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Dynamic connectedness between cryptocurrencies and currencies: Analyzing the impact of CHF and JPY on bitcoin and Ethereum

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Abstract

This study provides a comprehensive analysis of the dynamic interconnectedness between traditional fiat currencies (CHF and JPY) and cryptocurrencies (Bitcoin and Ethereum) across three distinct periods: the pre-COVID-19, the COVID-19 pandemic, and the Russia-Ukraine conflict. Our methodology employs the Quantile Vector Autoregressive (QVAR) connectivity approach, beginning with the average median and progressively extending to various quantiles over time revealing both short-term and long-term dynamic connectedness. Our findings reveal that Bitcoin and Ethereum exhibit significant interconnectedness and predominantly act as net transmitters of volatility, especially in the short term. In contrast, CHF and JPY generally serve as shock absorbers, showing strong self-dependency and conditional safe-haven properties. Particularly, the Swiss Franc occasionally transmits volatility during extreme market conditions, highlighting its dynamic role. The implications of our study are crucial for investors and portfolio managers aiming to adjust dynamically their portfolios by actively monitoring market trends to modify their allocations between traditional safe-haven currencies and cryptocurrencies. Specifically, in times of increased volatility, managers should temporarily reduce exposure to cryptocurrencies and increase allocations in stable fiat currencies such as CHF and JPY. Conversely, during more stable periods, higher investments in cryptocurrencies could yield better returns. implementing a real-time volatility monitoring system can aid managers in making well-informed choices to optimize risk management strategies. Dynamic hedging is preferred over static approaches.

Keywords: Bitcoin, CHF, Connectedness, Ethereum, JPY, Quantiles.

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1. Introduction

The relationship between traditional fiat currencies and cryptocurrencies has garnered increasing academic and practical interest as the adoption of digital assets such as Bitcoin and Ethereum expands. Cryptocurrencies, which were initially perceived as disconnected from traditional financial markets, are now recognized for their high volatility and sensitivity to market sentiment and to broader macroeconomic factors, including foreign exchange rates. Among these, the Swiss Franc (CHF) and the Japanese Yen (JPY) are of particular interest due to their reputation as stable, safe-haven currencies during periods of global economic uncertainty. Investors often flock to these assets during economic distress. However, while there is substantial literature on the effects of principal currencies like USD and EUR on cryptocurrency price dynamics, far less attention has been given to how the CHF and JPY might influence as stable currencies, have not been explored in-depth in relation to Bitcoin and Ethereum [1, 2].This lack of focus leaves a critical gap in understanding how these stable, low-yield currencies might affect the prices and volatility of major cryptocurrencies. Given the increasing integration of cryptocurrencies into global financial systems, it is essential to understand the interactions between these two distinct types of financial assets, particularly under conditions of economic uncertainty or financial stress [3].

Existing studies have examined the role of macroeconomic variables like inflation, interest rates, and investor sentiment in shaping cryptocurrency prices [4]. However, the influence of currencies known for their stability, such as the CHF and JPY, remains underexplored. While cryptocurrencies are often hailed for their decentralization and independence from traditional financial markets, their increasing integration with global economies suggests that fluctuations in key currencies could influence cryptocurrency market behavior [5]. Moreover, studies often focus on correlations with high-volatility or reserve currencies (e.g., USD or EUR), neglecting how low-volatility currencies such as CHF and JPY might differently impact the risk and return dynamics of cryptocurrencies [6].

This paper finds to address this gap by investigating how the CHF and JPY exchange rates influence the value of Bitcoin and Ethereum. We aim to determine whether these stable currencies have a mitigating effect on cryptocurrency volatility during periods of economic stress, as well as how investors may perceive cryptocurrencies in relation to fiat currencies traditionally viewed as safe havens. By employing econometric models that account for both direct and indirect interactions between these currencies and cryptocurrencies, this study will provide a more nuanced understanding of how traditional and digital financial assets are interconnected. This research could offer valued insights for investors looking to diversify their portfolios and manage risk, particularly in volatile or uncertain market conditions.

The remainder of this research is structured as follows. Section 2 reviews the literature, while Section 3 presented the data used in our empirical analysis and the econometric methodology. Section 4 discusses empirical results. Finally, Section 5 concludes with a discussion of the implications of the finding.

