Advances in Economics, Business and Management Research, volume 211
Proceedings of the 2022 7th International Conference on Financial Innovation and Economic Development (ICFIED 2022)

Dynamic Connectedness Between Cryptocurrencies, Gold, U.S. Dollar Index, and Oil During COVID-19

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ABSTRACT

This paper aims to find the connectedness between cryptocurrencies and traditional assets. Using daily data of three representative cryptocurrencies and three traditional assets over the period August 2015 to July 2021, this study explores the cross-sector connectedness between the cryptocurrencies market and the traditional assets market. The result shows that connectedness varies over time and External events (COVID-19, oil crisis) have a significant impact on connectedness. Furthermore, traditional assets are relatively independent of each other. Cryptocurrencies, as the main transmitter, can affect each other. During some COVID-19 pandemic, cryptocurrencies can give great shocks to the traditional assets market. The result sparks some new insights for investors and policymakers.

Keywords: *TVP-VAR, Gold, U.S. dollar index, Oil, COVID-19, Connectedness*

1. INTRODUCTION

Ubiquitous digital technology is developing exponentially, changing the economy we know. The development of the digital economy has triggered a lot of researches. For example, based on the comprehensive definition of "digital sharing economy" (DSE), Pouri and Hilty [1] proposed a theoretical framework, which includes and constructs various sharing platforms and the practices they promote. Burnes and Choi [2] show that mixing, extensive participation, and equal power in the economy are the core factors of virtual community development. The digital economy is developing at an exponential rate, especially in developing countries. [3] The digital economy has become a main factor in driving the future economy. [4] According to Shao, Ni, Wang [5], some extreme financial event such as global financial crisis (GFC) and the development of information technology in 2008 shows that people's life has gradually realized networking and digitization. Digital currency expressed by bitcoin came into being. The rise of digital currency brings investment opportunities and risks, and the traditional currency has been impacted. Digital currency bitcoin is famous for its energy hunger and related carbon footprint. However, cryptocurrency can bring us some new environmental, social, and government governance-related hidden dangers. [6] In recent years, external events have influenced financial assets that cannot be ignored. During COVID-19, the price of investment products will fluctuate sharply, and this fluctuation will be much more significant than before COVID. [7] During the outbreak of COVID-19, the volatility transmission between the energy and stock markets exceeded the record during GFC. [8]

However, the researches on the relationship between traditional assets and emerging assets are not very complete. This paper aims to determine which market will be impacted or changed and find the transmitter and receiver. This study also wants to find out: is there any external influence and the degree of impact? The time-varying parameter vector autoregressive (TVP-VAR) model is used for this paper to measures the connectedness index in order to analyze these problems. There are many potential channels to explain the relationship between cryptocurrencies and the traditional assets. On the one hand, international investment and investment strategy hedging will aggravate the level of asset spillover effect. If the banks strongly supported by the government are expected to be located in countries with high sovereign ratings, the guarantee channel will limit the international spillover effect. [9] On the other hand, foreign exchange rates also could be a factor to impact the connectedness between cryptocurrencies and traditional assets. From 2000 to 2018, the unexpected change in foreign exchange rates is the primary driver of risk spillover to the crude traditional assets market. [10]

We hope to add the literature contribution in the following lines: First, I try to introduce a framework and adds fintech research (e.g. Cryptocurrencies) and the traditional financial assets (e.g. oil, US dollar and gold) to my research. More fresh evidence will provide more perspectives and richer results. Second, The TVP-VAR model is estimated using rolling windows. Compared to the conventional VAR or regression method, this relatively novel method can detect the dynamics between cryptocurrencies and traditional assets. Third, COVID-19 has aroused extensive discussion in academic circles. Therefore, I considered the impact of the emergency covid-19 on the system. It could provide some guidance for investors and policymakers.

The main result in this paper shows that external events such as COVID-19 and the oil crisis have a crucial impact on connectedness and connectedness and dynamic relationship changes over time. Cryptocurrencies are the main transmitter. For example, Bitcoin is an enormous transmitter in this financial system. Traditional assets are relatively independent of each other, and they are not impacted by other fintech assets with ease. Transmitters can change into the receiver. For example, Ripple became a receiver after the oil crisis.

2. METHODOLOGY

To explore the time-varying transmission mechanism, this paper uses the TVP-VAR methodology of Antonakakis and Gabauer [11] and combines it with Diebold and Yılmaz's [12] connectedness approach. In this model, the framework relies on the decay factors, so the variance could change over time via a Kalman Filter estimation. TVP-VAR model can solve the problem of very unstable or flat parameters and loss of valuable observations caused by arbitrary selection of rolling window size. The TVP-VAR model can be written as follows:

$$Y_t = \beta_t Y_{t-1} + \epsilon_t \qquad \epsilon_t|F_{t-1} \sim N(0, S_t) \tag{1}$$

$$\beta_t = \beta_{t-1} + v_t \qquad v_t|F_{t-1} \sim N(0, R_t) \tag{2}$$

where Y_t represents an $N_p \times 1$ conditional volatilities vector, Y_{t-1} is a $N_p \times 1$ lagged conditional vector, β_t is a $N \times N_p$ dimensional time-varying coefficient matrix and ϵ_t is an N×1 dimensional error disturbance vector with an N × N time varying variance-covariance matrix, S_t. The parameters βt depend on their own values β_{t-1} and on an $N \times N_p$ dimensional error matrix with an $N_p \times N_p$ variance-covariance matrix.

