Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Systemic risk-sharing framework of cryptocurrencies in the COVID–19 crisis

Md Akhtaruzzaman, Sabri Boubaker, Duc Khuong Nguyen, Molla Ramizur Rahman

Peter Faber Business School, Australian Catholic University, Sydney, Australia
EM Normandie Business School, Metis Lab, France
International School, Vietnam National University, Hanoi, Vietnam
IPAG Business School, Paris, France
Faculty of Finance and Accounting, Prague University of Economics and Business, Prague, Czech Republic
Vinod Gupta School of Management, Indian Institute of Technology Kharagpur, India

ABSTRACT

We use the Conditional Value-at-Risk (CoVaR) model to develop the systemic contagion index (SCI) for cryptocurrencies and examine their spillover effects. The SCI exhibits the highest value during the COVID–19 period, indicating evidence of pandemic-driven contagion channels. Similarly, cryptocurrency systemic networks show that the COVID–19 period induced increased interconnections, highlighting a higher number of systemic contagion channels. Our study has practical implications for investors to identify the systemic vulnerability of each cryptocurrency and make informed decisions during the crisis and non-crisis periods.

1. Introductions

Cryptocurrencies have grown significantly over the years, with a market capitalization reaching USD 2.23 trillion on 5 January 2022. Given the significant rise of their market capitalization, cryptocurrencies have received considerable attention from retail and institutional investors, regulators, and policymakers. The recent literature debates on whether cryptocurrencies are efficient markets (Alvarez-Ramirez and Rodriguez, 2021; Urquhart, 2016), provide portfolio diversification (Akhtaruzzaman et al., 2020; Damianov and Elsayed, 2020), and play the role of currencies, speculative assets (Baur et al., 2018; Cheah and Fry, 2015), investable assets (Dyhrberg et al., 2018), and safe-haven assets (Corbet et al., 2020). As cryptocurrencies are getting prominence in the financial markets, the potential systemic risk spillover among them has become a topic of further investigation (Xu et al., 2021). Considering the systemic risk contributions of cryptocurrencies to the financial system, the US Senate Banking Committee had a panel of crypto industry experts in a
hearing titled “Cryptocurrencies: What are they good for?” Senator Elizabeth Warren urged the Treasury Secretary that “FSOC must act quickly to use its statutory authority to address cryptocurrencies’ risks and regulate the market to ensure the safety and stability of consumers and our financial system.”

Prior literature has investigated the risk spillovers among cryptocurrencies (Ji et al., 2019; Yi et al., 2018). For example, Yi et al. (2018) consider 52 cryptocurrencies and find Bitcoin as a net transmitter of volatility spillovers to other cryptocurrencies. Similarly, Ji et al. (2019) show that leading cryptocurrencies such as Bitcoin, Ethereum, and Litecoin are net transmitters of volatility spillovers. However, research on systemic contagion networks among cryptocurrencies is still limited. Our study fills this void in the literature by developing a systemic contagion index (SCI) for cryptocurrencies and examining whether even a systemically unimportant cryptocurrency or cryptocurrency with a small market size can play an important role in transmitting contagious shocks. During the COVID–19 pandemic, there have been wide fluctuations in cryptocurrencies’ prices, and some have lost safe-haven asset properties (Conlon and McGee, 2020). So, it is critical to uncover the SCI for cryptocurrencies over the pre- and during COVID–19 periods.

Our study employs the Conditional Value-at-Risk (CoVaR) to measure the systemic risk of cryptocurrencies. We find that the systemic risk reached the peak on 12 March 2020 but dropped to the lowest the next day, indicating that the dynamics of systemic risk-sharing among cryptocurrencies evolve quickly. Siacoin, a small market size cryptocurrency, appears to be the most vulnerable and remains the systemic node in pre-COVID–19 and COVID–19 periods.

The remainder of the paper is organized as follows Section 2. discusses the empirical design to construct the SCI Section 3. discusses the results Section 4. concludes.