2. Literature Review

The literature on Currencies and Cryptocurrencies has expanded considerably in recent years, indicating the growing interest in these assets. Currencies influence cryptocurrency prices indirectly, through market sentiment and volatility, as they play a pivotal role in implications for investment strategies, through their changes affecting investor sentiment toward cryptocurrencies. Recent studies deepen our understanding of the knotty relationship between traditional fiat currencies containing the Swiss Franc and Japanese Yen and cryptocurrencies, such as Bitcoin and Ethereum. Combining the traditional GARCH model with the machine learning approach, Peng, et al. [7] estimated the volatility of three cryptocurrencies and three currencies. Almansour and Inairat [8] studied the relationship between exchange rates for pairs of currencies and Bitcoin ‘s returns covering the period from 2014 to 2019. Results revealed a negative relationship between USD/JPY, USD/GBP, and USD/AUD and Bitcoin returns. Moreover, the changes in foreign currencies do not significantly influence Bitcoin returns. Andrada-Félix, et al. [9] applied both the framework developed by Diebold and Yılmaz [10] and the improved approach of Antonakakis and Gabauer [11] to investigate the interconnection between the main cryptocurrencies and traditional currencies from 2014 to 2018. They found that financial market variables are the main drivers of total connectedness within the traditional currencies and cryptocurrency-specific variables play a key role in determining total connectedness within the traditional currencies. In their study, Aharon, et al. [12] examined the connectedness between the major forex currencies, Bitcoin, and the components of the US yield curve. The findings found that Bitcoin is generally incompatible with shocks from any main currency and may not consistently provide the safe-haven benefits because of its erratic behavior. Similarly, Hsu, et al. [13] highlighted the significant co-volatility spillover effects between cryptocurrency and traditional currencies, especially during the COVID-19 epidemic. Moreover, Zhang, et al. [14] employing the quantile regression method, explored a considerable downside risk spillover effect between Bitcoin and traditional stock, commodity markets, currency and bond. They proposed that regulators should recompense close attention to the risk transmission of Bitcoin to indorse financial market stability. However, others’ research like Chemkha, et al. [15] highlighted the connection between cryptocurrencies and main fiat currencies. The authors deduced a low significant dependence is found between cryptocurrencies and the main conventional currencies. Memic, et al. [16] demonstrated the correlation between cryptocurrencies and various asset classes, containing web search results, commodities, currencies and equity indexes. The findings emphasize that there is strong evidence of EUR/CHF impact on Ethereum. By utilizing the quantile on quantile (QQ) regression method of Sim and Zhou [17] and Raza, et al. [18] investigated the connection among foreign exchange markets (CHF, CNY, EUR, GBP, RUB, YEN) and cryptocurrencies (Bitcoin, Litecoin, Ripple). These findings highlight the positive relationship between foreign exchange currencies and cryptocurrencies across all nine currencies, particularly Bitcoin, at minimal, high, and middle tail quantiles. In fact, using a Nonlinear Autoregressive Distributed Lag approach, Brathall [19] finds that the decline in Bitcoin and Ethereum resulted in volatility of THB/USD, THB/CNY, and THB/JPY, especially during the COVID-19 pandemic. This study highlights the asymmetric relationship between cryptocurrencies, such as Bitcoin, Ethereum, and Tether and three exchange rates in Thailand, before and during the Covid-19 outbreak. Mallick and Mallik [20] investigate the connection between Crypto-currencies (Bitcoin, Ethereum, Binance Coin, Litecoin) and Official Indian Currencies foreign exchange (USD, GBP, EURO, YEN) from 17 Decembre 2019 to 17 June 2021. The researchers concluded that Indian foreign exchange markets have little effect on cryptocurrency markets. Parrondo and Sala[21] explore the interconnectedness between traditional market indexes, cryptocurrencies, and DeFi assets during the post-COVID period. The findings emphasize the low level of interconnectedness between traditional and digital asset classes.

3. Data and Methodology

3.1. Data

The dataset spans from January 3, 2019, to February 7, 2025, and includes daily return data for four financial assets: JPY/USD (Japanese Yen to US Dollar exchange rate), CHF/USD (Swiss Franc to US Dollar exchange rate), Bitcoin, and Ethereum. These assets represent two major fiat currencies and two leading cryptocurrencies, providing a comprehensive view of both traditional and digital financial markets. The study aims to analyze and compare these assets' statistical properties over the given period, considering moments like mean, variance, skewness, and kurtosis, alongside tests for normality and autocorrelation. The average returns of Bitcoin and Ethereum stand at 0.002, reflecting their steady growth over the sample period. In contrast, JPY/USD and CHF/USD show almost zero mean returns, indicating that fiat currencies experienced relative stability. However, a stark difference emerges when examining variance. Cryptocurrencies, particularly Ethereum (0.003) and Bitcoin (0.002), exhibit significantly higher variance compared to the fiat currencies. JPY/USD and CHF/USD show negligible variances, underscoring their more stable price movements relative to the volatile nature of cryptocurrencies. The skewness values reveal a contrast between fiat currencies and cryptocurrencies. Bitcoin (-1.193) and Ethereum (-1.643) exhibit negative skewness, indicating a higher probability of large negative price movements during the sample period. Conversely, JPY/USD (0.405) and CHF/USD (0.315) show positive skewness, suggesting a tendency toward moderate gains rather than sharp declines. Moreover, all assets show excess kurtosis, with Bitcoin and Ethereum displaying extremely high values (16.804 and 18.194, respectively). This reflects the frequent occurrence of extreme price fluctuations in cryptocurrencies compared to the more moderate behavior of fiat currencies. The Jarque-Bera test confirms the non-normality of all assets, with cryptocurrencies showing particularly extreme deviations from normal distribution. Bitcoin and Ethereum exhibit significant JB statistics (18 939.535 and 22 476.190, respectively), underlining their frequent large price swings. In terms of stationarity, the Elliott-Rothenberg-Stock (ERS) test rejects the null hypothesis of a unit root for all assets, confirming their stationarity over the sample period. The Q-statistics at 20 lags indicate that autocorrelation is generally low for JPY/USD and CHF/USD, with only CHF/USD showing significant autocorrelation at the 20th lag. On the other hand, both Bitcoin and Ethereum exhibit significant autocorrelation, reinforcing their dynamic price movements and heightened volatility over the sample period.

In summary, the descriptive statistics provide valuable insights into the stark contrasts between fiat currencies and cryptocurrencies in terms of stability, skewness, and volatility, with the latter showing greater susceptibility to extreme price shifts and more complex distribution patterns.

Table1.
Descriptive statistics.

	Bitcoin	**Ethereum**	**JPY.USD**	**CHF.USD**
Mean	0.002*	0.002	0.000	0.000
Variance	0.002	0.003	0	0
Skewness	-1.193***	-1.643***	0.405***	0.315***
Ex.Kurtosis	16.804***	18.194***	5.615***	2.279***
JB	18939.535***	22476.190***	2116.229***	367.509***
ERS	-9.976	-7.803	-3.527	-8.790
Q(20)	20.467**	16.389*	10.347	20.033**
Q2(20)	23.372***	18.160**	237.230***	85.146***
Kendall	Bitcoin	Ethereum	JPY.USD	CHF.USD
Bitcoin	1.000***	0.589***	0.038**	0.066***
Ethereum	0.589***	1.000***	0.030	0.055***
JPY.USD	0.038**	0.030	1.000***	0.374***
CHF.USD	0.066***	0.055***	0.374***	1.000***

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

3.2. Methodology

To efficiently capture the spillover mechanism within a wide range of financial market contexts, we chose to apply the novel time-frequency connectedness method to control for the propagation mechanisms, as estimated via a frequency modeling framework. Recently applied by Ando, et al. [22] the time-frequency connectedness methodology was initially developed by Chatziantoniou, et al. [23]. In the context of our study, we began by presenting the overall connectedness measure by constructing a vector autoregression (VAR(p)) model, in the following form:

$$\mathrm{x}_t = \Phi_1 \mathrm{x}_{t-1} + \Phi_2 \mathrm{x}_{t-2} + \cdots + \Phi_p \mathrm{x}_{t-p} + u_t \quad (1)$$

Where: $\boldsymbol{x}_t$ and $\boldsymbol{x}_{t-j}$ are vectors that stand for endogenous variables, of dimensions $N \times 1$. The parameter p stands for the QVAR model lag length. $\boldsymbol{\Phi j}$ (τ) is an $N \times N$ QVAR coefficients' dimensional matrix, and (τ) designates an $N \times 1$ dimensional error vector, with an $N \times N$ dimensional error variance–covariance matrix.