Diebold and Yılmaz estimated the generalized connectivity process using time-varying coefficients and error covariance based on the generalized impulse response function (GIRF) and generalized prediction error variance decomposition (GFEVD) developed by Pesaran and Shin. [14] In order to calculate GIRF and GFEVD, VAR can be converted into vector moving average (VMA) representation and vector moving average (VMA) representation:

$$Y_t = \beta_t Y_{t-1} + \epsilon_t \tag{3}$$

$$Y_t = A_t \epsilon_t \tag{4}$$

$$A_{0,t} = I \tag{5}$$

$$A_{i,t} = \beta_{1,t} A_{i-1,t} + \cdots + \beta_{p,t} A_{i-p,t} \tag{6}$$

where $\beta_t = [\beta_{1,t}, \beta_{2,t}, \dots, \beta_{p,t}]'$ and $A_t = [\beta A_{1,t}, A_{2,t}, \dots, A_{p,t}]'$ and hence $\beta_{i,t}$ and $A_{i,t}$ are N × N dimensional parameter matrices.

The response of all variables after impact in the variable i is called GIRFs. The difference between the J-step-ahead prediction of primary impact variable i and primary nonimpact variable i can be calculated by the following formula:

$$GIR_t(J, \delta_{j,t}, F_{t-1}) = E(Y_{t+J}|\epsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(Y_{t+J}|F_{t-1}) \tag{7}$$

$$\Psi^g_{j,t}(J) = \frac{A_{J,t} S_t \epsilon_{j,t}}{\sqrt{S_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{S_{jj,t}}} \quad \delta_{j,t} = \sqrt{S_{jj,t}} \tag{8}$$

$$\Psi^g_{j,t}(J) = S^{-\frac{1}{2}}_{jj,t} A_{J,t} S_t \epsilon_{j,t} \tag{9}$$

J is the forecast horizon, $\delta_{j,t}$ is the selection vector with one on the jth position and zero otherwise. F_{t-1} is the information set before t – 1. Then, GFEVD can be calculated, which can be interpreted as the variance sharing of one variable to other variables. Then these variance shares need to be standardized, so each row adds up to one row, which means that all variables add up to explain 100% of the prediction error variance of the variables. The calculation method is as follows:

$$\emptyset^g_{i,j,t}(J) = \frac{\sum_{t=1}^{J-1} \Psi^{2,g}_{i,j,t}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \Psi^{2,g}_{i,j,t}} \tag{10}$$

With $\sum_{j=1}^{N} \tilde{\emptyset}^N_{ij,t}(J) = 1$ and $\sum_{j=1}^{N} \tilde{\emptyset}^N_{ij,t}(J) = N$ using the GFEVD, we construct the total connectedness index by:

$$C^g_t(J) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\emptyset}^g_{ij,t}(J)}{\sum_{i,j=1}^{N} \tilde{\emptyset}^g_{ij,t}(J)} * 100 \tag{11}$$

$$= \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\emptyset}^g_{ij,t}(J)}{N} * 100 \tag{12}$$

How a shock in one variable spills over to other variables could be showed by this connectedness approach. The first step is to observe that variable i transmits its shock to all other variables j, which is called the total directional connectedness with other variables, which is defined as:

$$C^{g}_{i\rightarrow j,t}(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}^{g}_{ij,t}(J)}{\sum_{j=1}^{N} \tilde{\phi}^{g}_{ji,t}(J)} * 100 \quad (13)$$

Secondly, the directional connectedness variable i is received from the variable j, which is called the total directional connectedness of other variables, which can be calculated as:

$$C^{g}_{i\rightarrow j,t}(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\phi}^{g}_{ij,t}(J)}{\sum_{j=1}^{N} \tilde{\phi}^{g}_{ij,t}(J)} * 100 \quad (14)$$

Finally, the "power" of variable i, or, its influence on the whole variable network can be calculated by subtracting the total directional connectedness of other variables from the total directional connectedness to obtain the net total directional connectedness:

$$C^{g}_{i,t} = C^{g}_{i\rightarrow j,t}(J) - C^{g}_{i\leftarrow j,t}(J) \quad (15)$$

The net total directional connectedness of variable i is positive, indicating that the influence of variable i on the network is greater than that on the network. On the contrary, the total directional connectedness of the network is negative, indicating that the variable i is driven by the network.