2. Empirical design

2.1. Estimation of systemic risk

The systemic risk is obtained by regressing cryptocurrency return against its market return and state variables using the quantile regression at 1% and 50% quantiles as:

\[ r_i = a_{0,i} + a_{1,i}^{\text{market}} r_i^{\text{market}} + \sum_{j=1}^{k} \beta_{i,q}^{j} SV_{t-1} + \epsilon_{i}^{1/0} \] (1)

where cryptocurrency market return is represented by \( r_i^{\text{market}} \) and cryptocurrency return by \( r_i \) at time \( t \) and \( t-1 \). SV represents returns of a set of state variables: the S&P 400 commodity chemical index, S&P 500 composite equity index, CBOE Volatility index, and Gold Bullion. The coefficient \( a_{1,i}^{\text{market}} \) measures the sensitivity of cryptocurrency \( i \) to a state of distress of the aggregate cryptocurrency market. Following Tobias and Brunnermeier (2016), CoVaR in Eq. (2) is obtained from the predicted value of Eq. (1).

\[ \text{CoVaR}_i^{q} = a_{0,i} + a_{1,i}^{q} \text{VaR}_i^{q} + \sum_{j=1}^{k} \beta_{i,q}^{j} SV \] (2)

\( \Delta \text{CoVaR} \) in Eq. (3) is the difference between the CoVaR of cryptocurrency \( i \) conditional on a state of distress (i.e., \( q = 1 \)) in the aggregate cryptocurrency market and the median state (i.e., \( q = 50 \)).

\[ \Delta \text{CoVaR}_i^{q} = \text{CoVaR}_i^{q = 1} - \text{CoVaR}_i^{q = 50} \] (3)

2.2. Designing cryptocurrency systemic network

Eq. (4) and (5) illustrate an interconnection between two cryptocurrencies. The significant Granger causal relation represents the existence of interconnection for systemic risk spillover between a pair of cryptocurrencies. When considering \( n \) cryptocurrencies altogether, the systemic cryptography network takes the form of \( k_{ij} \) in Eq. (6). \( k_{ij} \) is binary, with 1 representing a significant Granger causal relationship between two cryptocurrencies, and 0 otherwise.

\[ \Delta \text{CoVaR}_{ij} = \sum_{i=1}^{n} a_{i} \Delta \text{CoVaR}_{i,j-1} + \sum_{j=1}^{n} b_{j} \Delta \text{CoVaR}_{j,i-1} + \epsilon_{ij} \] (4)

\[ \Delta \text{CoVaR}_{ij} = \sum_{i=1}^{n} c_{i} \Delta \text{CoVaR}_{i,j-1} + \sum_{j=1}^{n} d_{i} \Delta \text{CoVaR}_{j,i-1} + \epsilon_{ij} \] (5)

2 See https://www.cnbc.com/2021/07/27/summit-banking-committee-presses-crypto-experts-on-systemic-risk-at-hearing.html
3 See https://www.cnbc.com/2021/07/27/elizabeth-warren-presses-yellen-financial-regulator-to-manage-crypto.html
4 Borri (2018) applies \( \Delta \text{CoVaR} \) to measure the vulnerability of an individual country to the aggregate systemic risk while Borri and Giorgio (2021) use \( \Delta \text{CoVaR} \) as a measure of a bank’s vulnerability to the aggregate systemic risk in the European banking sector. In their seminal paper, Tobias and Brunnermeier (2016) apply \( \Delta \text{CoVaR} \) to measure the vulnerability of the entire financial system with respect to a state of distress of an individual financial institution.
System network properties, namely, interconnections, centroid, total path length, the aggregate distance of all cryptocurrencies from the centroid and density are estimated. Centroid represents the systemically most concentrated network point as in Eq (7). Therefore, a higher value of centroid indicates a pronounced systemic network.

\[
\text{Cen}_{sys,t} = \sqrt{\sum_{i=1}^{n} (|\Delta \text{CoVaR}_i|)^2} 
\]

where \(\text{Cen}_{sys,t}\) represents the centroid of the systemic cryptocurrency network constructed during time \(t\).

