Equity, Cryptocurrency and Precious Metal Markets: a TVP-VAR Extended Joint Connectedness Approach

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Abstract: This paper examines the dynamic return and volatility connectedness among bitcoin, gold and MSCI World Index to analyze the effect of Russia-Ukraine War on the dynamic spillovers over these asset markets. Using daily data from December 10, 2017, when the first bitcoin future was launched in United States, to February 28, 2023, we employ the dynamic connectedness approach estimated from time-varying parameter vector autoregression (TVP-VAR) model. We find that both returns and volatility spillovers among the 3 markets surged with the outbreak of the invasion. During the COVID-19 outbreak and the Russian invasion, gold behaved as a net receiver of return and volatility spillover. Particularly, gold receives the most volatility spillover from other markets, especially during crises. Furthermore, the result in frequency domain connectedness analysis of the 3 markets revealed that the return linkages at very short term (1-5 days) is considerably larger than those in longer terms, suggesting the market information of volatility shocks is absorbed very quickly in these markets while volatility shocks can persist over longer term (20 days+). We also provide evidence of strengthened negative asymmetric volatility spillovers among the three markets during the crisis.

Keywords: Russia-Ukraine War, connectedness, time domain, frequency domain

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1. Introduction

The application of time-frequency domain spillover analysis provides useful information for investors on choosing investment horizons, asset class allocation and risk diversification and making informed short-term or long-term investment decisions.

In a rapidly changing world, it's important for portfolio managers or risk managers to learn from the latest changes of financial market dynamics in order to make more accurate decisions for risk control and risk diversification, and form a better hedged diversified portfolio. The results of the empirical analysis of this research will provide insights for risk managers or portfolio managers trading the mentioned markets for risk management and diversification purposes. The remaining parts of this paper are organized as follow: Section 2 reviews the literature; section 3 introduces the methodology used; section 4 describes the data that will be used in the research. In section 5, the empirical results are presented. The final section concludes.

2. Literature Review

Bitcoin was first proposed by Nakamoto (2008) and is the first decentralized digital currency in the world (Corbet, Lucey, Urquhart, & Yarova, 2019). Since its introduction, many researches on the digital asset market have been performed to study different properties of the digital assets. Many researchers found benefits of including bitcoin in financial portfolios for optimizing risks and returns. For example, Brière et al. (2015) found that the inclusion of bitcoin, even a small percentage in a portfolio, could improve the risk-return trade-off. Employing the time-frequency connectedness analysis to study the cryptocurrency markets and other financial markets, such as currency, commodity, equity, bond, and market volatility (VIX index), Corbet et al. (2018) found evidence that cryptocurrency markets is a new investment asset class and that investors with short investment horizon would get diversification benefits by including cryptocurrencies in their portfolios. Similarlly, Guesmi et al. (2019) estimated the volatility spillover between bitcoin and other financial assets and found evidence that bitcoin offers diversification benefits and hedging opportunities for investors. Particularly, the results shows that hedging strategies involving gold, oil, emerging stock markets and Bitcoin reduce considerably a portfolio's variance in comparison to the variance of a portfolio composed of gold, oil and stocks from emerging stock only.

The connectedness approach is widely adopted in equity market analysis, Sun et al. (2021) adopted the time-frequency connectedness approach and found that different groups of stocks play a leading position in the spillover dynamic under different time scale, Consumable fuel-related stocks are also found to be the drivers in the spillover of Chinese energy stocks. Xia, Yao, & Geng (2020) found that in the short term, China's stock and housing market, second and third-tier cities are net transmitters of information spillovers, while in the long term the net information transmitters are first-tier cities, economic policy uncertainty, and stock markets. Chatziantoniou et al. (2021) used TVP-VAR connectedness approach to analyze the sector indexes of the Indian stock market and found that connectedness was strongest during the crisis period in the country.

Baruník et al. (2016) extended Diebold & Yilmaz (2012)'s methodology and introduced a Spillover Asymmetry Measure (SAM) to quantify the extent of asymmetry in volatility spillover and found that the US intra–market connectedness rose steeply during the 2007-2008 financial crisis, and asymmetries in volatility spillover were detected. In this approach, negative and positive changes in returns are considered separately via realized semi-variances in computing the volatility spillover index. This approach is further used by multiple researchers in studying the asymmetry in volatility spillover in asset markets during crises. Jebabli et al. (2022) found significant (negative) asymmetries in volatility spillovers in energy and stock markets during COVID-19 pandemic crisis. Shahzad et al. (2021) discovered that bad volatility spillover shocks dominated good volatility spillover shocks among Chinese stock market sectors and the asymmetry was intensified during the COVID-19 period.

3. Methodology

3.1 Total Spillover Index

The Spillover Index was first introduced by Diebold & Yilmaz (2009) and was further improved by Diebold & Yilmaz (2012), in which the estimation is based on a generalized vector autoregressive framework where the forecast error variance decompositions (GFVED) are invariant to the variable ordering.

The total spillover index aggregates spillover effects across the variables in the system into a single measure.

$$Total\ Spillover\ Index = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100 \quad (1)$$

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \quad (2)$$

where $\theta_{ij}(H)$ is the H-step-ahead forecast error variance decomposition.

3.2 Directional Spillover (Receive)

The directional spillover index (receive) aggregates spillover effects of a variable *i* from all other variables *j*.

$$Directional\ Spillover\ Index\ (receive)_{i,j} = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100 \quad (3)$$

3.3 Directional Volatility Spillover (Transmit)

The directional spillover index (transmit) aggregates spillover effects of a variable *i* to all other variables *j*.

$$Directional\ Spillover\ Index\ (transmit)_{i,j} = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ji}(H)}{N} \times 100 \quad (4)$$

3.4 Net Spillover Index

The Net Spillover Index measure the net spillover contribution of a variable *i* to the system.

$$Net\ Volatility\ Spillover_{i,j} = Directional\ Spillover\ Index\ (transmit)_{i,j} - Directional\ Spillover\ Index\ (receive)_{i,j} \quad (5)$$

Due to the relative simplicity in its computation, it is often useful to perform rolling-sample analysis with the spillover index to observe the movement of spillover dynamic over a period.

3.5 Spillovers in Frequency Domain

The spillovers at frequency domain can be described as the spectral representation of variance decomposition based on frequency responses to shocks (Barunı́k & Krehlı́k, 2018). Let the moving average coefficients Ψ_h calculated at $h = 1,2,\dots,H$ horizons approximate $\Psi(\mathrm{L})$. Consider a frequency response function $\Psi\left(\mathrm{e}^{-i\omega}\right) = \sum_{\mathrm{h}} e^{-i\omega}\Psi_h$ obtained from a Fourier transform of the coefficients Ψ_{h} with $i = \sqrt{-1}$. The spectral density of x_t at frequency ω can then be formulized as a Fourier transform of MA(∞) filtered series as

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h}) e^{-i\omega h} = \Psi(\mathrm{e}^{-i\omega})\Sigma\Psi'(\mathrm{e}^{+i\omega}) \tag{6}$$

If x_t is wide-sense stationary with $\sigma_{kk}^{-1}\sum_{h=0}^{\infty}(\Psi_h\Sigma)_{j,k} \mid < +\infty, \forall j,k$, the spectral representation of the variance decomposition from *j* to *k* is expressed as

$$(\varphi_\infty)_{j,k} = \frac{1}{2\pi}\int_{-\pi}^{\pi} \Gamma_j(\omega)\left(f(\omega)\right)_{j,k} d\omega \tag{7}$$

where the weighting function $\Gamma_{\mathrm{j}}(\omega)$ is defined as

$$\Gamma_{\mathrm{j}}(\omega) = \frac{\Psi\left(\mathrm{e}^{-i\omega}\right)\Sigma\Psi'\left(\mathrm{e}^{+i\omega}\right)}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\Psi(\mathrm{e}^{-i\lambda})\Sigma\Psi'(\mathrm{e}^{+i\lambda}))_{j,j} d\lambda} \tag{8}$$

For a frequency band $d = (a,b): a,b \in (-\pi,\pi), a < b$, the generalized variance decompositions on frequency band d are defined as

$$(\varphi_d)_{j,k} = \frac{1}{2\pi}\int_{d} \Gamma_j(\omega)\left(f(\omega)\right)_{j,k} d\omega \tag{9}$$

The scaled generalized variance decomposition on the frequency band $d = (a,b): a,b \in (-\pi,\pi), a < b$ can be defined as

$$(\tilde{\varphi}_d)_{j,k} = (\varphi_d)_{j,k} \,/\, \sum_k (\varphi_\infty)_{j,k} \tag{10}$$

where $(\varphi_d)_{j,k}$ is defined in equation 27 and $(\varphi_\infty)_{j,k}$ is defined in equation 25 respectively.