3. DATA AND EMPIRICAL RESULTS

3.1. Data

The daily observations of the gold (GOLD), oil, U.S. dollar index (DX), Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) over the period August 2015 to July 2021 are collected from Yahoo Finance. According to Soylu, (2021), Bitcoin, Ethereum, and Ripple are the three most popular cryptocurrencies. *The log return of all the prices were calculated before running the TVP-VAR model because the b*enefit of using *returns* versus prices is *normalization.*

3.2. Empirical Results

The summary statistics of the transformed series are presented in Table 1. It describes the statistics of the return sequence of the three cryptocurrencies, GOLD, OIL, and DX sector, during the sample period. All factors show that their performances are close to 0. DX and GOLD present the lowest mean whereas the ETH is characterized by the highest. In addition, it can be seen that the smallest standard deviation, hence the smallest risk, is found with the DX and GOLD, while the largest is detected in XRP. Augmented-Dickey-Fuller (ADF) is used to test the stationarity of time series in this study to test the unit root. In this case, we can obtain a takeaway that the series in this paper are all stationary.

I show the connectedness measurement in Table 2, which is characterized by the unconditional spillover effect between cryptocurrency, gold, oil and traditional assets.

One can obtain some key points in Table 2 to get the average value of the connectedness level. It characterizes the unconditional spillover effects across the new assets (cryptocurrencies) and traditional assets (gold, oil, and U.S. dollar). Our model is based on the TVP-VAR model and the connectedness index is the variance decomposition with 20 days.

The sum of offline elements in line i is “Contribution FROM others”, indicating the total directional connectedness between all other variables and variable i. The sum of offline elements in column jth gives the total directional connectivity of all other variables and represents the spillover effect of variable J on all other variables, which is "contribution to other variables". The difference between “TO” and “FROM” can be shown by the “Net” row.

The total spillover index (27.85%) means that about one-third of the market's volatility between cryptocurrencies and traditional assets is attributed to their inter-connectedness during the sample period. When considering the “FROM” connectedness index for each sector in Table 2, for bitcoin (BTC), Ethereum (ETH) and ripple (XRP), the most significant contribution comes from ETH, and BTC (20.63%, 20.49% and 12.51%, respectively), while the most considerable contribution for the U.S. dollar index (DX), gold and oil

Table 1. Summary Statistics

	BTC	DX	ETH	GOLD	OIL	XRP
Mean	0.003	0	0.004	0	0.001	0.002
Variance	0.002	0	0.004	0	0.001	0.005
Skewness	-0.931***	0.051	0.021	-0.08	0.277***	0.585***
Kurtosis	12.373***	2.471***	7.509***	5.609***	25.995***	15.535***
ADF	-38.799***	-36.905***	-37.061***	-38.534***	-37.001***	-24.786***

Note: (*), (**) and (***) stand for 90%, 95% and 99% significance levels, respectively.

Table 2. Dynamic Connectedness Table

	BTC	DX	ETH	GOLD	OIL	XRP	FROM others
BTC	63.42	1.36	20.63	1.99	0.67	11.92	36.58
DX	3.96	73.84	2.12	16.55	1.95	1.58	26.16
ETH	20.49	0.84	62.07	1.21	0.96	14.44	37.93
GOLD	4.6	16.7	2.44	73.28	1.4	1.59	26.72
OIL	2.85	1.72	1.74	1.6	90.73	1.36	9.27
XRP	12.51	0.58	16	0.73	0.62	69.54	30.46
TO others	44.41	21.2	42.93	22.09	5.61	30.88	167.12
Inc. own	107.83	95.04	105	95.36	96.34	100.42	TCI
NET	7.83	-4.96	5	-4.64	-3.66	0.42	27.85
NPDC	1	4	0	4	4	2	

is from gold (16.55%)), DX (16.7% and BTC (2.85%), respectively. Diagonal elements (own connectivity) refer to their contribution to variance, from 62.07% to 90.73%. In general, oil is a relatively independent sector with about 9.27% of its forecast error variance attributed to all other sectors combined, whereas its shocks explain approximately 90.73%.

From the row "Contribution TO others", it is found that the gross directional connectedness ("TO" connectedness) is very different from each other. The BTC industry has the highest "To" connectedness (about 44.41%), ETH sector has the highest connectedness with other sectors (see the column "Contribution FROM others", about 37.93%). With 5.61% of "TO" connectedness and 9.27% of "FROM connectedness, the sector of OIL is the industry with the lowest correlation. Followed by the sector of DX, the total share of other industries in its volatility is about 21.2%, while it accounts for about 26.16% of the total variance of different sectors.

The difference between "To" and "From" explains the net spillover effect of different sectors represented by the "NET" line. During the sample period of August 2015 to July 2021, the "TO" connectedness of BTC (44.41%) exceeds its "FROM" connectedness (36.58%) by 7.83%, making this industry the industry with the highest net connectedness among the five industries in the market. Similarly, the ETH sector is another major transmitter of shocks (with a net connectedness of 5%).

In contrast, the table shows that the main receiver of shocks (with "Net" connectedness − -4.96%) is the sector of the U.S. dollar, the second one is the sector of gold (with "Net" connectedness − -4.64%), the third one is the sector of oil (with "Net" connectedness − -3.66%).