Next, to calculate the forward M-step Generalized Forecast Error Variance Decomposition (GFEVD), we undertook to transform Eq. (1) into the form of VMA (∞) through the implementation of Wold's theorem, as depicted in Equation 2 below:

$$\mathrm{x}_t = \mu + \sum_{j=1}^{p} \Phi_j \,\mathrm{x}_{t-j} + u_t = \mu + \sum_{i=0}^{\infty} \Psi_i \, u_{t-i} \qquad (2)$$

We then proceed to compute the generalized forecast-error variance decomposition (GFEVD) for a forecast horizon H, as a critical part of the connectedness approach [24, 25]. This refers to the effect of series j on variable i concerning the forecast error variances, as follows:

$$\tilde{\tilde{\theta}}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{k=1}^{N} \theta_{ij}(H)} \qquad (3)$$

Since the rows of θ_{ij} (H) were not summed up to one, we had to normalize them by the row sum, which culminated in $\tilde{\tilde{\theta}}_{ij}$. Through the normalization process, the row sum turned out to be equal to one, thereby representing how a shock in series i affects not only the series itself but also the entirety of the other series. Thus, the following identities were reached.

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

Hence, all connection measures could be calculated. Initially, we proceed with determining the net pairwise connectivity, as follows:

$$NPDC_{ij}(\mathrm{H}) = \tilde{\theta}_{ij}(\mathrm{H}) - \tilde{\theta}_{ji}(\mathrm{H}) \qquad (4)$$

If $NPDC_{ij}(\mathrm{H}) > 0$ $(NPDC_{ij}(\mathrm{H}) < 0)$, then series j demonstrates a higher (lower) influence on series i than the other way around.

Thus, the overall trend of connectedness, in regard to others, highlights the extent to which an impact in series i could affect the entirety of the other series j.

$$TO_i(H) = \sum_{i=1, i\neq j}^{N} \tilde{\tilde{\theta}}_{ji}(\mathrm{H}) \qquad (5)$$

Therefore, the total directional connectedness from the others helps quantify the degree of impact on series i resulting from shocks incurred by all the other series j:

$$FROM_i(\mathrm{H}) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ij}(\mathrm{H}) \qquad (6)$$

Hence, the general net total directional connectedness enables us to estimate the difference between the total directional connectedness directed towards others and that emanating from others. Such a discrepancy can be referred to as the net impact of series i on the predefined network, wherein:

$$NET_i(H) = TO_i(\mathrm{H}) - FROM_i(\mathrm{H}) \qquad (7)$$

If NETi> 0 (NETi< 0), then the series i tends to demonstrate a higher (lower) impact on the entirety of the other series j relative to the extent of impact it receives from them and is therefore considered a net transmitter (receiver) of shocks.

Thus, computing the total connectedness index (TCI) should enable us to estimate the overall degree of interconnectedness within the net. Accordingly, a higher TCI value should denote a persistence of increased market risk, while a lower value would imply the opposite, as follows:

$$TCI(H) = N^{-1}\sum_{i=1}^{N} TO_i(H) = N^{-1}\sum_{i=1}^{N} FROM_i(H) \qquad (8)$$

It is worth noting at this level that determining the temporal domain-associated connectedness entails estimating connectivity within the frequency domain through the implementation of Stiassny [26] spectral decomposition technique. To this end, we **initiate** by estimating the following frequency response function, $\boldsymbol{\Psi}$ $(e^{-i\omega})= \sum_{\mathrm{h}=0}^{\infty} e^{-iwh}\, \Psi_{\mathrm{h}}$, wherein, $i = \sqrt{-1}$ and ω denotes the frequency. We then proceed with determining the spectral density of x_t at a specific frequency ω, which could only be attained through the implementation of a Fourier transformation on the *QVMA (∞)*, as follows:

$$\boldsymbol{S}_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h})\, e^{-iwh} = \boldsymbol{\Psi}(e^{-i\omega h}) \textstyle\sum_t \boldsymbol{\Psi}'(e^{+i\omega h}) \qquad (9)$$

Similarly, since the frequency based Generalized Forecast Error Variance Decomposition (GFEVD) is merely the fusion of spectral density and GFEVD, then GFEVD could be normalized in the frequency domain in the same manner required for normalizing its time domain, such as:

$$\theta_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1}\left|\sum_{h=0}^{\infty}\left(\boldsymbol{\Psi}(\tau)(e^{-iwh})\Sigma(\tau)\right)_{ij}\right|^2}{\sum_{h=0}^{\infty}\left(\boldsymbol{\Psi}(e^{-iwh})\Sigma(\tau)\boldsymbol{\Psi}(\tau)(e^{iwh})\right)_{ii}} \qquad (10)$$

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

The expression $\tilde{\theta}ij$ (ω) refers to the i^{th} series spectrum fraction at a given frequency ω that can be attributed to an effect on the j^{th} series. This measure is widely recognized as an intra-frequency indicator. Thus, for connectedness across both of the short-term and long-term time frames to be effectively evaluated, and rather than focusing on a single frequency, we considered aggregating the entirety of frequencies within a specified range, denoted as: $d= (a, b)$: $a, b \in (-\pi, \pi)$, $a<b$, such as:

$$\tilde{\theta}_{ij}(\mathrm{d}) = \int_{\mathrm{a}}^{\mathrm{b}} \tilde{\theta}_{ij}(\mathrm{w})\mathrm{dw} \qquad (12)$$

