <https://doi.org/10.1016/j.najef.2022.101838>.
- Elnahass, M., Trinh, V.Q., & Li, T. (2021). Global banking stability in the shadow of Covid-19 outbreak. *Journal of International Financial Markets, Institutions and Money*, 72, 101322. <https://doi.org/10.1016/j.intfin.2021.101322>.
- Fakhfekh, M., Manzli, Y.S., Béjaoui, A., & Jeribi, A. (2023). Can Cryptocurrencies be a Safe Haven During the 2022 Ukraine Crisis? Implications for G7 Investors. *Global Business Review*, 25(4), 1007–1030. <https://doi.org/10.1177/09721509231164808>.
- Fakhfekh, M., Bejaoui, A., Bariviera, A. F., & Jeribi, A. (2024). Dependence structure between NFT, DeFi and cryptocurrencies in turbulent times: An Archimax copula approach. *The North American Journal of Economics and Finance*, 70, 102079. <https://doi.org/10.1016/j.najef.2024.102079>
- Guesmi, K., Saadi, S., Abid, I., & Ftit, Z. (2019). Portfolio diversification with virtualcurrency: Evidence from Bitcoin. *International Review of Financial Analysis*, 63,431–437. <https://doi.org/10.1016/j.irfa.2018.03.004>.
- Giudici, G., Milne, A., & Vinogradov, D. (2020). Cryptocurrencies: market analysis and perspectives. *Journal of Industrial and Business Economics*, 47, 1–18. <https://doi.org/10.1007/s40812-019-00138-6>.
- Ghorbel, A., Frikha, W., & Snene-Manzli, Y. (2022). Testing for asymmetric non-linear short- and long-run relationships between crypto-currencies and stock markets. *Eurasian Economic Review*, 12, 387-425. <https://doi.org/10.1007/s40822-022-00206-8>.
- Galati, L., and Capalbo, F. (2023). Silicon Valley Bank Bankruptcy and Stablecoins Stability. Available at SSRN: <https://ssrn.com/abstract=4488220> or <http://dx.doi.org/10.2139/ssrn.4488220>.
- Gökgöz, H., Afjal, M., Bejaoui, A., & Jeribi, A. (2024). Comparative Analysis of Gold, Bitcoin and Gold-backed Cryptocurrencies as Safe Havens During Global Crises: A Focus on G7 Stock Market and Banking Sector Indices. *Global Business Review*, 26(1), 193–218. <https://doi.org/10.1177/09721509241251547>
- Hai Le, T., Do, H.X., Nguyen, D.K., and Sensoy, A. (2021). Covid-19 pandemic and tail-dependency networks of financial assets. *Finance Research Letters*, 38, 101800. <https://doi.org/10.1016/j.frl.2020.101800>.

- Jeribi, A., Chamsa, D., & Snene-Manzli, Y. (2020). Emerging stock markets' reaction to COVID-19: Can cryptocurrencies be a safe haven? *Journal of Management and Economic Studies*, 2(3), 152–165. <https://doi.org/10.26677/TR1010.2020.619>.
- Jeribi, A., & Snene-Manzli, Y. (2020). Can cryptocurrencies be a safe haven during the novel COVID-19 pandemic? Evidence from the Tunisian Stock Market. *Journal of Research in Emerging Markets*, 3(1), 14–31. <https://doi.org/10.30585/jrems.v3i1.555>.
- Koop, G., Pesaran, M.H. and Potter, S. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74, 119–147. [https://doi.org/10.1016/0304-4076\(95\)01753-4](https://doi.org/10.1016/0304-4076(95)01753-4).
- Kim, S., & In, F. (2007). On the relationship between changes in stock prices and bond yields in the G7 countries: Wavelet analysis. *Journal of International Financial Markets, Institutions and Money*, 17(2), 167–179. <https://doi.org/10.1016/j.intfin.2005.10.004>.
- Kirkulak Uludag, B., & Khurshid, M. (2019). Volatility spillover from the Chinese stock market to E7 and G7 stock markets. *Journal of Economic Studies*, 46(1), 90–105. <https://doi.org/10.1108/JES-01-2017-0014>.
- Kanamura, T. (2023). A difference in COVID-19 impact on bank stocks between Japan and the US. *SN Business & Economics*, 3, 131. <https://doi.org/10.1007/s43546-023-00485-6>.