Distance (\(\text{Dis}_{sys,t}\)) in Eq (8) is the aggregate path length of all the contagion channels in the network. A larger distance arises due to more contagion channels and higher systemic risk, indicating a highly contagious network. Nodal distance (\(\text{Dis}_{i,t}\)) in Eq. (9) for a cryptocurrency \(i\) indicates the aggregate contagious distance associated with a particular node. A higher nodal distance indicates the cryptocurrency to be contagious.

\[
\text{Dis}_{sys,t} = \sum_{i=1}^{n} \sum_{j=1}^{n} k_{ij} [\text{abs}(\Delta \text{CoVaR}_i) - \text{abs}(\Delta \text{CoVaR}_j)] 
\]

\[
\text{Dis}_{i,t} = \sum_{j=1}^{n} k_{ij} * [\text{abs}(\Delta \text{CoVaR}_i) - \text{abs}(\Delta \text{CoVaR}_j)] 
\]

Total interconnections in a network (\(\text{Con}_{sys,t}\)) in Eq. (10) represent the aggregate links between all possible pairs of cryptocurrencies. Higher interconnections in a network indicate more contagion channels, and hence, the network is considered a highly systemic network. However, total interconnections for a particular cryptocurrency \(i\) (\(\text{Con}_{i,t}\)) in Eq (11) represent the node’s outdegree with a higher outdegree indicating the node to have higher contagion channels.

\[
\text{Con}_{sys,t} = \sum_{i=1}^{n} \sum_{j=1}^{n} k_{ij} 
\]

\[
\text{Con}_{i,t} = \sum_{j=1}^{n} k_{ij} 
\]

The aggregate distance of all nodes from the centroid of a network is estimated in Eq. (12). A larger distance from the centroid indicates that nodes are far away from the systemically most concentrated point of the network, and, hence, the system is considered stable. Finally, the individual distance of each node from the centroid (\(\text{DC}_{i,t}\)) is estimated in Eq. (13).

\[
\text{DC}_{sys,t} = \sum_{i=1}^{n} [\text{Cen}_{sys,t} - \text{abs}(\Delta \text{CoVaR}_i)] 
\]

\[
\text{DC}_{i,t} = [\text{Cen}_{sys,t} - \text{abs}(\Delta \text{CoVaR}_i)] 
\]

The network density (\(\text{Den}_{sys,t}\)) in Eq. (14) signifies the concentration of the network. Denser network indicates the cryptocurrency market to be contagious. The nodal density (\(\text{Den}_{i,t}\)) in Eq. (15) highlights the nature of a cryptocurrency responsible for systemic risk spillover.

\[
\text{Den}_{sys,t} = \frac{\text{Con}_{sys,t}}{\sum_{i=1}^{n} C} 
\]

\[
\text{Den}_{i,t} = \frac{\text{Con}_{i,t}}{\text{Con}_{sys,t}} 
\]

We finally use the above network characteristics, i.e., \(\text{Dis}_{i,t}\), \(\text{Con}_{i,t}\), \(\text{DC}_{i,t}\), and \(\text{Den}_{i,t}\), to formulate the SCI through Principal Component Analysis, where a higher SCI value indicates the cryptocurrency responsible for systemic risk spillover.

3. Empirical results

3.1. Data

We have selected 17 cryptocurrencies that have their complete historical daily prices for the sample period from 1 January 2017 to...
30 June 2021 and that comprise 76.11% of the total market capitalization of cryptocurrencies as of 8 July 2021. Their prices are obtained from https://coinmarketcap.com. In addition, we construct two sub-samples, i.e., pre-COVID–19 (1 January 2017–31 December 2020) and COVID–19 (1 January 2020–30 June 2021), to examine whether the risk-sharing differs during the crisis and non-crisis periods. Data for S&P 400 commodity chemical index, S&P 500 composite equity index, Gold Bullion, and CBOE Volatility index are obtained from Bloomberg.

3.2. Systemic risk

Systemic risk reaches its peak when $\Delta \text{CoVaR}_{1\%}$ is lowest at $-38.03\%$ on 12 March 2020 (see Fig. 1). However, on the next day, on 13 March 2020, it drastically drops as $\Delta \text{CoVaR}_{1\%}$ reaches an all-time high of $-4.74\%$. This indicates that systemic risk gets rapidly

---

5 We have included Tether, a leading stablecoin because stablecoin returns, volatility, volume are highly correlated with Bitcoin (Hoang & Baur, 2021).
shared among the cryptocurrencies through contagion channels in the network. Fig. 2 depicts the average daily estimated systemic risk for cryptocurrencies over the entire period. The results show that Siacoin is systemically most vulnerable, followed by DigiByte, Neo, Stellar, and Waves.