The within connectedness on the frequency band d can then be defined as

$$C_d^W = 100 \,.\, (1 - \frac{Tr\{\tilde{\varphi}_d\}}{\sum \tilde{\varphi}_d}) \tag{11}$$

- The frequency connectedness on the frequency band d can then be defined as

$$C_d^F = 100 \,.\, (\frac{\sum \tilde{\varphi}_d}{\sum \tilde{\varphi}_\infty} - \frac{Tr\{\tilde{\varphi}_d\}}{\sum \tilde{\varphi}_\infty}) \tag{12}$$

where $Tr\{.\}$ is the trace operator, and $\sum \tilde{\varphi}_d$ referred to the sum of all elements of $the\ \tilde{\varphi}_d$ matrix.

The frequency domain connectedness analysis would provide deeper insights into the risk and spillover dynamic of the markets of different time-horizon.

3.6 Time-Varying Parameter Vector Autoregression

For a dynamic connectedness analysis, a rolling-window size of the VAR has to be arbitrarily chosen with Diebold & Yilmaz (2012)'s methodology. The connectedness measures could be sensible to chosen size.

This paper estimates the connectedness in the time and frequency domains based on TVP-VAR using the methodology of Antonakakis et al. (2020). This approach avoids the necessity of an arbitrarily chosen rolling-windows size for a dynamic connectedness analysis, and can capture recent changes in the parameters more quickly than in the rolling-window-based VAR approach. This is important in studying the behavior of the system under a crisis. There is also no loss of observations in computing the dynamic measures as in the rolling-windows approach. This makes dynamic estimates more reliable with the limited number of daily observations after the RIU event.

For a TVP-VAR model with a lag length of order 1, the model is (Balcilar, Gabauer, & Umar, 2021)

$$y_t = \beta_t y_{t-1} + \epsilon_t \qquad \epsilon_t \sim N(0, \Sigma_t) \tag{13}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + v_t \qquad v_t \sim N(0, R_t) \tag{14}$$

where $vec(\beta_t)$ and v_t are $K^2 \times 1$vectors and R_t is a $K^2 \times K^2$ matrix.

3.7 The Extended Joint Connectedness Approach

Caloia et al. (2019) showed that the results of directional net connectedness from the original connectedness approach proposed by Diebold & Yilmaz (2012) could be sensitive to the choice of the normalization technique used and particularly the row normalization technique is suboptimal.

Lastrapes and Wiesen (2021) derived the joint connectedness index by using the reduction in the unconditional variance of variable i by conditional jointly forecasting that variable on all other variables in the system. This index $S_{\cdot \to i}^{jnt}$ is naturally bounded by 0 and 100% and therefore avoided the need to normalize the individual index. The joint spillover index is therefore:

$$jSOI = \frac{1}{K}\sum_{i=1}^{K} S_{\cdot \to i}^{jnt} \tag{15}$$

They further introduced a scaling parameter λ

$$\widetilde{gSOT}_{ij} = \lambda \cdot gSOT_{ij} \tag{16}$$

$$\lambda = \frac{jSOI}{gSOI} \tag{17}$$

where $gSOT_{ij}$ is the spillover table element at row i and column j and $gSOI$ the spillover index following Diebold & Yilmaz (2012), and $jSOI$ is the joint spillover index.

The total directional connectedness from variable j to all other variables is:

$$S^{jnt}_{i\leftarrow \cdot} = \sum_{i\neq j}^{K} \widetilde{gSOT}_{ij} \tag{18}$$

The join net total spillover of variable *i* is therefore:

$$S^{jnt}_{net,i} = S^{jnt}_{i\leftarrow \cdot} - S^{jnt}_{\cdot \to i} \tag{19}$$

One issue of this approach is that the calculation of the net directional pairwise spillovers is not possible. Balcilar, M., Gabauer, D., & Umar, Z. (2021) further extended this approach by allowing each row to have its own scaling factor:

$$\lambda_i = \frac{S^{jnt,from}_{i\to \cdot,t}}{S^{gen,from}_{i\to \cdot,t}} \tag{20}$$

which sum to the same scaling parameter λ in the joint connectedness approach:

$$\lambda = \frac{1}{K}\sum_{i=1}^{K} \lambda_i \tag{21}$$

In a time-varying parameter context, programming these steps:

1. $jSOT_{ij,t} = \lambda_i gSOT_{ij,t}$
2. $jSOT_{ii,t} = 1 - S^{jnt,from}_{i\to \cdot,t}$
3. $S^{jnt,to}_{\cdot\leftarrow j,t} = \sum_{i\neq j}^{K} jSOT_{ij,t}$

The net directional pairwise spillover index can then be computed with:

$$S^{jnt,net}_{ij} = gSOT_{ji} - gSOT_{ij} \tag{22}$$

The interpretations of the net directional pairwise spillover indexes are identical to the original connectedness approach.

3.8 Spillover Asymmetry Measure

The realized variance could be stated as, according to Barndorff-Nielsen et al. (2010) as follow:

$$RV_t = \sum_{i=1}^{W} r_i^2 \quad (23)$$

where RV is the realized variance for day t, W the rolling-window size parameter in number of days, r_i^2 the squared log difference of price at time i.

The realized variance can be further decomposed into negative semi-variance RS^- and positive semi-variance RS^+, which capture changes in returns corresponding to negative and positive shocks respectively. They are defined as follow:

$$RS^- = \sum_j \mathrm{I}(r_i < 0)\, r_i^2 \quad (24)$$

$$RS^+ = \sum_j \mathrm{I}(r_i \geq 0)\, r_i^2 \quad (25)$$

The RV is the sum of positive semi-variance RS^+ and negative semi-variance RS^-, i.e. $RV = RS^+ + RS^-$.

The Asymmetric Spillovers Measure (SAM) was introduced by Baruník et al. (2016)

and is defined as:

$$SAM = S^+ - S^- \quad (26)$$

where S^+ and S^- are the spillovers from volatility due to positive returns and the spillovers from volatility due to negative returns respectively (i.e. total spillover indices estimated by using RS^+ and RS^-).

When $SAM = 0$, the volatility spillovers are considered symmetric. If SAM is larger than zero (less than zero), the volatility spillovers are considered asymmetric, where positive (negative) spillover dominates the market.

4. Data

The return series of the variables are obtained using the first difference of the natural logarithm of the prices multiplied by 100%. The formula for the return of an asset *a* at time *t* is:

$$R_{a,t} = [\ln(Price_{a,t}) - \ln(Price_{a,t-1})] \times 100\% \quad (27)$$

Daily volatility is estimated using daily high and low prices, following the tradition of literature, such as Parkinson (1980) and Diebold & Yilmaz (2012). The formula for the estimated daily volatility of an asset *a* at time *t* is:

$$\tilde{\sigma}_{at}^2 = 0.361[\ln(High_{a,t}) - \ln(Low_{a,t})]^2 \quad (28)$$

The bitcoin daily price series is obtained from CoinMarketCap (2023). Daily gold price and MSCI World Index data is obtained from Nasdaq (2023) and Yahoo Finance (2023).