Figure 1 visualizes the standardized data, and all the graphs show that the return of each asset is stationary and volatility clustering. The first three graphs are the group of the traditional assets. The remaining graphs are the group of cryptocurrencies. Over the period 2020, COVID-19 has negative effects on both traditional assets and cryptocurrencies assets. When comparing the two groups, it is easy to find that the COVID-19 impact on traditional assets is more robust than cryptocurrencies.

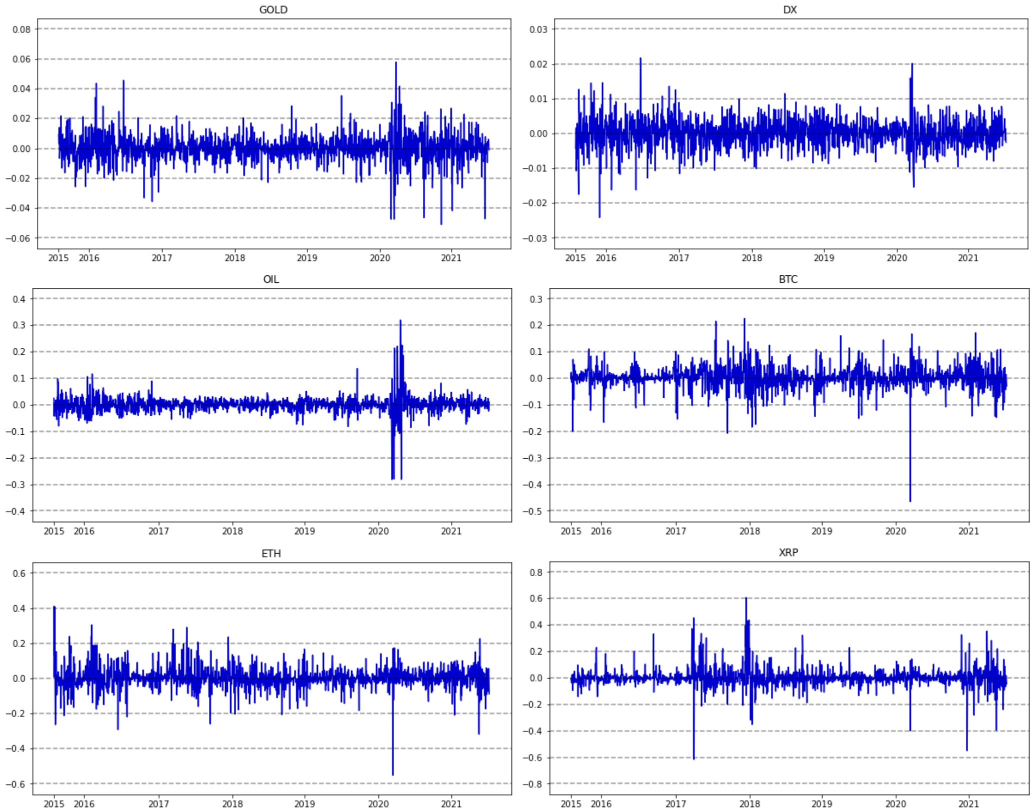


Figure 1. Transform Data

The evolution of the total connectedness index of the system is shown in Figure 2. The total connectedness index ranges from 7.95% to 80.11%. The time-varying model of spillover effect in the sample period can be provided by it. In Figure 2, large spikes are observed around 2015 and 2020. There was a sharp decline during 2015 to 2017. The oil price had its most significant and longest lasting decline after 2015 in modern history. [15] Early on in crypto markets, retail investors dominated the crypto trading ecosystem, but they lacked institutional investors' heft and trading volume. Price movements for cryptocurrencies have not always followed a predictable pattern. Cryptocurrency prices could be inversely correlated to stock prices during this period. The total connectedness index slowly increased after 2017 and rocketed during the 2020 pandemic. That price trajectory almost moved in the same trend as the major stock.