As Siacoin has lower market capitalization, it is less expected to withstand systemic disruption. This result implies that a small market capitalized cryptocurrency may not survive for a very long time. Bitcoin ranks second to last for being systemically vulnerable, with $\Delta CoVaR_{1\%}$ of $-14.33\%$. The trend remains similar for both periods.

The cryptocurrency market most influences systemic risk for Stellar, followed byNeo, XRP, and Dash, and least for Decred. Bitcoin

\[ \text{Dis}_{i,t} = \sum_{j=1}^{n} k_{ij} \cdot |\text{abs}(\Delta CoVaR_{i,t}) - \text{abs}(\Delta CoVaR_{j,t})| \quad (9). \]
\[ \text{Con}_{i,t} = \sum_{j=1}^{n} k_{ij} \quad (11). \]
\[ \text{DC}_{i,t} = [\text{Cen}_{sys,t} - \text{abs}(\Delta CoVaR_{i,t})] \quad (13). \]
\[ \text{Den}_{i,t} = \frac{\text{Con}_{i,t}}{\text{Con}_{sys,t}} \quad (15). \]

Table 1

| Cryptocurrency | Pre-COVID‒19 | COVID‒19 |
|----------------|--------------|----------|
| Bitcoin        | 2.391        | 5.000    |
| Ethereum       | 5.086        | 5.079    |
| Tether         | 1.284        | 6.927    |
| XRP            | 0.274        | 3.020    |
| Dogecoin       | 5.222        | 2.922    |
| Litecoin       | 1.343        | 4.510    |
| Ethereum Classic| 4.565        | 4.619    |
| Stellar        | 4.717        | 5.170    |
| Monero         | 4.502        | 5.591    |
| Neo            | 6.339        | 7.355    |
| Decred         | 4.077        | 1.853    |
| Waves          | 4.692        | 6.848    |
| Zcash          | 4.591        | 2.373    |
| Dash           | 4.625        | 5.689    |
| NEM            | 6.834        | 5.206    |
| Siacoin        | 6.415        | 6.416    |
| DigiByte       | 4.734        | 7.943    |
| Mean           | 4.217        | 5.089    |

Notes: Using the principal component analysis, the SCI is constructed from the nodal distance ($\text{Dis}_{i,t}$ in Eq. (9)), total interconnections ($\text{Con}_{i,t}$ in Eq (11)), individual distance of each node from the centroid ($\text{DC}_{i,t}$ in Eq. (13)) and nodal density ($\text{Den}_{i,t}$ in Eq. (15)).

Fig. 2 and Table A2 in the Internet Appendix show the estimates for Eq. (3) and the summary statistics of $\Delta CoVaR_{1\%}$ respectively.

To conserve the space, results are provided in Table A2 in the Internet Appendix.

---

6 Table A2 and A3 in the Internet Appendix show the estimates for Eq. (3) and the summary statistics of $\Delta CoVaR_{1\%}$ respectively.

7 To conserve the space, results are provided in Table A2 in the Internet Appendix.
ranks sixth for the cryptocurrency market’s impact on its systemic risk. S&P 500 index most influences systemic risk for DigiByte, followed by Siacoin, Neo, and Waves. However, S&P 500 index negatively influences systemic risk for Stellar, Tether, and NEM.

3.3. Cryptocurrency systemic network

Fig. 3 provides cryptocurrency systemic networks that show the COVID–19 period experienced increased interconnections, thereby highlighting a higher number of systemic contagion channels during the pandemic. The results also reveal that centroid is highest for the network constructed during COVID–19 pandemic, indicating a pronounced systemic network. Moreover, the number of interconnections and network density is highest during COVID–19, highlighting the prominent contagion channels during the pandemic.