In this way, we were able to calculate similar connectedness measurements as already stated and evaluate them following the same procedure. At this level, such measures came to be recognized as frequency connectedness measures, which enabled us to depict the transmission of impacts within specified frequency ranges (denoted d), similarly interpretable as:

$$NPDC_{ij}(d) = \tilde{\tilde{\theta}}_{ij}(d) - \tilde{\tilde{\theta}}_{ji}(d) \quad (13)$$

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

$$FROM_i(d) = \sum_{i=1, i \neq j}^{N} \tilde{\tilde{\theta}}_{ij}(d) \quad (15)$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \quad (16)$$

$$TCI(d) = N^{-1}\sum_{i=1}^{N} TO_i(d) = N^{-1}\sum_{i=1}^{N} FROM_i(d) \quad (17)$$

Throughout the scope of our study, two frequency bands have so far been defined to capture short and long-term dynamics. While the first band, $d1 = (\pi/5, \pi)$, helps in covering a one-to-five-day time span, the second band, $d2 = (0, \pi/5]$, encloses timeframes ranging from six days to an infinite horizon. Hence, $NPDC_{ij}(d1)$, $TO_i(d1)$, $FROM_i(d1)$, $NET_i(d1)$, and $TCI(d1)$ were designed to stand respectively for 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 indexes. As regards $NPDC_{ij}(d2)$, $TO_i(d2)$, $FROM_i(d2)$, $NET_i(d2)$, and $TCI(d2)$, they respectively denote 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. Additionally, we considered establishing a relationship associating the frequency-domain measures advanced by Baruník and Křehlík [27] [27] and the time-domain measures put forward by Diebold and Yilmaz [28]; Diebold and Yilmaz [29] and Diebold and Yılmaz [10]. Hence:

$$NPDC_{ij}(H) =\cdot \sum_{d} NPDC_{ij}(d) \quad (18)$$

$$TO_i(H) = \sum_{d} (\mathrm{d}) \cdot TO_i(d) \quad (19)$$

$$FROM_i(d) = \sum_{d} (\mathrm{d}) \cdot FROM_i(d) \quad (20)$$

$$NET_i(H) = \sum_{d} (\mathrm{d}) \cdot NET_i(d) \quad (21)$$

$$TCI(H) = \sum_{d} (\mathrm{d}) \cdot TCI(d) \quad (22)$$

In other words, the total connectedness measures can be derived by aggregating the entirety of the frequency connectedness measures, computed using a specified quantile dubbed τ.2.

4. Results

4.1. Averaged Joint Connectedness Results

The values reflect in Table 2 the overall spillovers among the four assets: JPY/USD, CHF/USD, Bitcoin, and Ethereum. Both JPY/USD and CHF/USD demonstrate a strong self-dependency, with 73,76% and 73,79% of the total variance, respectively, being explained by their own movements. Bitcoin (60,92) and Ethereum (61, 33) exhibit also self-dependence, meaning that most of their movements are explained by their own past values. These results suggest that traditional currencies largely depend on their own economic fundamentals, with minimal influence from the other assets. These outcomes are in line with the study of Andrada-Félix, et al. [9].

In the system, Bitcoin and Ethereum influence the market by 40,68 and 40,55 and contribute the most to other assets, making them the main influencers. In contrast, JPY/USD (24,70) and CHF/USD (24.27) have weaker impacts, suggesting they are less significant in this framework. Bitcoin and Ethereum are shown to be significant transmitters of volatility to other assets. The net spillover index reveals that Bitcoin and Ethereum are net transmitters of shocks in the system, while JPY/USD and CHF/USD are net receivers. Bitcoin (39,08) and Ethereum (38,67) are more influenced than JPY (26,24) and CHF (26,21). Bitcoin and Ethereum reveal a much higher level of interconnectedness with each other. Bitcoin explains 36.82% of Ethereum's variance, while Ethereum accounts for 36.75% of Bitcoin's fluctuations. This high degree of mutual spillover highlights the close linkage between these two cryptocurrencies, which often move in tandem due to shared market factors and investor sentiment. Consequently, we note that fiat currencies receive less influence overall, meaning they are less exposed to shocks from other assets. Therefore, cryptos transmit more shocks than they receive, whereas JPY and CHF behave as more stable and less reactive assets. The connectedness across all assets totals 43,40 %, with Bitcoin and Ethereum serving as the primary sources of risk transmission.

We can conclude that Bitcoin and Ethereum drive the market by influencing fiat currencies while remaining largely unaffected by them, highlighting their dominant role as volatility transmitters. In contrast, JPY and CHF act as "shock absorbers," responding to external factors rather than driving market movements. Crypto assets exhibit stronger interconnections compared to fiat currencies, meaning fluctuations in Bitcoin and Ethereum can create cascading effects across the market. However, during periods of financial instability, CHF and JPY may serve as safe-haven assets, though their overall impact on crypto-forex connectedness remains limited.

Table 2.
Averaged joint connectedness.

	Bitcoin	Ethereum	JPY.USD	CHF.USD	FROM
Bitcoin	60.92	36.75	1.34	1.00	39.08
Ethereum	36.82	61.33	0.97	0.88	38.67
JPY.USD	1.97	1.87	73.76	22.40	26.24
CHF.USD	1.88	1.93	22.39	73.79	26.21
TO	40.68	40.55	24.70	24.27	130.21
Inc.Own	101.60	101.88	98.45	98.07	cTCI/TCI
NET	1.60	1.88	-1.55	-1.93	43.40/32.55
NPT	3.00	2.00	0.00	1.00	

Note: Results are based on a TVP-VAR model based generalized forecast error variance decomposition.