- Kang, S.H., Hernandez, J.A., Rehman, M.U., Shahzad, S.J.H., & Yoon, S.M. (2023). Spillovers and hedging between US equity sectors and gold, oil, islamic stocks and implied volatilities. *Resources Policy*, 81, 103286. <https://doi.org/10.1016/j.resourpol.2022.103286>.
- Kayral, I.E., Jeribi, A., and Loukil, S. (2023). Are Bitcoin and Gold a Safe Haven during COVID-19 and the 2022 Russia–Ukraine War? *Journal of Risk and Financial Management* 16(5), 222. <https://doi.org/10.3390/jrfm16040222>.
- Matos, P., Costa, A., & da Silva, C. (2021). On the risk-based contagion of G7 banking system and the COVID-19 pandemic. *Global Business Review*. 09721509211026813. <https://doi.org/10.1177/09721509211026813>.
- Manda, V. K. (2023). The Collapse of Silicon Valley Bank. *MAR-Ekonomi: Jurnal Manajemen, Akuntansi Dan Rumpun Ilmu Ekonomi*, 2(1), 59–70. Retrieved from <https://jurnal.seaninstitute.or.id/index.php/marekonomi/article/view/232>.
- Maouchi, Y., Fakhfekh, M., Charfeddine, L., & Jeribi, A. (2024). Is digital gold a hedge, safe haven, or diversifier? An analysis of cryptocurrencies, DeFi tokens, and NFTs. *Applied Economics*. <https://doi.org/10.1080/00036846.2023.2299217>.
- Oosterlinck, K., Reyns, A., Szafarz, A. (2022). Gold, Bitcoin, and portfolio diversification: lessons from the Ukrainian war. Solvay Brussels School, Economics & Management. Available at SSRN: <https://ssrn.com/abstract=4354876> or <http://dx.doi.org/10.2139/ssrn.4354876>.
- Pesaran, M.H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58, 17–29. [https://doi.org/10.1016/S0165-1765\(97\)00214-0](https://doi.org/10.1016/S0165-1765(97)00214-0).
- Pandey, D.K., Hassan, M.K., Kumari, V., and Hasan, R. (2023). Repercussions of the Silicon Valley Bank collapse on global

- stock markets. *Finance Research Letters*, 55(B), 104013. <https://doi.org/10.1016/j.frl.2023.104013>.
- Stiassny, A. (1996). Spectral representation for variance decompositions and connectedness measures. In *Proceedings of the 1996 Conference on General Systems Theory* (pp. 361-371).
- Shahzad, S.J.H., Bouri, E., Roubaud, D., & Kristoufek, L. (2020). Safe haven, hedge, and diversification for G7 stock markets: Gold versus Bitcoin. *Economic Modelling*, 87, 212–224. <https://doi.org/10.1016/j.econmod.2019.07.023>.
- Snene Manzli, Y., & Jeribi, A. (2024a). Shelter in Uncertainty: Evaluating Gold and Bitcoin as Safe Havens Against G7 Stock Market Indices During Global Crises. *Scientific Annals of Economics and Business*, 71(EB), 2024, 1-xx. <https://doi.org/10.47743/saeb-2024-0011>.
- Snene Manzli, Y., & Jeribi, A. (2024b). Connectedness Between Gold-Backed Cryptocurrencies and the G7 Stock Market Indices During Global Crises: Evidence From the Quantile Vector Autoregression Approach. *Journal of Alternative Finance*, 1(2), 131-157. <https://doi.org/10.1177/27533743241259496>.
- Snene Manzli, Y. and Jeribi, A. (2024c). Assessing Bitcoin, gold and gold-backed cryptocurrencies as safe havens for energy and agricultural commodities: insights from COVID-19, Russia–Ukraine conflict and SVB collapse. *Journal of Financial Economic Policy*, Advance online publication. <https://doi.org/10.1108/JFEP-12-2023-0386>.
- Triki, M. B., & Maatoug, A. B. (2021). The GOLD market as a safe haven against the stock market uncertainty: Evidence from geopolitical risk. *Resources Policy*, 70, 101872. <https://doi.org/10.1016/j.resourpol.2020.101872>.
- Tut, D. (2022). Bitcoin: Future or Fad? MPRA Working Paper, 112376.