The cryptocurrency market experienced the ICO boom in 2017-2018 (Allen, Fatas, & di Mauro, 2022). During the period the cryptocurrency market became popular as an alternative investment. On December 10, 2017, the first bitcoin future contracts traded in the United States was offered by Cboe Global Markets[1], and the CME Group also launch its Bitcoin futures contact a week later on December 18, 2017 [2]. This signaled the popularity of the bitcoin and its recognition as an alternative investment by investors. The introduction of bitcoin future would have made bitcoin a better investable asset. Corbet et al. (2018) suggest that the introduction of Bitcoin futures would have resulted in lower variance of bitcoin prices, or enabled hedging strategies to manage risks in the bitcoin spot market. This study therefore chose December 10, 2017 as the start date of the analysis in order to analyze the market dynamics of bitcoin, gold and equity markets when cryptocurrency started to attract investors in the public. The data under the study span December 10, 2017, through February 28, 2023.

[1] CBOE beats CME to bitcoin futures launch with December 10 start. https://www.reuters.com/article/uk-cboe-bitcoin-idUSKBN1DY1SV

[2] CME Group Self-Certifies Bitcoin Futures to Launch Dec. 18. https://www.cmegroup.com/media-room/press-releases/2017/12/01/cme_group_self-certifiesbitcoinfuturestolaunchdec18.html

5. Empirical Results

To estimate the average connectedness during the 2 periods, the data set are divided into two subsamples - before the RIU (before February 24, 2022), and during the RIU (on or after February 24, 2022).

5.1 Spillover Indexes

5.1.1 Average Connectedness

Table 1: Average Return Connectedness Table, before the RIU and during the RIU

Return	Before the RIU				During the RIU			
	EQUITY	**GOLD**	**BTC**	**FROM**	**EQUITY**	**GOLD**	**BTC**	**FROM**
EQUITY	88.53	3.53	7.93	11.47	62.48	4.24	33.28	37.52
GOLD	2.96	94.55	2.49	5.45	6.41	90.49	3.10	9.51
BTC	7.63	2.51	89.86	10.14	31.56	2.36	66.08	33.92
TO	10.59	6.04	10.42	27.05	37.97	6.60	36.38	80.95
NET	-0.88	0.60	0.28	**TCI=9.02%**	0.45	-2.91	2.46	**TCI=26.98%**

Table 2: Average Volatility Connectedness Table, before the RIU and during the RIU

Volatility	Before the RIU				During the RIU			
	EQUITY	**GOLD**	**BTC**	**FROM**	**EQUITY**	**GOLD**	**BTC**	**FROM**
EQUITY	82.2	14.76	3.03	17.8	71.93	11.98	16.09	28.07
GOLD	17.91	78.55	3.54	21.45	11.99	81.15	6.85	18.85
BTC	3.39	2.02	94.6	5.40	13.39	6.01	80.6	19.4
TO	21.3	16.78	6.57	44.65	25.38	17.99	22.95	66.32
NET	3.50	-4.67	1.17	**TCI=14.88%**	-2.69	-0.86	3.55	**TCI=22.11%**

Table 1 shows the estimation results of the return spillovers prior to and during the RIU period. The Total Connectedness Index for return series increased from 9.02% to 25.01%. The intensity of spillover to and from other assets increased considerably for all three assets.

Table 2 shows that the Total Connectedness Index for volatility series. from 4.55% to 13.26%. The value of the total spillover index was 4.55% before the RIU period and increased to 13.26% during the RIU period.

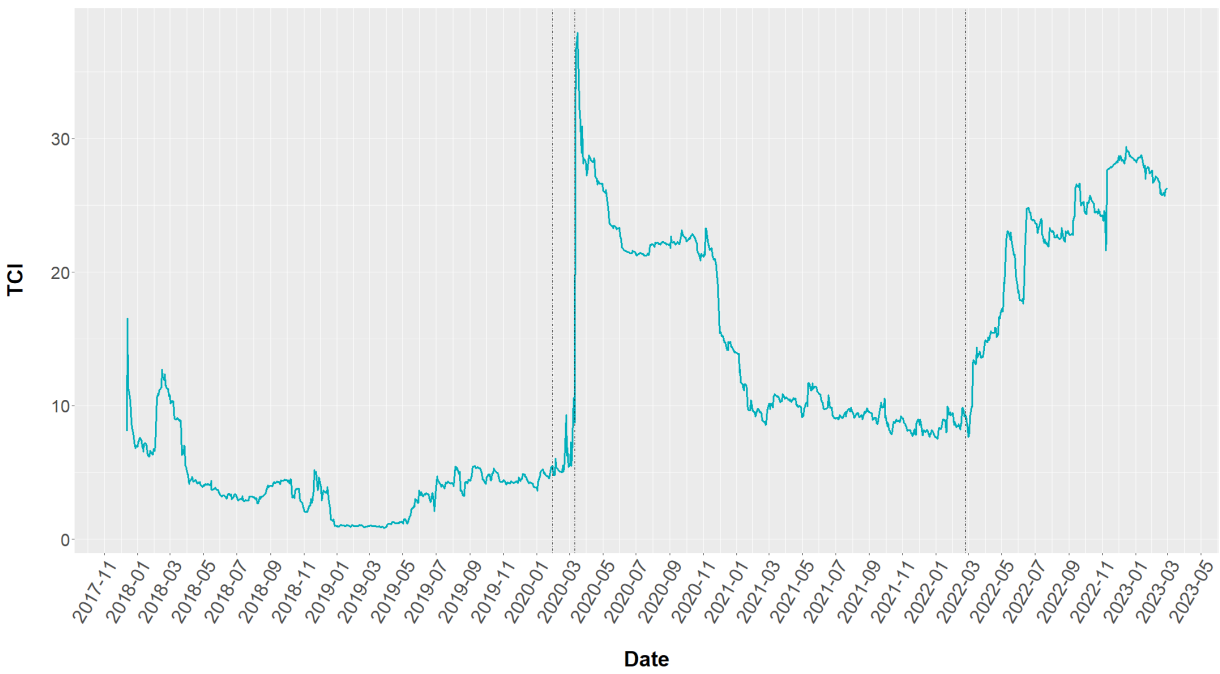
During the RIU, both the return and volatility connectedness are strengthened among equity, gold and cryptocurrency markets.

The result is consistent to rising connectedness among financial market during crisis such as the COVID-19 pandemic (Le, Abakah, & Tiwari, 2021).

5.1.2 Dynamic Connectedness

With a TVP-VAR model, the dynamic connectedness in the full sample is also estimated for evaluating the connectedness among these assets during the period.