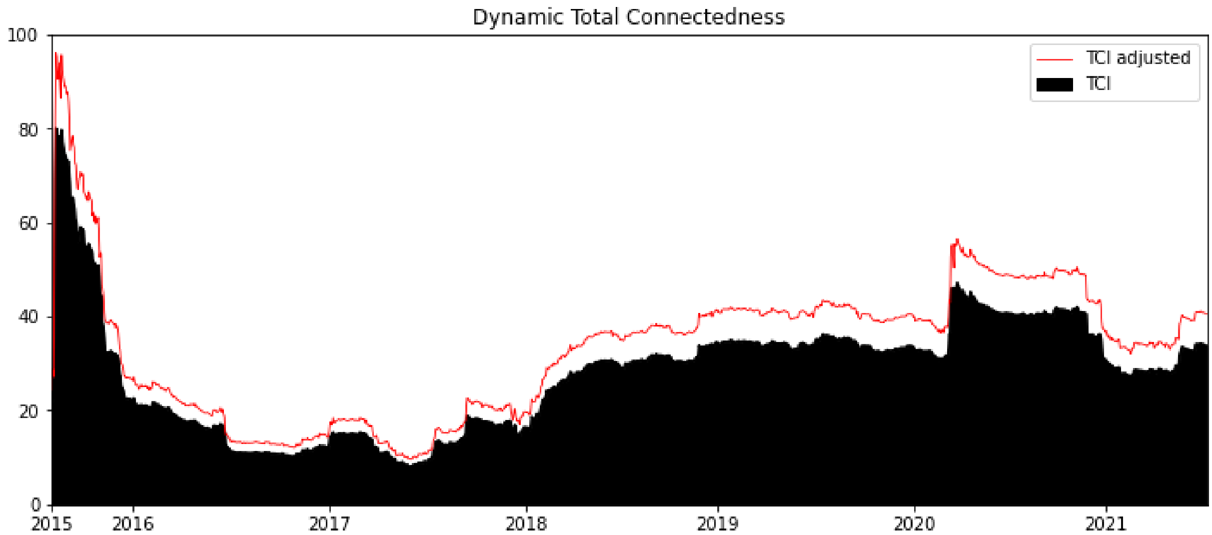


Figure 2. Dynamic Total connectedness

Notes: The black shaded area illustrates the total connectedness index (TCI) with external spillovers. The red line illustrates the adjusted TCI.

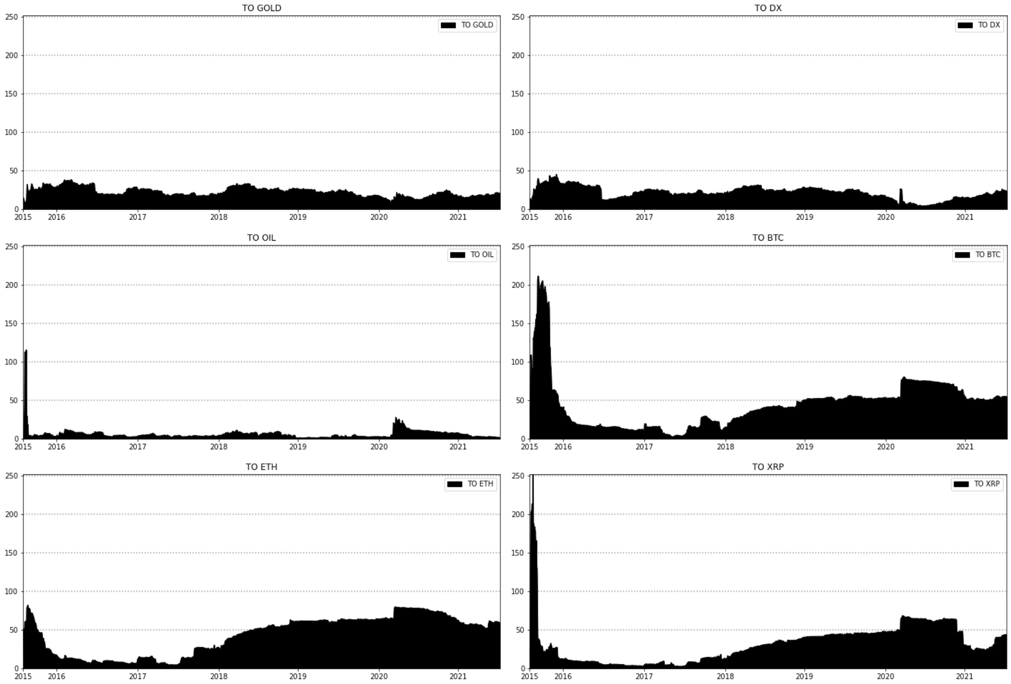


Figure 3. To Others

Figure 3 measures the directional connectivity of each of the six factors with other factors. It shows the dynamics of "TO" connectedness. By emphasizing the crucial role of cross-sectoral correlation in volatility connectedness, these figures highlight the complexity and differences of directional connectivity dynamics between various factors and other factors. In the whole sample period, the spillover effect of gold and the U.S. dollar index on other industries is lower than that of other industries, with an average of 22.09% and 21.2%, respectively. Youssef [16] find that changes in oil prices have little impact on stock market returns. Such a result can explain that the level of a spillover effect from oil to others is much smaller than other factors, with an average of 5.61%. The fluctuation characteristics of cryptocurrencies are similar because the "TO" connectedness series between the three cryptocurrency markets is very similar in periodicity, trend, and scale. The level of spillover effects from bitcoin to others is the largest with an average of 44.4.