- Wang, G.J., Ma, X.Y., & Wu, H.Y. (2020). Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests? *Research in International Business and Finance*, 54, 101225. <https://doi.org/10.1016/j.ribaf.2020.101225>.
- Xie, Y., Kang, S. B., & Zhao, J. (2021). Are stablecoins safe havens for traditional cryptocurrencies? An empirical study during the COVID-19 pandemic. *Applied Finance Letters*, 10, 2-9. <https://doi.org/10.24135/afl.v10i.342>.
- Yarovaya, L., Mirza, N., Abaidi, J., & Hasnaoui, A. (2020). Human Capital efficiency and equity funds' performance during the COVID-19 pandemic. *International Review of Economics & Finance*, 71, 584–591. <https://doi.org/10.1016/j.iref.2020.09.017>.
- Yousaf, I., & Ali, S. (2021). Linkages between Stock and Cryptocurrency Markets during the COVID-19 Outbreak: an Intraday Analysis. *The Singapore Economic Review*. <https://doi.org/10.1142/S0217590821470019>.
- Yousaf, I., & Yarovaya, L. (2022). Spillovers between the Islamic gold-backed cryptocurrencies and equity markets during the COVID-19: A sectorial analysis. *Pacific-Basin Finance Journal*, 71, 101705, <https://doi.org/10.1016/j.pacfin.2021.101705>.
- Yousaf, I., Riaz, Y., & Goodell, J.W. (2023). The impact of the SVB collapse on global financial markets: Substantial but narrow. *Finance Research Letters*, 55(B), 103948. <https://doi.org/10.1016/j.frl.2023.103948>.

Table 3. Total connectedness through time frequencies

Total												
	US.BAKNING.Total	CANADA. Total	UK. Total	FRANCE. Total	GERMANY. Total	ITALY. Total	JAPAN. Total	Bitcoin. Total	Gold. Total	DGX. Total	PAXG. Total	FROM. Total
US.BAKNING	11.41	10.84	8.05	10.35	8.94	10.46	7.49	8.39	8.53	6.82	8.72	88.59
CANADA	10.08	12.16	8.18	10.47	8.97	10.47	7.54	8.26	8.57	6.70	8.60	87.84
UK	9.73	10.56	9.79	10.73	9.12	10.52	7.65	8.11	8.40	6.74	8.66	90.21
FRANCE	9.48	10.43	8.43	11.94	9.31	10.91	7.63	8.25	8.42	6.66	8.55	88.06
GERMANY	9.67	10.25	8.33	10.77	10.61	10.76	7.75	8.17	8.38	6.76	8.55	89.39
ITALY	9.56	10.37	8.18	10.81	9.10	12.11	7.72	8.27	8.46	6.75	8.66	87.89
JAPAN	9.97	10.43	8.23	10.20	8.74	10.41	9.61	8.33	8.54	6.87	8.67	90.39
Bitcoin	9.61	10.28	8.16	10.11	8.71	10.31	7.64	10.97	8.66	6.79	8.76	89.03
Gold	9.51	10.30	8.00	10.36	8.92	10.36	7.73	8.33	10.35	6.71	9.43	89.65
DGX	9.38	10.10	7.95	9.85	8.54	10.05	7.55	8.42	8.45	11.21	8.50	88.79
PAXG	9.55	10.33	8.13	10.24	8.82	10.24	7.58	8.53	9.30	6.74	10.54	89.46
T0	96.53	103.89	81.65	103.89	89.18	104.47	76.29	83.04	85.70	67.54	87.11	979.29
Inc.Own	107.94	116.05	91.44	115.83	99.79	116.58	85.91	94.02	96.05	78.75	97.65	cTOI/TCI