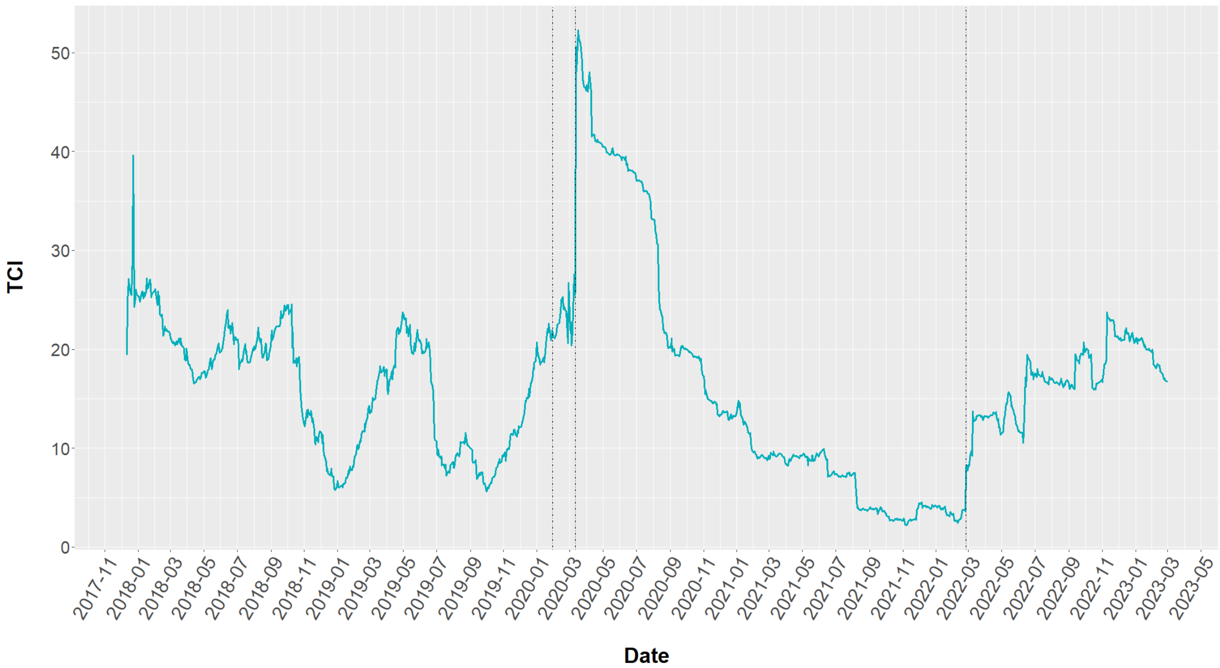
Figure 1: Total Connectedness Index (TCI), Return



* Dotted Vertical Lines:
1st – 2020-01-30: WHO declared COVID-19 outbreak a Public Health Emergency of International Concern
2nd – 2020-03-11: WHO declared COVID-19 a pandemic
3rd – 2022-02-24: The Russian Invasion of Ukraine (RIU)

Figure 1 reveals that following the mild increase of the Total Connectedness Index (TCI) of the return series after COVID-19 considered a Public Health Emergency of International Concern by the WHO (World Health Organization) on January 30, 2020, the TCI further surged significantly after the declaration of the COVID-19 outbreak a pandemic, until it returned to a lower level in early 2021. However, with the rising tension between the Ukraine-Russia in late 2021, it began to gradually rise again. On February 24, 2022, President Vladimir Putin formally announced a "special military operation" against Ukraine. The total connectedness index rose immediately following the announcement. It’s important to note that the TCI still stayed in high level at the end of the sample period.

Figure 2: Total Connectedness Index (TCI), Volatility



* Refer to Figure 1 for the meaning of the 3 Dotted Vertical Lines

The dynamic connectedness of volatility behaved similar to the return connectedness. Volatility connectedness among the assets in the study rose remarkably in the COVID-19 outbreak. After the COVID-19 outbreak, the dynamic volatility connectedness gradually decreased, until the RIU. During the RIU, the volatility connectedness rose again and stayed in high level at the end of the sample period. The result is consistent to many studies that the volatility spillover surges during the crisis period, such as (Mensi, Ur Rehman, & Vo, 2020) and Jebabli et al. (2022).