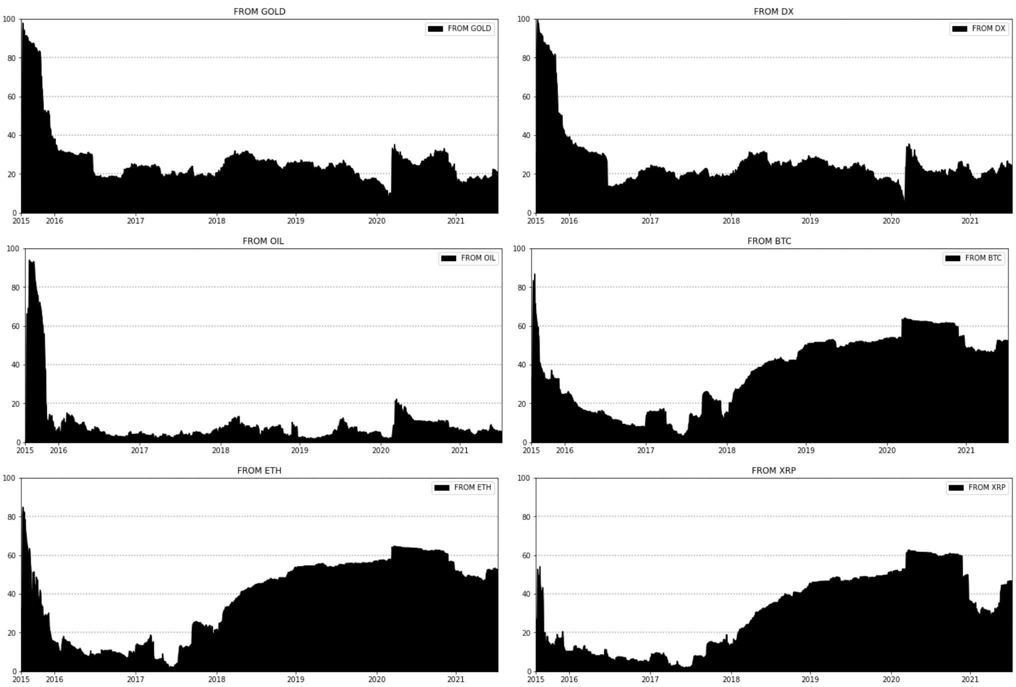


Figure 4. From Others

Figure 4 shows the “Contribution FROM others”, which measures the directional connectedness between each department and other departments. Two similar trends for the group of traditional assets and the group of cryptocurrencies are presented in the “FROM” connectedness figures. In the sample period, the spillover effects of all other factors on each sector vary greatly, ranging from 9.27% to 36.58%. After 2018, the level of the spillover effect of other sectors on the cryptocurrency market has steadily increased, then it rocketed during the 2020 pandemic, and it decreased at the beginning of 2021. After 2018, cryptocurrency has been sought after by investors and is more affected by other markets, and the connectedness index has become more significant. In contrast, the oil sector seems to be less sensitive to the impact of other markets. In the same period, other markets have a low level of spillover effects from different sectors. Oil is a finite energy resource, and it will be eventually run out after people consume them for long enough. [17] The market of oil is relatively independent. It is affected less by other markets, whether traditional asset market or virtual currency market.

Figure 5 is the net directional connectedness; it explains how the spillover connectedness index switches from the recipient of the impact to the sender. As shown in the first three figures, it is evident that the sector of traditional assets received shocks to other sectors nearly during 2015-2016. In contrast, as shown in the last three figures, the cryptocurrencies market transmitted shocks to the commodity sectors during this period. Gold and the U.S. dollar index received another shock during the 2020

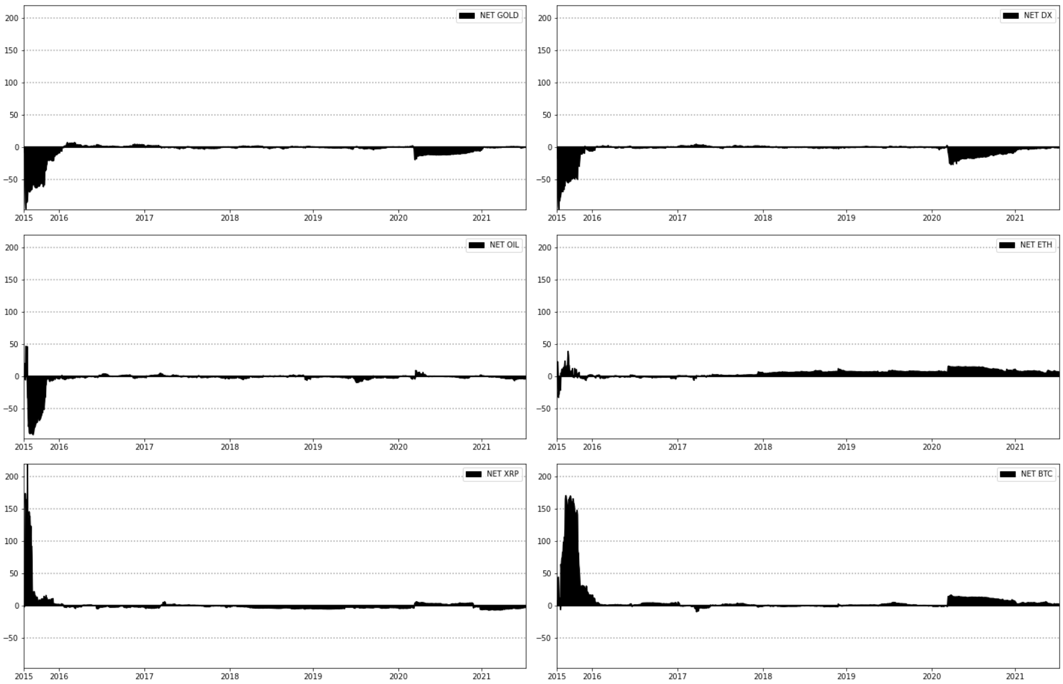
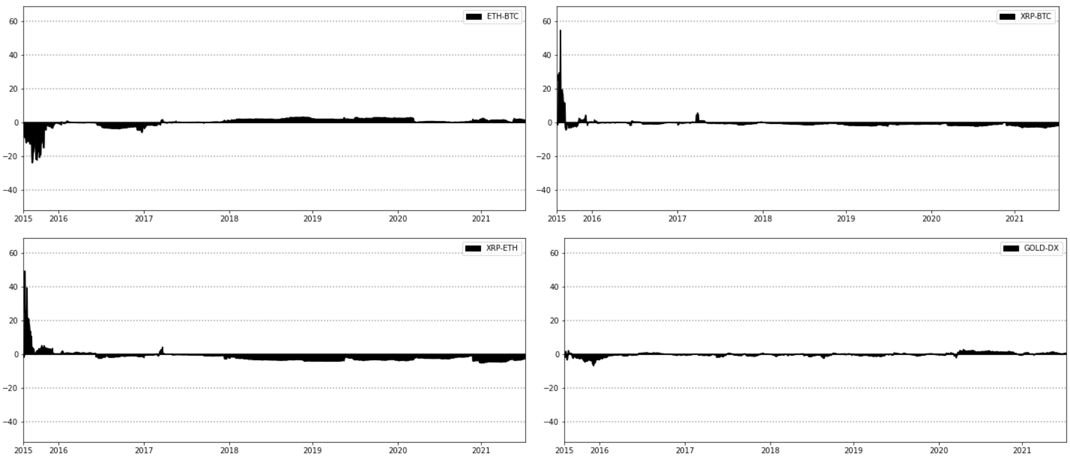