Net	7.94	16.05	-8.56	15.83	-0.21	16.58	-14.09	-5.98	-3.95	-21.25	-2.35	97.93/89.03
NPDC	7.00	8.00	3.00	9.00	6.00	10.00	1.00	2.00	4.00	0.00	5.00	

Short term frequency												
	US.BAKNING. 1-5	CANADA. 1-5	UK.1-5	FRANCE. 1-5	GERMANY. 1-5	ITALY. 1-5	JAPAN. 1-5	Bitcoin. 1-5	Gold. 1-5	DGX. 1-5	PAXG. 1-5	FROM. 1-5
US.BAKNING	9.59	8.63	6.48	8.30	7.25	8.24	6.07	6.76	6.77	5.68	7.03	71.21
CANADA	8.32	9.50	6.46	8.34	7.13	8.15	5.97	6.64	6.74	5.52	6.85	70.12
UK	8.16	8.42	7.97	8.69	7.43	8.32	6.22	6.60	6.68	5.63	6.95	73.09
FRANCE	7.85	8.19	6.71	9.51	7.45	8.48	6.09	6.59	6.63	5.47	6.81	70.27
GERMANY	8.04	8.10	6.69	8.57	8.56	8.45	6.26	6.55	6.59	5.63	6.81	71.70
ITALY	7.87	8.14	6.57	8.62	7.36	9.48	6.16	6.66	6.67	5.58	6.90	70.52
JAPAN	8.32	8.28	6.56	8.20	7.05	8.18	7.83	6.72	6.76	5.71	6.89	72.68
Bitcoin	7.98	8.13	6.49	8.04	7.03	8.14	6.10	8.88	6.85	5.60	6.95	71.32
Gold	7.97	8.22	6.34	8.34	7.23	8.16	6.17	6.72	8.23	5.57	7.46	72.18
DGX	7.95	8.24	6.46	8.06	6.98	8.02	6.18	6.97	6.80	9.60	6.90	72.56
PAXG	8.08	8.35	6.53	8.35	7.22	8.24	6.15	6.99	7.45	5.64	8.58	72.99
TO	80.55	82.70	65.30	83.51	72.13	82.38	61.36	67.20	67.94	56.02	69.56	788.65
Inc.Own	90.14	92.20	73.27	93.01	80.69	91.87	69.18	76.08	76.16	65.62	78.14	cTOI/TCI
Net	9.34	12.58	-7.79	13.23	0.44	11.86	-11.32	-4.12	-4.24	-16.53	-3.44	78.86/71.70
NPDC	7.00	8.00	2.00	10.00	6.00	9.00	1.00	4.00	4.00	0.00	4.00	

Long term frequency												
	US.BAKNING. 5-Inf	CANADA. 5-Inf	UK. 5-Inf	FRANCE. 5-Inf	GERMANY. 5-Inf	ITALY. 5-Inf	JAPAN. 5-Inf	Bitcoin. 5-Inf	Gold. 5-Inf	DGX. 5-Inf	PAXG. 5-Inf	FROM. 5-Inf
US.BAKNING	1.82	2.21	1.57	2.05	1.69	2.22	1.42	1.63	1.76	1.14	1.69	17.38
CANADA	1.75	2.66	1.72	2.13	1.84	2.31	1.57	1.62	1.84	1.18	1.75	17.72
UK	1.57	2.14	1.82	2.04	1.69	2.20	1.43	1.51	1.72	1.11	1.71	17.11
FRANCE	1.63	2.24	1.72	2.43	1.86	2.43	1.54	1.66	1.79	1.20	1.74	17.79
GERMANY	1.63	2.15	1.64	2.20	2.05	2.31	1.50	1.62	1.79	1.13	1.74	17.69
ITALY	1.69	2.23	1.60	2.19	1.74	2.63	1.57	1.61	1.79	1.18	1.76	17.36
JAPAN	1.65	2.16	1.66	2.00	1.68	2.22	1.79	1.61	1.78	1.16	1.77	17.70
Bitcoin	1.63	2.15	1.68	2.07	1.68	2.17	1.54	2.09	1.80	1.19	1.81	17.71
Gold	1.53	2.07	1.66	2.02	1.69	2.20	1.57	1.60	2.12	1.14	1.98	17.47
DGX	1.43	1.87	1.49	1.80	1.56	2.02	1.37	1.45	1.65	1.61	1.60	16.23
PAXG	1.48	1.97	1.60	1.89	1.59	2.00	1.44	1.54	1.85	1.10	1.96	16.47
TO	15.98	21.19	16.35	20.39	17.04	22.08	14.94	15.84	17.76	11.52	17.55	190.64
Inc.Own	17.80	23.84	18.17	22.82	19.10	24.71	16.72	17.93	19.89	13.13	19.51	cTO/TCI
Net	-1.40	3.47	-0.77	2.60	-0.65	4.72	-2.77	-1.87	0.29	-4.71	1.09	19.06/17.33
NPDC	3.00	9.00	3.00	8.00	5.00	10.00	1.00	3.00	6.00	0.00	7.00	