Figure 3: Dynamic Net Connectedness Index, Return, All Assets

* Refer to Figure 1 for the meaning of the 3 Dotted Vertical Lines

Figure 4: Dynamic Net Connectedness Index, Return - MSCI World Index

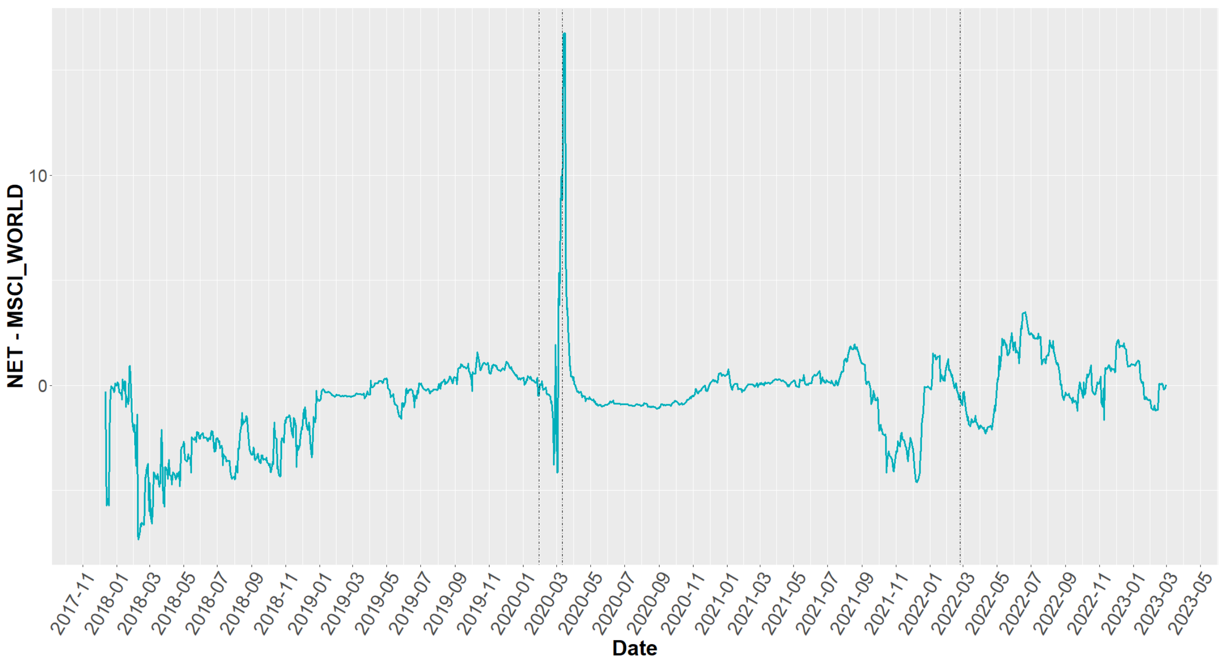


Figure 5: Dynamic Net Connectedness Index, Return - Bitcoin

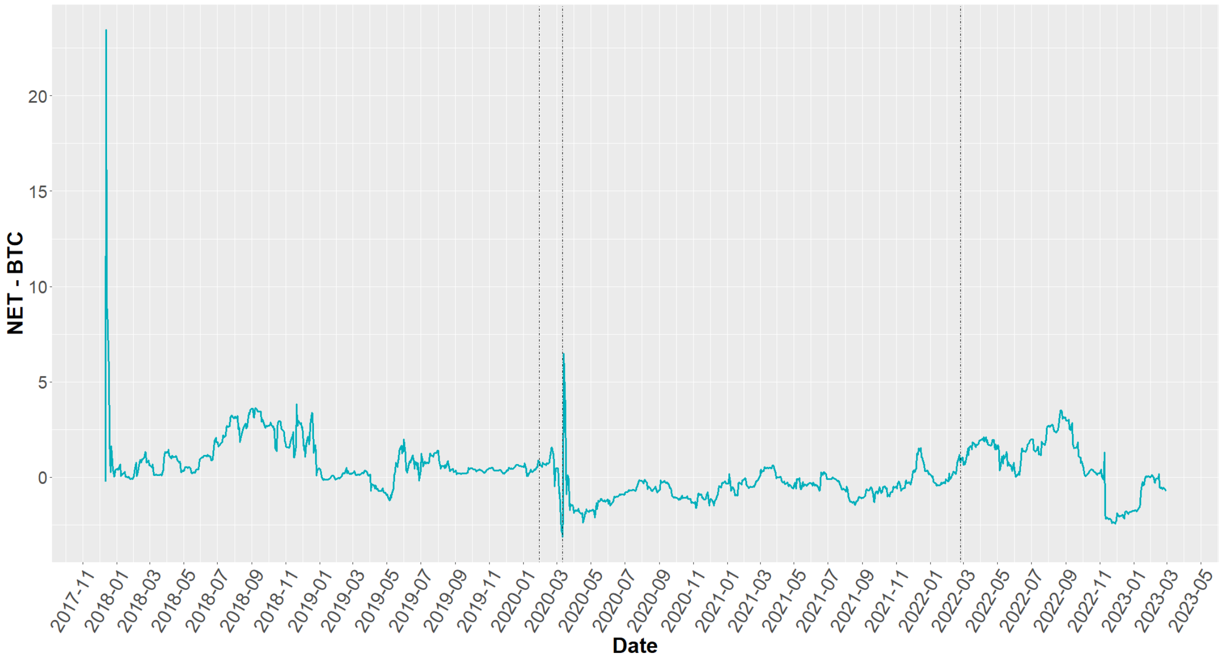
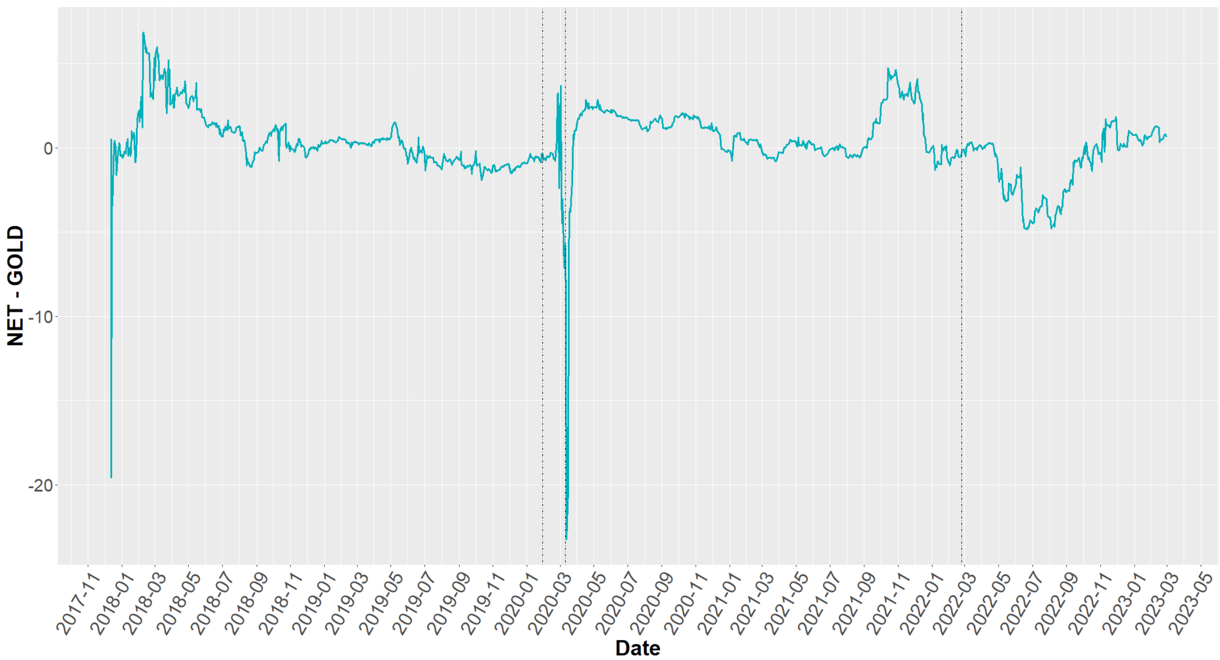
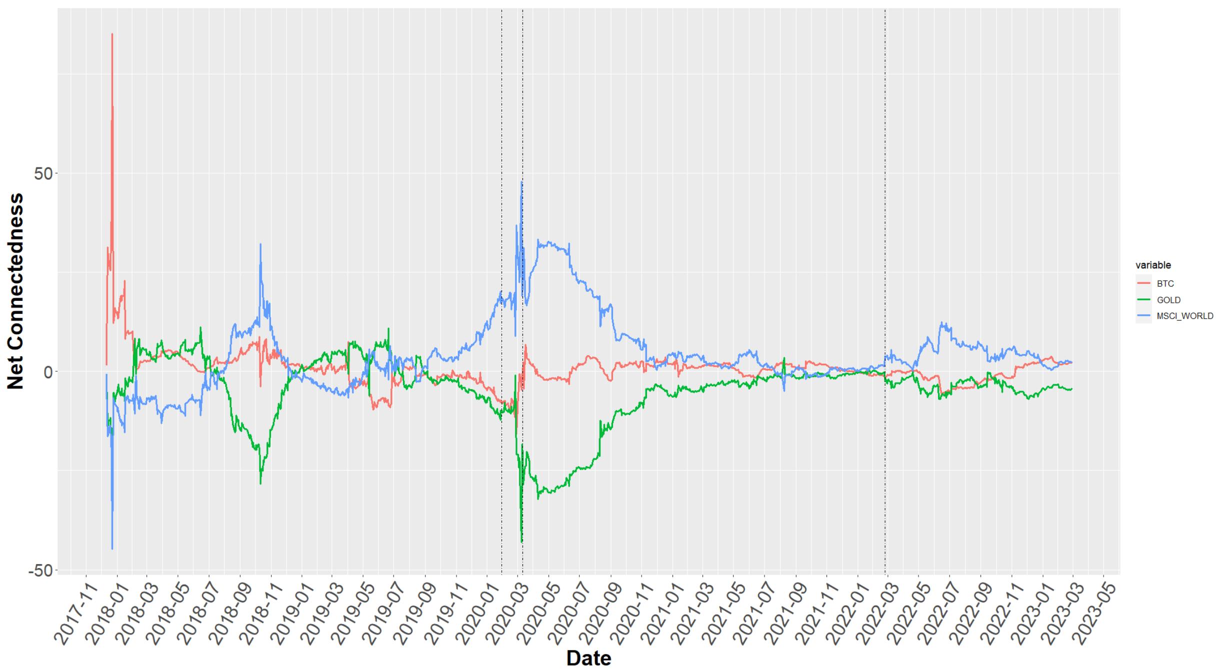