Figure 5. Net Total Directional Connectedness



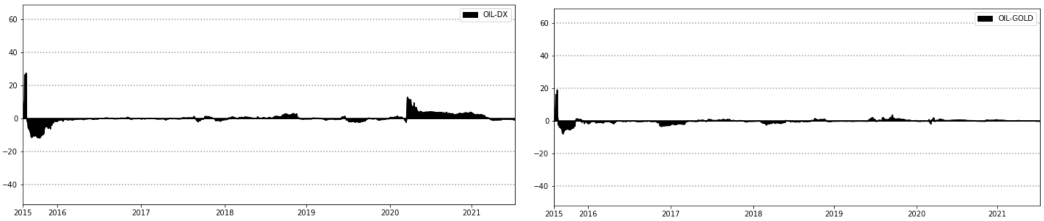


Figure 6. Net pairwise directional connectedness (Internal)

pandemic, but the gold market had an average of 0 during the whole sample period. In the cryptocurrency market, it is of note that net connectedness of our economic variables between cryptocurrencies and traditional assets have changed from negative to positive, which implies that the role of cryptocurrencies and traditional assets can switch from receiver to transmitter. In addition, the power of net connectedness index for ETH increases significantly.

On the other hand, Figure 6 shows the net pairwise directional connectedness to stress the inter-connectedness in traditional assets. The net directional connectedness level between GOLD & DX and OIL & GOLD is near zero which means that these traditional assets relatively independent and not easily influenced by other assets in this dynamic system. Due to the strong correlation among the cryptocurrencies, [18] they can affect each other, and the connectedness index is larger than the second group of traditional assets.