4.2. The Quantile Connectedness Analysis

In this subsection, we shift our focus to market risk by quantiles depending on the intensity of quantile correlation varying over time as shown in Figure 1. This figure highlights how the relationships and influences between markets change across different quantiles. The color scale ranges from light yellow (low values) to dark red (high values), suggesting the strength of connectedness at different quantiles. We find that the market interconnectedness is higher at the extremes – lowest and highest quantiles- along the horizontal axis, so the dynamic overall connectedness was symmetric. We also observed that in 2021 and 2023, the dynamic overall connectedness was very large at all market circumstances indicating stronger spillover effects among the assets. This situation may be due to the COVID-19 waves, which severely affected cryptocurrencies. Furthermore, it is noticeable that under stable market event, the overall connectedness became very weak at the quantile range [3, 7]. Suggesting a very low interdependency between markets.

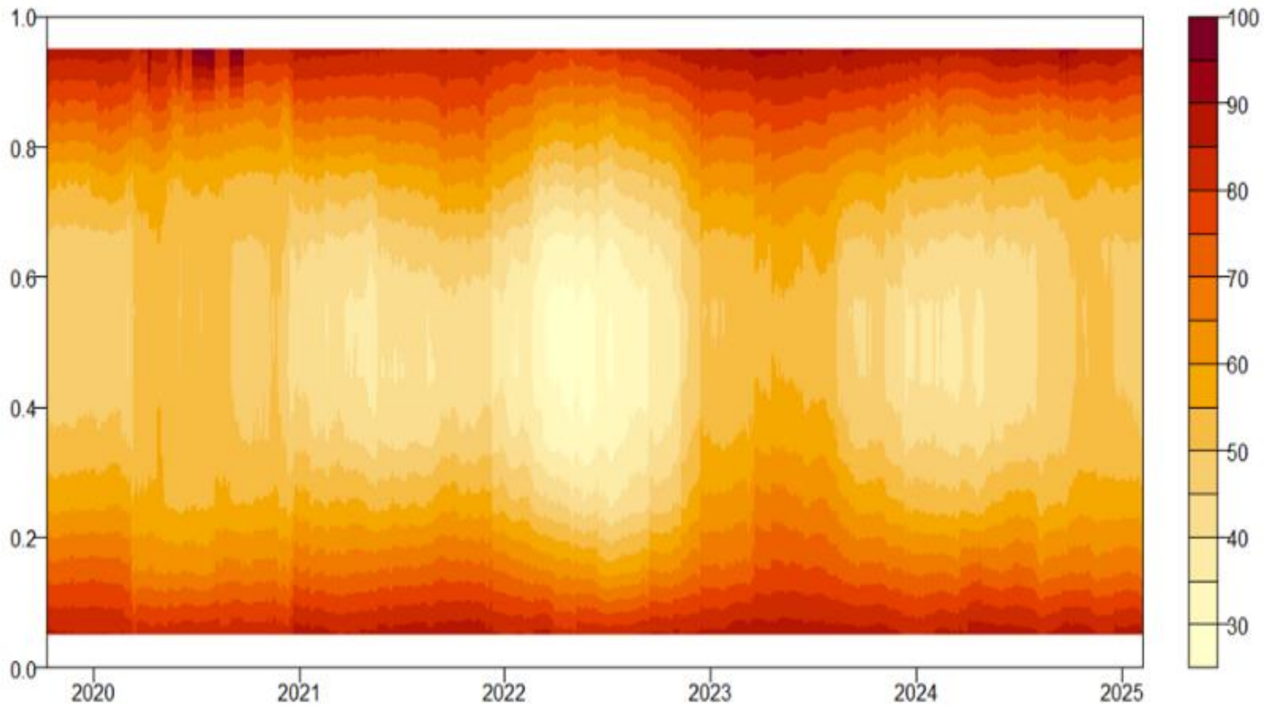

Figure 1.
Total dynamic connectedness across quantiles.

Figure 2 illustrates the quantile connectedness of JPY/USD, Bitcoin, Ethereum and CHF/USD from 2020 to 2025 during various market conditions. Bitcoin and Ethereum emerge as a dominant sender of shocks, with strong red zones indicating high volatility spillovers, especially in 2020, 2021, and 2023. In contrast, JPY and CHF predominantly function as shock absorbers, with deep blue regions in 2020–2021 and 2024. This behavior underscores their role as safe-haven assets during times of financial turbulence. However, both fiat currencies occasionally exhibit red patches, signaling temporary phases of spillover transmission. Overall, while Bitcoin and Ethereum drive market volatility, JPY and CHF act as defensive assets absorbing volatility during crisis periods but occasionally transmitting shocks during economic shifts.