Figure 6: Dynamic Net Connectedness Index, Return - Gold



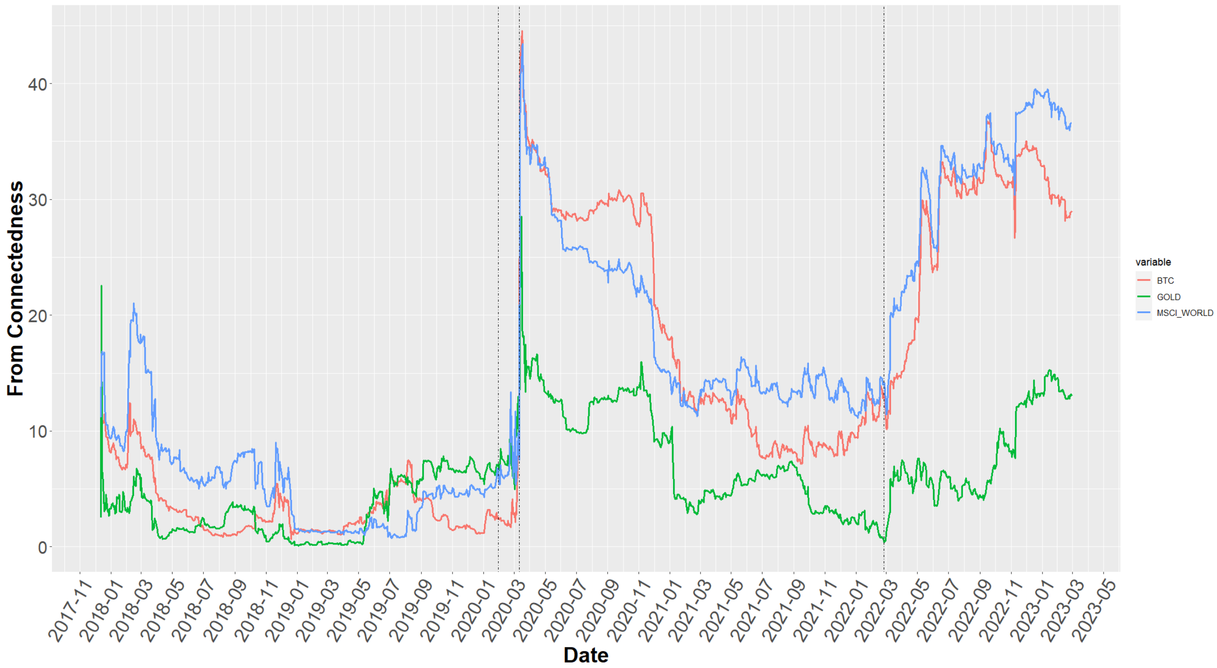
The dynamic net connectedness indexes of returns show a clear pattern that during crises, both in the COVID-19 and the RIU, the directional net connectedness of the MSCI World Index and bitcoin increase, while the directional net connectedness of gold decrease and become a net receiver of return spillover from the markets.

Figure 7: Dynamic Net Connectedness Index, Volatility



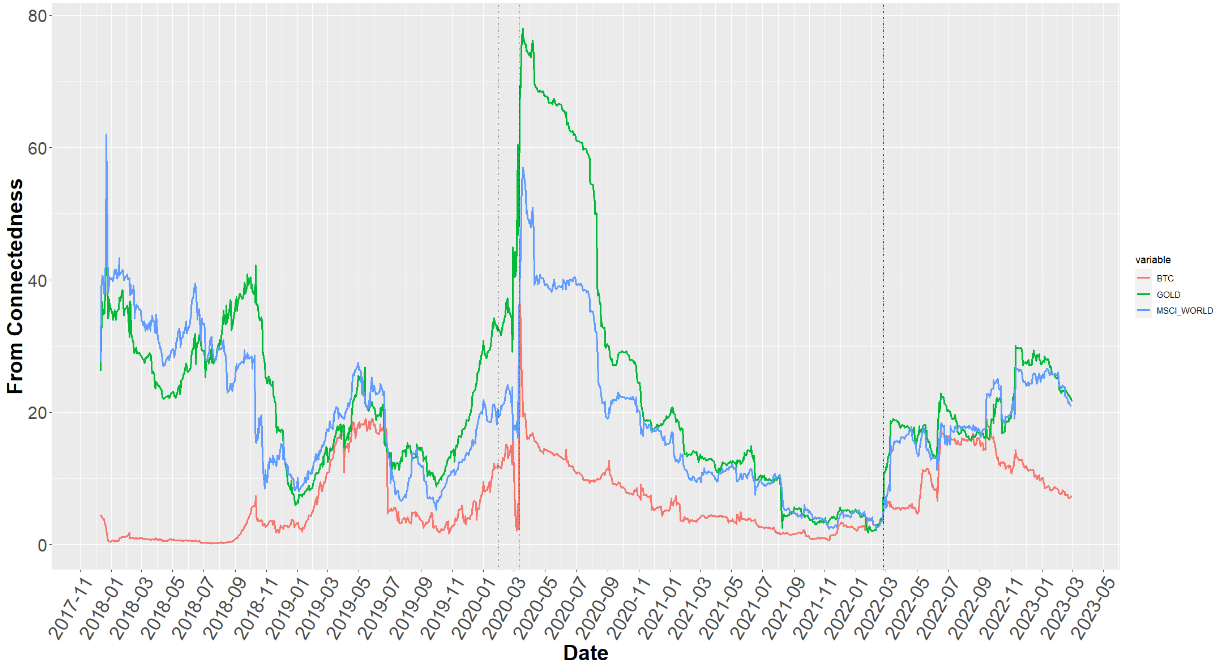
The dynamic net connectedness indexes of volatility are similar to that of returns connectedness. In both COVID-19 and the RIU crises, gold became a net receiver of volatility spillover from the markets. Notably in the persistence of becoming a strong net receivers of volatility spillover is higher and takes around 6 months to return to the normal level after the outbreak of COVID-19.

Figure 8: **From-Connectedness Index of Return**



From risk management perspective, it's useful to inspect the from-connectedness index, which indicates the intensity of an asset receiving return and volatility spillover from the other markets. Figure 8 reveals that both Bitcoin and equity receive significant return spillover from the other markets, especially during crises in both the COVID-19 outbreak and the RIU. Gold, on the other hand, received comparatively less return spillover from the market at crisis. Noticeably during RIU, the from-connectedness index for gold adjusted downward after only few months of the RIU. Overall, the from-connectedness (measuring the spillover received from other assets) of gold responded to crisis more gently and tends to revert to lower level in shorter period of time.

Figure 9: **From-Connectedness Index of Volatility**

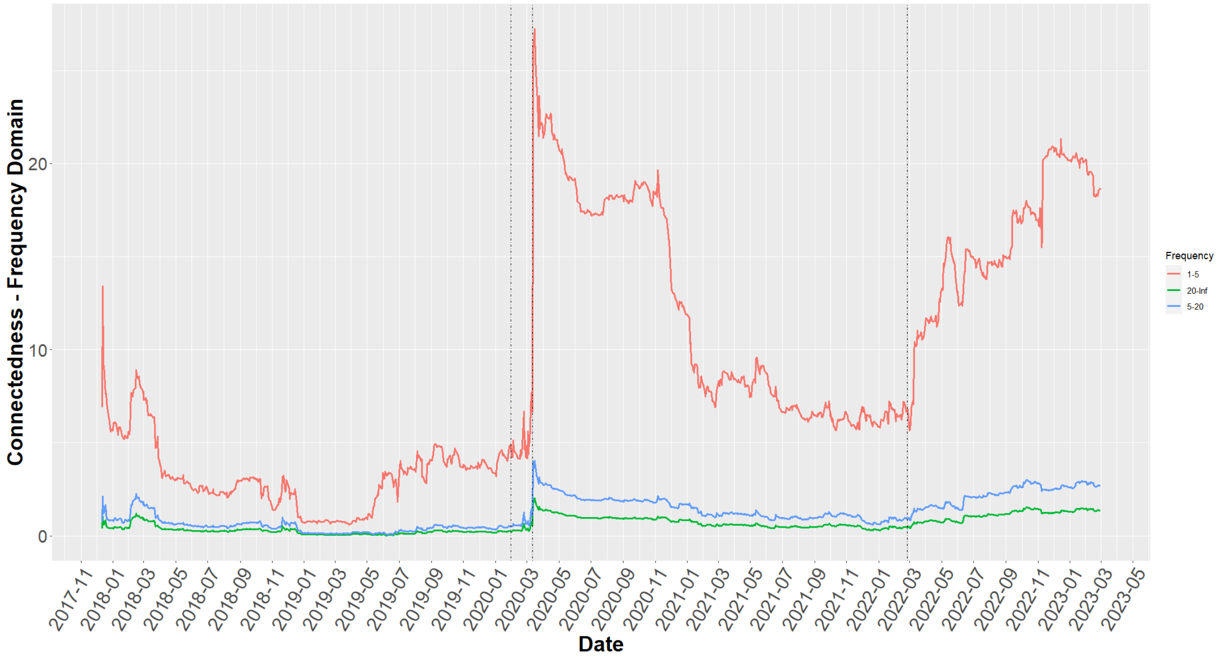


* Refer to Figure 1 for the meaning of the 3 Dotted Vertical Lines

The volatility from-connectedness in figure 9 provide a contrary result. It is found that during the crisis periods in COVID-19 and the RIU, gold received the most spillover from the other markets.