3.4. Systemic contagion index (SCI)

The SCI exhibits the highest value during the COVID–19 pandemic, indicating that contagion channels become more prominent. However, few cryptocurrencies such as Dogecoin, Decred, and Zcash exhibit lower SCI values during the health crisis, implying that they are systemically stable because of their limited interconnections with other cryptocurrencies. This finding indicates their lower vulnerability to shocks in the cryptocurrency market. As a result, investors can consider these cryptocurrencies to reduce their risk during the pandemic. Bitcoin has an SCI value lower than the mean for cryptocurrencies in both periods (before and after the emergence of the pandemic), indicating that Bitcoin is systemically stable and has the lower potential to cause systemic disruption. This result points to a more mature status of Bitcoin among the cryptocurrencies (Table 1).

4. Conclusions

Cryptocurrencies attracted particular attention from investors during the COVID–19 pandemic, given their diversifying and hedging potential for stock portfolios. This study shifts the focus to the systemic risk of cryptocurrencies using the CoVaR model and SCI constructed from a PCA analysis of cryptocurrency network structures. The empirical findings show an increase in the systemic risk during the COVID–19 period, thus pointing out the higher transmission of contagious shocks. The identified systemic networks of cryptocurrencies also experienced increased interconnections and, therefore, more systemic contagion channels during the pandemic. As one of the most mature cryptocurrencies, Bitcoin is relatively stable and less systemically vulnerable. Investors can consider our results in terms of cryptocurrency-specific systemic vulnerability when making investment decisions in the cryptocurrency markets. The higher SCI value suggests not investing in it due to its contagious nature and vulnerability. Future research can extend our study to examine the factors influencing the systemic risk in the cryptocurrencies market. Another research direction is to explore the predictive ability of the SCI in the cryptocurrency market in the same spirit as Chatziantoniou et al. (2021).

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2022.102787.

References

Akhtaruzzaman, M., Sensoy, A., Corbet, S., 2020. The influence of Bitcoin on portfolio diversification and design. Finance Res. Lett. 37, 101344.
Alvarez-Ramirez, J., Rodriguez, E., 2021. A singular value decomposition approach for testing the efficiency of Bitcoin and Ethereum markets. Econ. Lett. 206, 109997.
Baur, D.G., Hong, K., Lee, A.D., 2018. Bitcoin: medium of exchange or speculative assets? J. Int. Financ. Market. Inst. Money 54, 177-189.
Borri, N., 2018. Local currency systemic risk. Emerg. Market. Rev. 34, 111-123.
Borri, N., Giorgio, G.d., 2021. Systemic risk and the COVID challenge in the European banking sector. J. Bank. Financ., 106073.
Chatziantoniou, I., Delis, P., Degiannakis, S., Filis, G., 2021. Forecasting oil price volatility using spillover effects from uncertainty indices. Finance Res. Lett. 42, 101885.
Cheah, E.-T., Fry, J., 2015. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. Econ. Lett. 130, 32–36.
Conlon, T., McGee, R., 2020. Safe haven or risky hazard? Bitcoin during the COVID–19 bear market. Finance Res. Lett. 35, 101607.
Corbet, S., Hou, Y., Hu, Y., Larkin, C., Oxley, L., 2020. Any port in a storm: cryptocurrency safe-havens during the COVID–19 pandemic. Econ. Lett. 194, 109377.
Damianov, D.S., Elsayed, A.H., 2020. Does Bitcoin add value to global industry portfolios? Econ. Lett. 191, 108935.
Dyhrberg, A.H., Foley, S., Svec, J., 2015. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. Econ. Lett. 36, 10143.
Haang, T.L., Baur, D.G., 2021. How stable are stablecoins? Eur. J. Finance 1–17.
Ji, Q., Bouri, E., Lau, C.K.M., Roubaud, D., 2019. Dynamic connectedness and integration in cryptocurrency markets. Int. Rev. Financ. Anal. 63, 257-272.
Tobias, A., Brunnermeier, M.K., 2016. CoVaR. Am. Econ. Rev. 106 (7), 1705.
Urquhart, A., 2016. The inefficiency of Bitcoin. Econ. Lett. 148, 80-82.
Xu, Q., Zhang, Y., Zhang, Z., 2021. Tail-risk spillovers in cryptocurrency markets. Finance Res. Lett. 38, 101453.
Yi, S., Xu, Z., Wang, G.-J., 2018. Volatility connectedness in the cryptocurrency market: is Bitcoin a dominant cryptocurrency? Int. Rev. Financ. Anal. 60, 98-114.