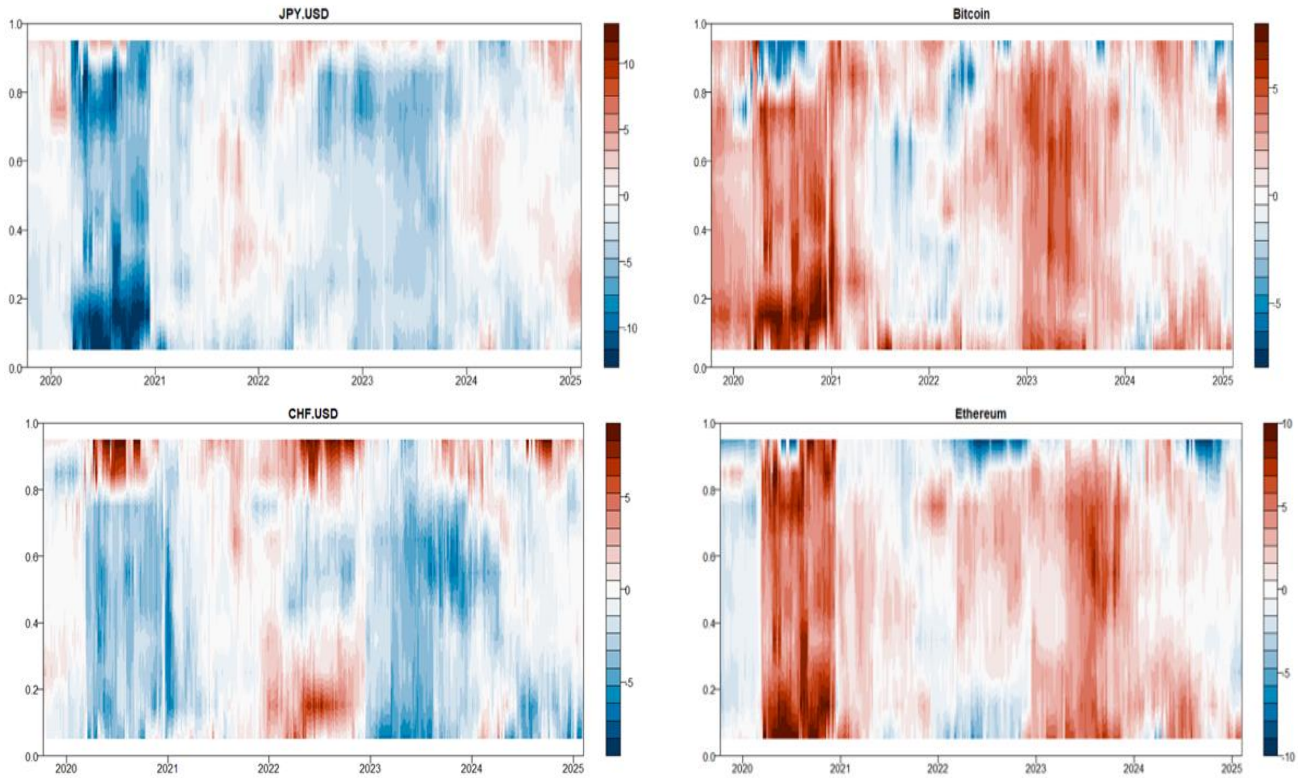

Figure 2.
Net dynamic connectedness across quantiles.

4.3. Connectedness Assessment in the Frequency Domain

We are starting by presenting average median and quantile results, now we focus on the median short-term, long-term dynamic connectedness.

4.3.1. Median Dynamic Total Connectedness

Table 3 illustrates the frequency domain connectedness measures in the short and long run. In the short term (1-5 days), the results indicate similar patterns, with JPY/USD and CHF/USD remaining largely self-contained, explaining 64,79% and 64,68% of their own variance, respectively. Bitcoin and Ethereum continue to be highly interconnected, as Bitcoin explains 33,52% of Ethereum's fluctuations, and Ethereum accounts for 33,21% of Bitcoin's. These cryptocurrencies again show significant spillover effects, indicating that shocks in one can quickly influence the other, especially over short-term horizons. This finding is in line with Seyram Kumah and Baafi [30] who shows Bitcoin is the primary contributor to and recipient of total spillover effects in short-term connectedness. JPY/USD and CHF/USD are still net receivers of volatility in the short term, while Bitcoin and Ethereum remain dominant transmitters. The total connectedness in the short term is slightly lower than the total connectedness index, reflecting more contained spillovers in shorter timeframes. For the long term (5 days and beyond), the results do not shift notably. JPY/USD and CHF/USD continue to be predominantly influenced by their own movements, with JPY/USD explaining 6.54% of its variance and CHF/USD explaining 7,07%. However, the influence of cryptocurrencies is markedly lower in the long term compared to the short term. Bitcoin and Ethereum still transmit some spillovers, but at a reduced rate, with Bitcoin explaining just 2.66% of Ethereum's variance and Ethereum accounting for 2.78% of Bitcoin's movements. This suggests that while cryptocurrencies have strong short-term spillover effects, their influence diminishes over longer periods. Additionally, JPY/USD and CHF/USD exhibit much lower connectedness with other assets in the long term, reinforcing their stability as net receivers of risk over extended horizons. Overall, total connectedness is lower in the long term compared to the short term, indicating that spillovers are more concentrated over short horizons, especially between Bitcoin and Ethereum.

Considering Figure 3, the Total Connectedness Index (TCI) provides insights into the interrelationships among the Japanese Yen (JPY), Swiss Franc (CHF), Bitcoin (BTC), and Ethereum (ETH) over time, particularly focusing on their volatility spillovers. The graph comprises a black line indicating the overall connectedness and shaded areas representing different time horizons of connectedness.

The black line showcases the TCI, which reflects the aggregate level of connectedness between the assets. Higher values indicate a stronger transmission of shocks among the currencies and cryptocurrencies, suggesting that fluctuations in one asset significantly influence the others. The red shaded area represents short-term connectedness (1-5 days), while the green area indicates long-term connectedness (5+ days). The graph demonstrates a dominant presence of the red area, suggesting that short-term market reactions play a more significant role in the dynamics of these assets compared to long-term movements. This observation highlights the importance of immediate market sentiments and their effects on the interrelations of these currencies.

Table 3.
Averaged return connectedness.

Short Run (1–5 traded days)					
	Bitcoin.	**Ethereum.**	**JPY.USD**	**CHF.USD**	**FROM**
Bitcoin	54.94	33.21	2.19	1.66	37.05
Ethereum	33.52	55.86	1.40	1.46	36.38
JPY.USD	3.42	2.82	64.79	19.85	26.08
CHF.USD	2.75	2.87	20.04	64.68	25.66
TO	39.69	38.90	23.63	22.96	125.18
Inc.Own	94.63	94.76	88.42	87.65	cTCI/TCI
Net	2.63	2.52	-2.45	-2.70	41.73/31.29
NPDC	3.00	2.00	1.00	0.00	
Long Run (5-infinite traded days)					
	Bitcoin	**Ethereum**	**JPY.USD**	**CHF.USD**	**FROM**
Bitcoin	4.82	2.78	0.23	0.17	3.18
Ethereum	2.66	4.86	0.10	0.14	2.90
JPY.USD	0.25	0.19	6.54	2.14	2.58
CHF.USD	0.23	0.27	2.09	7.07	2.59
TO	3.13	3.24	2.43	2.45	11.25
Inc.Own	7.95	8.10	8.97	9.52	cTCI/TCI
Net	-0.05	0.35	-0.16	-0.14	3.75/2.81
NPDC	2.00	3.00	0.00	1.00	

In the pre-2020 period, the TCI hovers around 30-40%, indicating a moderate level of interconnection among the JPY, CHF, BTC, and ETH. The predominance of the red area implies that short-term volatility largely drives the relationships between these assets. This foundational understanding sets the stage for examining how external shocks might influence market dynamics. During the COVID-19 impact from 2020 to 2021, a notable spike in TCI is observed, reaching above 50%. This surge likely corresponds to heightened volatility due to global financial uncertainty caused by the pandemic, resulting in stronger interconnectedness between traditional and digital assets. Investors' reactions to market fluctuations during this crisis underline the growing interplay between fiat and cryptocurrency markets. Following the pandemic, the TCI experiences a decline in 2022, stabilizing around 30-40%. This reduction suggests a potential decoupling of the assets, where short-term correlations lessen. It may reflect market adjustments as investors reassess risk post-crisis, emphasizing the need to monitor evolving economic conditions.