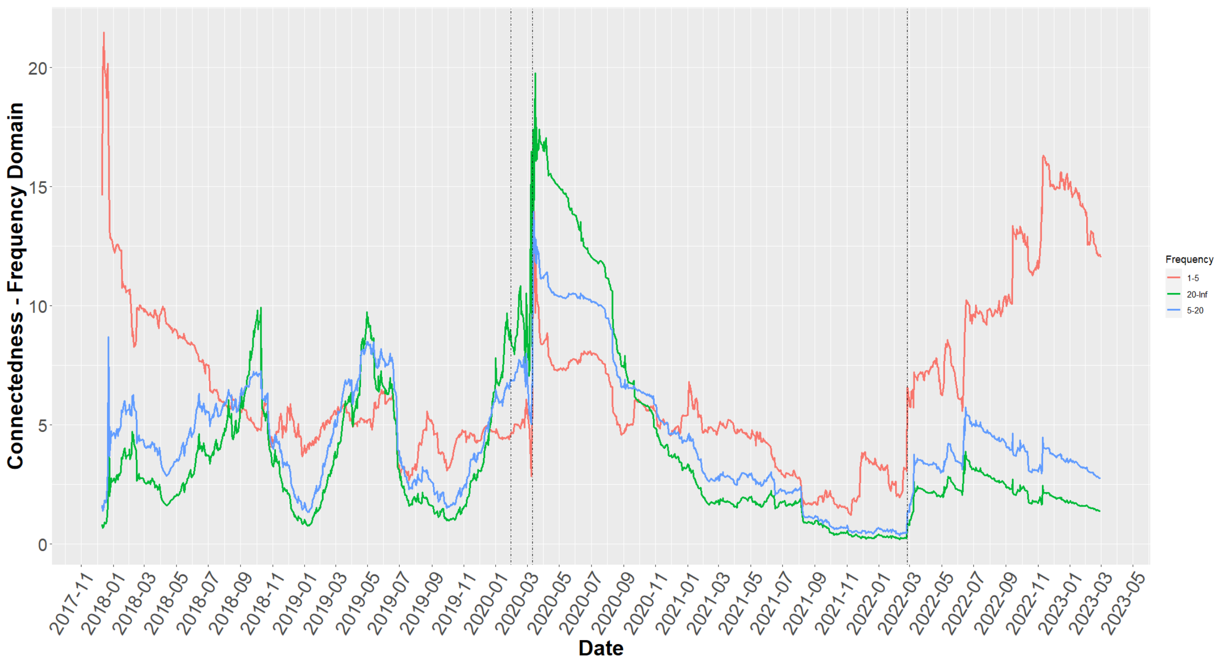
5.1.3 Spillover Indexes – Frequency Domain

Figure 10: Very Short-term, Short-term and Long-term Return Connectedness



* Refer to Figure 1 for the meaning of the 3 Dotted Vertical Lines

Figure 5: Very Short-term, Short-term and Long-term Volatility Connectedness



* Refer to Figure 1 for the meaning of the 3 Dotted Vertical Lines

The connectedness for returns and volatility is further analyzed in 3 frequency terms, namely, "very short term" (1–2 days), short term (2-5 days) and long term (more than 20 days).

Figure 10 shows that the return linkages at very short term dominates. This reflects that market information of returns shocks is absorbed very quickly in these markets. In contrast, figure 11 shows that volatility linkages at very short term, short term and long term all played an important role in the overall spillover. Particularly, during the COVID-19 period the volatility linkage at long term are considerably larger than others. This reflects that market information of volatility shocks can persist over longer term.

5.1.4 Spillover Asymmetry Measure

Figure 12: **Dynamic Volatility Connectedness based on Realized Variance**

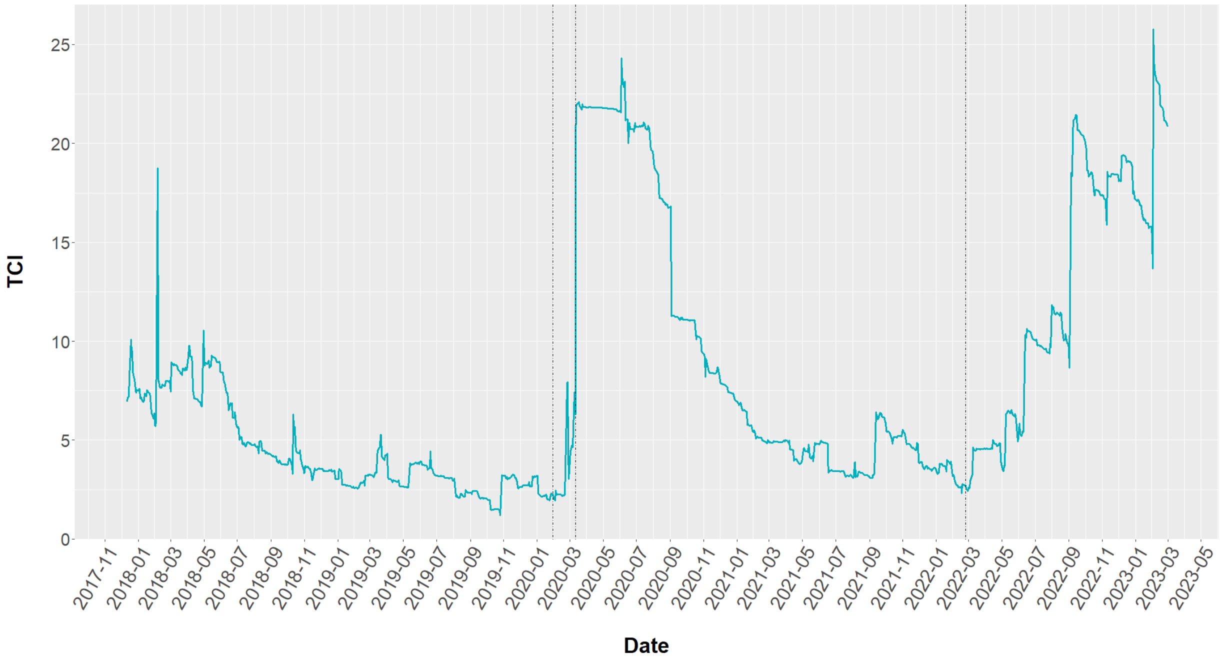


Table 3: Spillover Asymmetry Measures, before RIU, during RIU, Full Sample

Item	Spillover Asymmetry Measure
Before RIU	-1.42
During RIU	-11.34
Full Sample	-3.23

In order to examine the asymmetry of the volatility spillover during the RIU, the realized variance is calculated using rolling-window 60-day returns. All realized variances are found to be non-stationary with ADF unit root test. The realized variances are therefore first differenced before computing the realized variance-based volatility spillover index. It revealed similar pattern as in the range-based daily volatility estimates in earlier section. The realized volatility spillover rose during both COVID-19 and RIU. The realized semi-variances are further computed and first differenced. The resulting Spillover Asymmetry Measure (SAM) not just indicate the existence of asymmetry in the markets, but also the fact that the asymmetry intensified considerably during RIU. Spillover of "Bad" volatility, i.e. volatility from negative returns, dominate. Strong negative asymmetry is detected during RIU.