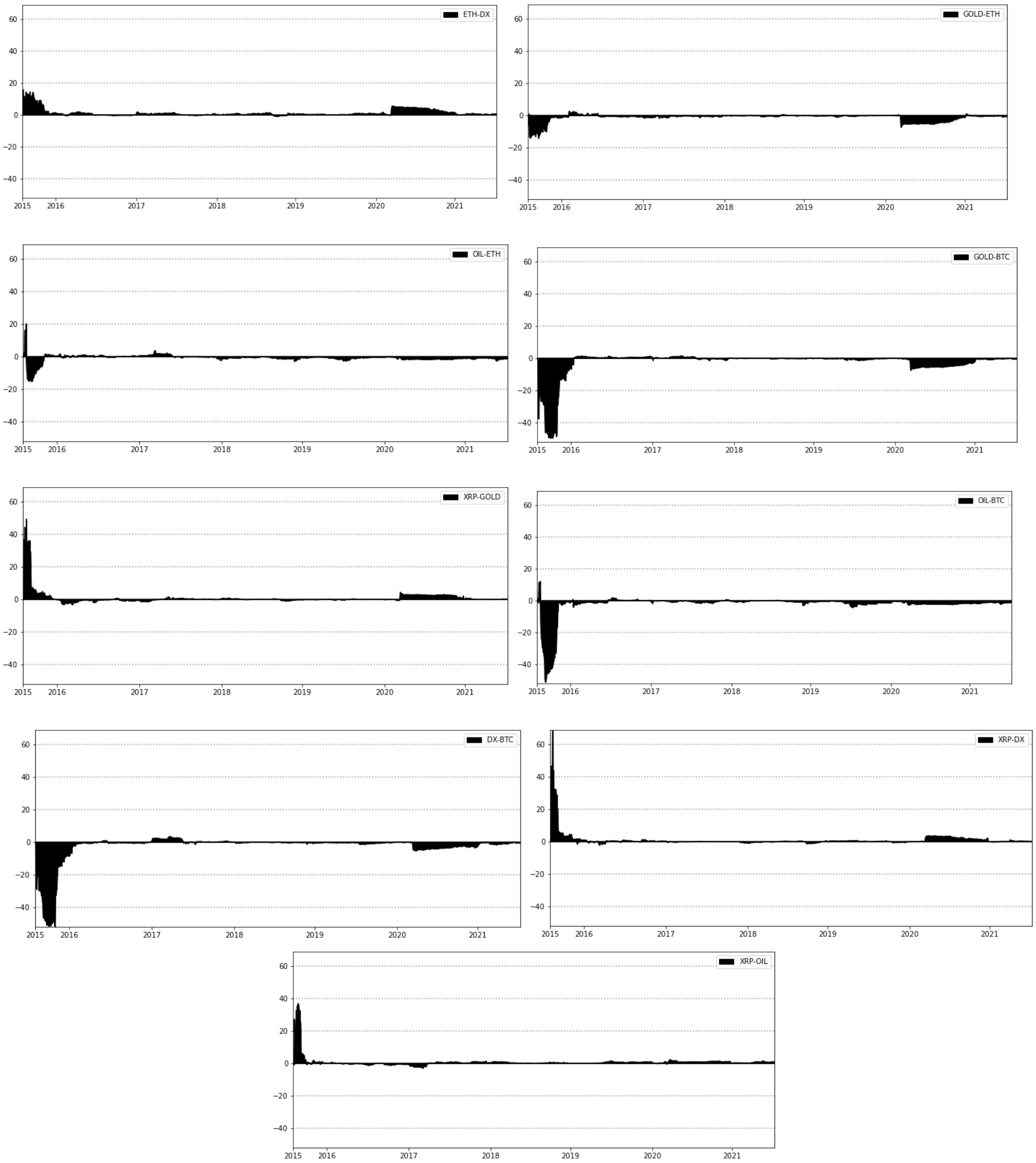


Figure 7. Net pairwise directional connectedness (External)

Similarly, Fig. 7 show the net pairwise directional connectedness for the cryptocurrencies market. It can be observed that the cryptocurrencies like ETH and XRP could be said to be the net volatility transmitters. In most cases, the traditional assets (OIL, GOLD, and DX) all received the shock from the cryptocurrencies (Bitcoin, Ethereum, and Ripple) during 2015-2016, which is also the start-up and booming stage of cryptocurrencies. [19] Similarly, the shock during the 2020 COVID-19 pandemic is also obvious. According to Mnif, Jarboui, and Mouakhar [20], the COVID-19 pandemic had a positive impact on the cryptocurrency market efficiency which is in line with our results.

5. CONCLUSION

I try to investigates the pattern of interdependence structure of cryptocurrencies and traditional assets by using the time-varying parameter vector autoregressive (TVP-VAR) methodology. The advantage of the TVP-VAR model is that it is estimated using rolling windows, which is better than the VAR model. When calculating the dynamic connectedness measure generated by rolling window analysis, there is no observation loss. The data used by this paper includes the daily observations of gold (GOLD), oil, U.S. dollar index (DX), Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) over the period August 2015 to July 2021 are collected from Yahoo Finance. This period covers some extreme events, such as the oil crisis and the COVID-19 pandemic. Investors who want to build an optimal portfolio and decision-makers who make effective macroeconomic policies should consider these findings.

Connectedness changes over time and the COVID-19 can have a significant impact on the connectedness index in this paper. Traditional assets are the main shock receivers, and they are relatively independent of each other. For example, the connectedness index of oil is close to zero, which shows that it is unlikely to affect others or be affected by others. In contrast, cryptocurrencies are the transmitter, and they can affect each other. ETH is a typical example, and it gives shocks to other cryptocurrencies. In most cases, the traditional assets (OIL, GOLD, and DX) all receive the shock from the cryptocurrencies, especially during extreme events such as the CIVID-19 pandemic.

Our results can highlight some deeper insights into the market of cryptocurrencies and traditional assets. Therefore, I can use my results to show some policy implications. The government and policymakers should pay attention to the fluctuation transmission and risk contagion between cryptocurrencies, which is conducive to the implementation of policies and promote the stability of the cryptocurrency market. In particular, given the dominant position of bitcoin in the cryptocurrency market, we must pay attention to its potential impact. Investor needs to consider the linkages of the cryptocurrencies and the traditional assets when deciding for the portfolio. When traditional assets and cryptocurrencies are included in the portfolio, assessing the time change of their relationship is very important to optimize the portfolio strategy.

AUTHORS' CONTRIBUTIONS

Zhou carried out the conceptualization, validation, calculation, writing and editing.

ACKNOWLEDGMENTS

I thank for the academic supervision from Mr. Nie.

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