In the current trends of 2023, an increase in TCI signals a resurgence in the interconnectedness of these assets, possibly driven by ongoing macroeconomic challenges such as inflation and interest rate adjustments. This indicates that as economic conditions fluctuate, the co-movements between traditional currencies and cryptocurrencies are becoming more pronounced, reinforcing the necessity for market participants to be vigilant about macroeconomic indicators.

In conclusion, the TCI figure illustrates that short-term dynamics are the primary drivers of volatility and spillover effects among JPY, CHF, BTC, and ETH. Major spikes in connectedness indicate that during periods of economic turmoil, the relationships between these assets intensify, with shocks in one market significantly impacting the others. Conversely, long-term connectedness remains relatively weak, this finding is consistent with the results of Chemkha, et al. [15] suggesting that these assets do not necessarily follow sustained trends together, but rather respond to immediate market stimuli. This insight underscores the importance of monitoring macroeconomic factors and market sentiment in understanding the interactions between fiat currencies and cryptocurrencies.

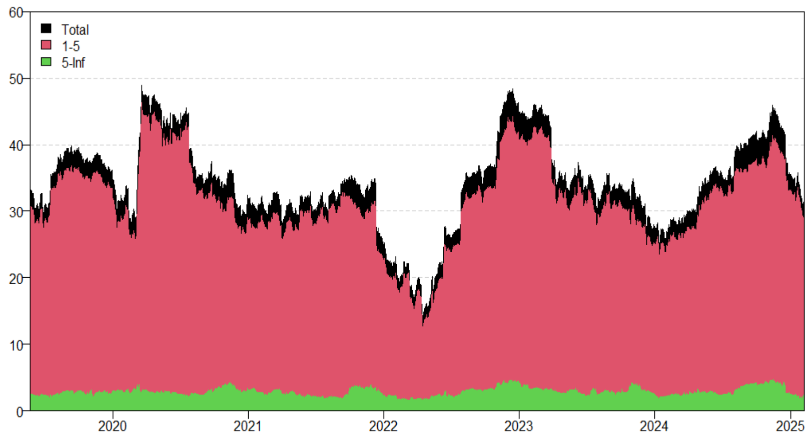

Figure 3.
Dynamic total volatility connectedness.

4.3.2. Net Transmission Power of Each Series

Figure 4 represents the net transmission (positive values) and reception (negative values) of shocks for Bitcoin, Ethereum, CHF/USD, and JPY/USD across different quantiles over time revealing both short-term and long-term dynamics. In the short term (1-5 days, represented in red), Bitcoin and Ethereum exhibit strong net transmission, particularly during periods of heightened volatility such as 2020 and 2022. This suggests that shocks originating in the crypto market rapidly propagate to other assets, making them key contributors to financial instability in turbulent times. These results are inconsistent with the empirical findings of Belkhir [31]who emphasized that during the COVID-19 pandemic, Bitcoin acted as a strong net receiver of shocks. Conversely, JPY/USD and CHF/USD show mixed behavior, acting as short-term shock receivers during financial stress, reinforcing their role as safe-haven assets. However, CHF/USD occasionally transmits short-term shocks, indicating that its stability can weaken under extreme conditions. Over longer horizons (beyond five days, represented in green), the dynamics shift, with Bitcoin and Ethereum still being net transmitters but with reduced intensity. This suggests that while they have strong short-term spillover effects, their long-term influence stabilizes. On the other hand, JPY/USD and CHF/USD continue to be dominant shock absorbers over longer periods, reinforcing their role as stabilizing assets in a diversified portfolio. However, CHF/USD exhibits occasional long-term transmission, particularly during global financial disruptions, indicating that its safe-haven properties are not absolute. So, we can conclude that the short-term dominance of Bitcoin and Ethereum as net transmitters makes them unsuitable for risk mitigation but valuable for high-frequency trading and speculative strategies. In contrast, JPY/USD is a consistent safe-haven asset in both short- and long-term horizons, making it an ideal hedge against market downturns. CHF/USD, while generally absorbing shocks, shows transmission power in extreme conditions, suggesting that investors should not fully rely on it for crisis hedging. Balancing exposure between these assets based on time horizons can enhance portfolio resilience.