6. Conclusion

This study provides insights into the time and frequency connectedness among the representative asset of 3 different asset classes, namely bitcoin, gold and MSCI World Index with a focus on the impact of the Russia's invasion of Ukraine (RIU). Due to the non-negligibly strong impact of the outbreak of COVID-19, its impact is also addressed for comparison purpose. When the world is absorbing the market shocks of the COVID-19 outbreak, the geopolitical uncertainties from the RIU suppressed the recovery and continued to create instability in the global financial markets. This study provides insights for risk management purpose by analyzing the dynamic connectedness of the gold, bitcoin and the traditional equity market during the RIU. Consistent to most studies from other researchers, the total connectedness index of return and volatility spillover increased during the RIU.

With the TVP-VAR connectedness analysis over the whole period, gold exhibits a special behavior that it became a strong net receiver of return shocks, absorbing the stronger net transmitter of bitcoin and MSCI WORLD INDEX during the RIU. Notably, the volatility spillover received from other markets as measured by the from-connectedness is the highest in gold. This suggests that while gold is traditionally considered a safe haven during crises, it has to receive large spillover of volatility from other assets during such events. This finding can be useful for devising optimal portfolio diversification strategies during crisis periods.

Moreover, connectedness at very short term has dominating proportion of volatility spillovers compared to the short term (5-20 days) and long-term connectedness (20 days or more), reflecting that market information of volatility shocks involving highly volatile markets like bitcoin can be absorbed very quickly. In contrast. The connectedness at very short term of return spillover alone does not dominate the overall impact. The short-term and long-term return spillover play a non-negligible role in the overall return spillover. In summary, volatility shocks are absorbed very quickly while comparatively the impact from return shocks could be persistent in the longer term (20 days or more). This suggests the importance of portfolio reallocation at a higher frequency to control the risk from volatility spillover during crisis events. It can be observed that the rising connectedness levels in the markets are still in their rising trend, under the RIU impact. Future research can be conducted when the RIU is over in order to have a complete analysis of the behaviors of the dynamic connectedness of the markets over the full crisis cycles.

References

Allen, F., Fatas, A., & di Mauro, B. (2022). Was the ICO boom just a sideshow of the Bitcoin and Ether Momentum? *Journal of International Financial Markets, Institutions and Money, 80,* 101637. doi:https://doi.org/10.1016/ j.intfin.2022.101637

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined Measures of Dynamic Connectedness based on Time-Varying Parameter Vector Autoregressions. *Journal of Risk and Financial Management, 13*(4), 84. doi:https://doi.org/10.3390/jrfm13040084

Balcilar, M., Gabauer, D., & Umar, Z. (2021). Crude Oil futures contracts and commodity markets: New evidence from a TVP-VAR extended joint connectedness approach. *Resources Policy, 73*, 102219. doi:https://doi.org/ 10.1016/j.resourpol.2021.102219

Barndorff-Neilsen, O., Kinnebrock, S., & Shephard, N. (2010). Measuring Downside Risk-Realised Semivariance. In J. R. T. Bollerslev, *Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle* (pp. 117-136). Oxford University Press.

Barunı´k, J., & Krehlı´k, T. (2018). Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk*. *Journal of Financial Econometrics, 16*(2), 271-296. doi:https://doi.org/10.1093/jjfinec/nby001

Baruník, J., Kočenda, E., & Vácha, L. (2016). Asymmetric connectedness on the U.S. stock market: Bad and good volatility spillovers. *Journal of Financial Markets, 27*, 55-78.

Brière, M., Oosterlinck, K., & Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management, 16*(6), 365-373. doi:Briere, Marie and Oosterlinck, Kim and Szafarz, Ariane, Virtual Currency, Tangible Return: Portfolio Diversification with Bitcoin (2015). Journal of Asset Management, 16, 6, 365-373, doi:10.1057/jam.2015.5 , Available at SSRN: https://ssrn.com/abstract=23

Caloia, F., Cipollini, A., & Muzzioli, S. (2019). How do normalization schemes affect net spillovers? a replication of the diebold and yilmaz (2012) study. *Energy Economics, 84*, 104536.

Chatziantoniou, I., Gabauer, D., & Marfatia, H. (2021). Dynamic connectedness and spillovers across sectors: Evidence from the Indian stock market. *Scottish Journal of Political Economy, 69*(3), 283-300. doi:https://doi.org/10.1111/ sjpe.12291

CoinMarketCap. (2023, January 5). *Today's Cryptocurrency Prices by Market Cap*. Retrieved from CoinMarketCap: https://coinmarketcap.com/

Corbet, S., Larkin, C., Lucey, B., Meegan, A., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters, 165*(1), 28-34. doi:http://dx.doi.org/10.2139/ssrn.3070288

Corbet, S., Lucey, B., Peat, M., & Vigne, S. (2018). Bitcoin Futures—What use are they? *Economics Letters, 172,* 23-27. doi:https://doi.org/10.1016/ j.econlet.2018.07.031

Corbet, S., Lucey, B., Urquhart, A., & Yarova, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis, 62*, 182-199. doi:https://doi.org/10.1016/j.irfa.2018.09.003

Diebold, F., & Yilmaz, K. (2009). Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *The Economic Journal, 119*(534), 158-171. doi:https://doi.org/10.1111/j.1468-0297.2008.02208.x

Diebold, F., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting, 28*, 57-66.

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis, 63*, 431-437. doi:https://doi.org/10.1016/j.irfa.2018.03.004

JEBABLI, I., KOUAISSAH, N., & AROURI, M. (2022). Volatility Spillovers between Stock and Energy Markets during Crises: A Comparative Assessment between the 2008 Global Financial Crisis and the Covid-19 Pandemic Crisis. *Finance Research Letters, 46*, 102363.

Lastrapes, W., & Wiesen, T. (2021). The joint spillover index. *Economic Modelling, 94*, 681-691.

Le, T.-L., Abakah, E., & Tiwari, A. (2021). Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution. *Technological Forecasting and Social Change, 162*, 120382. doi:https://doi.org/10.1016/ j.techfore.2020.120382

Mensi, W., Ur Rehman, M., & Vo, X. (2020). Spillovers and co-movements between precious metals and energy markets: Implications on portfolio management. *Resources Policy, 69*, 101836. doi:https://doi.org/10.1016/ j.resourpol.2020.101836

Nakamoto, S. (2008). *Bitcoin: A peer-to-peer electronic cash system.* Retrieved from Bitcoin - Open source P2P money: https://Bitcoin.org/Bitcoin.pdf .

Nasdaq. (2023, January 5). *Gold Price: Latest Futures Prices, Charts & Market News | Nasdaq*. Retrieved from Nasdaq: https://www.nasdaq.com/market-activity/commodities/gc:cmx

Parkinson, M. (1980). The Extreme Value Method for Estimating the Variance of the Rate. *Journal of Business, 53*, 61-65.

Shahzad, S., Naeem, M., Peng, Z., & Bouri, E. (2021). Asymmetric volatility spillover among Chinese sectors during COVID-19. *International Review of Financial Analysis, 75*, 101754.

Sun, Q., Gao, X., An, H., Guo, S., Liu, X., & Wang, Z. (2021). Which time-frequency domain dominates spillover in the Chinese energy stock market? *International Review of Financial Analysis, 73*, 101641. doi:https://doi.org/ 10.1016/j.irfa.2020.101641

Xia, T., Yao, C.-X., & Geng, J.-B. (2020). Dynamic and frequency-domain spillover among economic policy uncertainty, stock and housing markets in China. *International Review of Financial Analysis, 67*. doi:https://doi.org/10.1016/ j.irfa.2019.101427

Yahoo Finance. (2023, January 5). *S&P 500 (^GSPC) Charts, Data & News*. Retrieved from Yahoo Finance: https://finance.yahoo.com/quote/ %5EGSPC?p=^GSPC&.tsrc=fin-srch