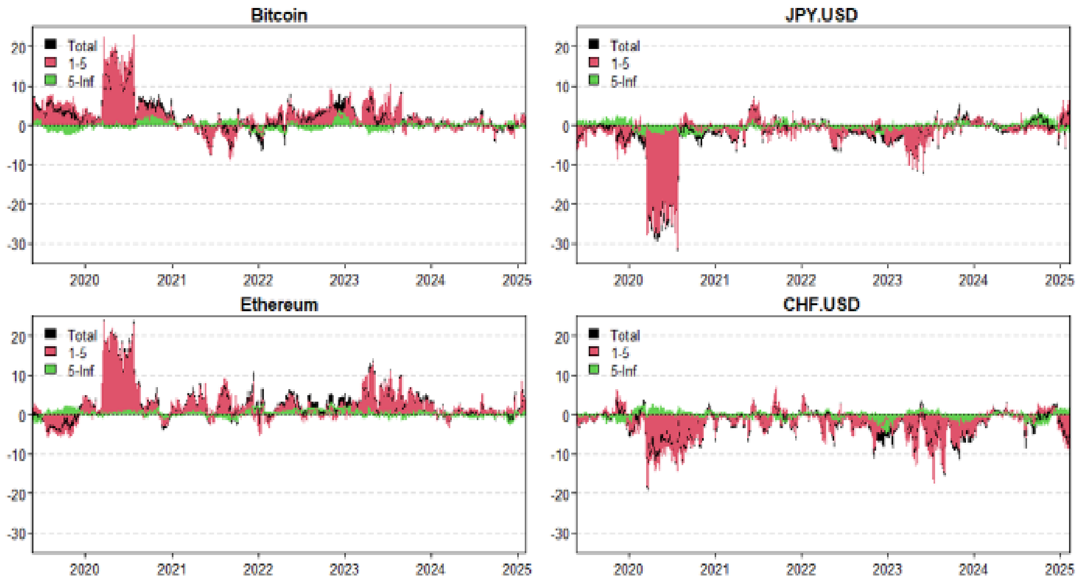

Figure 4.
Total net connectedness across frequencies.

4.3.3. Net Pairwise Directional Connectedness

Figure 5 illustrates the net pairwise directional connectedness between Bitcoin, Ethereum, CHF/USD, and JPY/USD across different quantiles, revealing insights into short-term and long-term spillover effects. Considering Bitcoin and Ethereum, the figure highlights strong bidirectional spillovers, especially during market turbulence. Bitcoin and Ethereum are highly interconnected, meaning shocks in one cryptocurrency tend to propagate to the other. The intensity of spillovers increases during bullish and bearish periods, reinforcing their co-movement and risk exposure. Concerning Ethereum, Bitcoin and JPY/USD, we note that both Bitcoin and Ethereum exhibit stronger spillovers to JPY/USD during periods of market stress 2020 -2021, indicating that JPY/USD absorbs crypto-related shocks in certain periods. However, JPY/USD does not significantly transmit influence back to Ethereum or Bitcoin, reinforcing its role as a passive recipient rather than an active driver in the crypto-forex relationship. Regarding Bitcoin, Ethereum and CHF/USD, the transmission pattern indicates that CHF/USD is sensitive to crypto shocks but plays a potential role as a financial stabilizer or risk distributor under extreme conditions. In the relationship between JPY/USD and CHF/USD, JPY /USD appears to act as a stronger transmitter, while CHF/USD functions as a stabilizing force. Their interplay suggests that both currencies have conditional safe-haven characteristics, but JPY/USD tends to influence CHF/USD more during extreme events. The figure confirms that Bitcoin and Ethereum are dominant risk transmitters, whereas JPY/USD and CHF/USD primarily function as recipients of crypto-induced shocks. These findings suggest that portfolio strategies should account for the shifting roles of fiat currencies as conditional safe havens, while Bitcoin and Ethereum remain highly interconnected and influential within financial markets. These observations are inconsistent with the findings of Aharon, et al. [12].

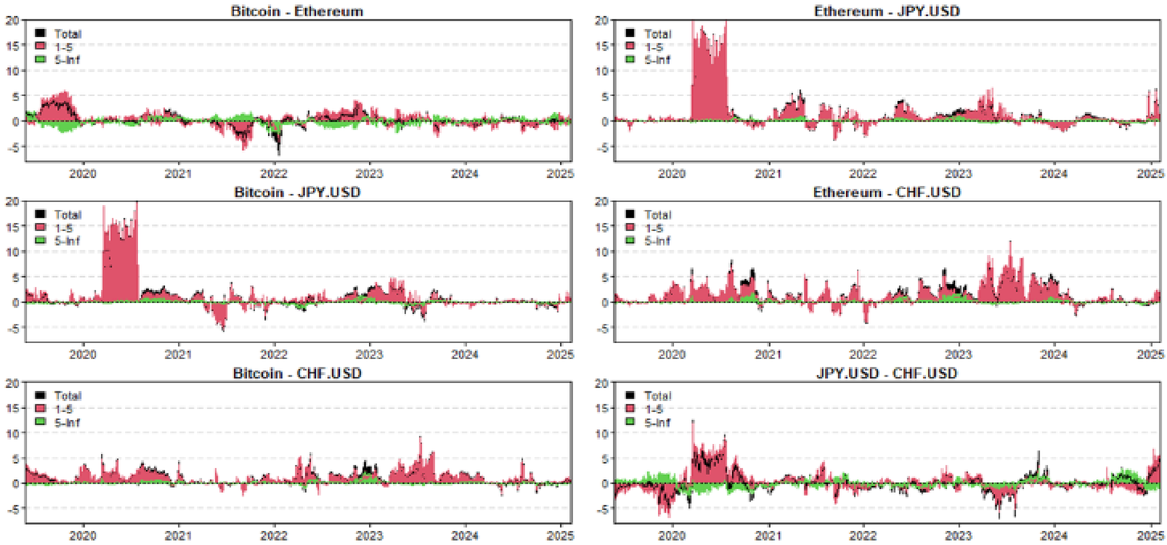

Figure 5.
Net pairwise directional connectedness.

5. Conclusion

This study explores the intricate relationships between traditional fiat currencies, specifically the Swiss Franc and Japanese Yen, and major cryptocurrencies like Bitcoin and Ethereum. Our findings illustrate that during times of economic uncertainty, the interconnectedness between these financial assets intensifies, with cryptocurrencies often amplifying volatility across markets. While the CHF and JPY serve as stable benchmarks, their influence on cryptocurrency valuations suggests a nuanced interaction that warrants further exploration. The analysis reveals that short-term fluctuations primarily drive market dynamics, while long-term connectedness remains relatively weak. This indicates that market participants must remain vigilant about macroeconomic factors and investor sentiment, as these elements significantly impact the behavior of both fiat and digital currencies. Ultimately, our research underscores the importance of understanding these interrelationships to effectively manage risks and optimize investment strategies in an increasingly volatile financial environment. For Policymakers, the growing influence of cryptocurrencies necessitates robust regulatory frameworks.

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