Draft
Please do not cite without author's permission

Working Paper (WP/23-04)

Cryptocurrencies and Banking Sector Connectedness: Don't Worry, Be Happy … for Now

Jorge A. Chan-Lau and Toan Long Quach

November 2023

[This page is intentionally left blank]

Crypto Currencies and Banking Sector Connectedness:
Don't Worry, Be Happy . . . for Now

Prepared by Jorge Antonio Chan-Lau and Toan Long Quach[1] [2]

Authorized by Li Lian Ong

November 2023

Abstract

Growing involvement of the traditional banking system with the crypto ecosystem raises concerns about systemic risk and financial stability. The "Crypto Winter" of 2022 and 2023 showed that the crypto ecosystem was susceptible to liquidity risk and runs. The paper finds, using time-varying vector autoregressions and long-short term memory multipliers, weak connectedness between cryptocurrencies and globally systemically important banks. The absence of strong linkages suggests limited scope for spillover risks and gives authorities room to strengthen and enhance macroprudential management of crypto ecosystem risks.

JEL classification: C32, G21, G23

Keywords: banks, connectedness, cryptocurrencies, spillovers, systemic risk, TVP-VAR, LSTM.

[1] Authors' e-mails: jchanlau@gmail.com; Jorge.Chan-Lau@amro-asia.org; and Quach.ToanLong@amro-asia.org;

[2] The views expressed in this working paper are those of the authors and do not necessarily represent the views of AMRO, its Board, or Management. The paper benefits from some data analysis by Liyang Tang and comments by participants at the 2023 Workshop on "Recent Developments and Future Prospects of the International Monetary System" held on August 24-25, 2023, at the Hong Kong Monetary Authority. The authors are solely responsible for any errors and omissions.

Abbreviations

ACG	Antonakakis-Chatziantoniou-Gabauer
BIS	Bank for International Settlements
COVID-19	coronavirus disease 2019
FROM	total directional connectedness from others
GFEVD	generalized forecast error variance decomposition
GSIB	globally systemically important bank
LSTM	Long Short-Term Memory
LSTMM	Long Short-Term Memory multiplier
NET	net connectedness
PDC	pairwise directional connectedness
PNT	pairwise net transmitters
RMSE	root mean squared error
TCI	total connectedness index
TO	total directional connectedness to others
TVP-VAR	Time-Varying Parameter Vector Autoregression
VAR	Vector Autoregression

Contents

Figures

Tables

[This page is intentionally left blank]

I. Introduction

The crypto ecosystem, which comprises cryptocurrencies, crypto platforms, stablecoins, and smart contracts, has grown rapidly since its inception in 2009. Recent Bank for International Settlements (BIS) estimates put the ecosystem market capitalization at approximately USD 1 trillion (BIS 2023). Market practitioners and policy makers generally agree that the rapid growth of the crypto ecosystem could bring about significant transformations of the financial system. The crypto ecosystem holds the promise of improving the efficiency of the financial system by reducing transaction costs, streamlining settlement and record keeping processes, decentralizing financial transactions, and deepening financial inclusion. However, there are serious concerns that the realization of risks in the crypto ecosystem could spill over to the traditional financial system. These risks are related to structural flaws in the ecosystem, such as fragmentation and congestion of validation processes, that make it vulnerable to manipulation and runs (IMF 2022, BIS 2023).

Despite being promoted as more robust than the traditional financial system, the crypto ecosystem is similarly fragile and vulnerable to liquidity risk. Rather than becoming a trustless and decentralized financial system (Harvey and others 2021), its evolution has closely mirrored that of the traditional banking and financial system. In 2022 and early 2023, the crypto ecosystem was rocked by the large failures of several stablecoins and crypto firms, a period known as the *Crypto Winter*. These adverse events demonstrated the potential for idiosyncratic shocks to spread widely within the crypto universe. A key mechanism underlying the propagation and amplification of the shocks was the substantial vulnerability of cryptocurrencies and platforms to runs. Similar to traditional banks, crypto firms borrow short and lend long, which exposes them to liquidity risk. The absence of a crypto lender of last resort makes the crypto ecosystem highly vulnerable to changes in investor sentiment (Brainard 2022; Gorton and Zhang 2023; Arner and others 2023; Liu, Makarov, and Schoar 2023).

Systemic risk in the crypto ecosystem seems self-contained but it might change as integration with the traditional financial system continues. The Crypto Winter failures, which caught a lot of attention in the press, did not have major repercussions outside the crypto ecosystem. However, there is ongoing integration between the crypto ecosystem and the traditional financial system. Crypto firms are expanding into lending and borrowing services traditionally offered by banks. Banks are gradually increasing their cryptocurrency holdings driven by growing demand from their clients. While banks' involvement is modest at present, it could scale up rapidly (Auer and others 2022). Money laundering and and financial malfeasance might exacerbate potential systemic risks (Makarov and Schoar 2022).

Moreover, limited understanding of the linkages and connections between the crypto ecosystem and the financial system could impair proper macroprudential management of crypto risks. Connections between the two systems could evolve rapidly, mirroring mainly innovations and technological developments in the former. In the absence of a clear picture of where the sources of risk are and what firms or markets they affect, it is difficult if not impossible to assess nascent threats, identify systemically important firms, review and broaden the perimeter of regulation, and design and implement adequate regulatory and supervisory frameworks.

This study aims to assess how connected the crypto space and the traditional banking sector are. It focuses on analyzing the linkages between two major cryptocurrencies, Bitcoin and Ethereum, and globally systemically important banks (GSIBs). We assess the dynamic connectedness between cryptocurrencies and banks using two complementary methods: the Time-Varying Parameter Vector Autoregression (VAR) (TVP-VAR) variance-decomposition method of Antonakakis and others (2020) and the Long Short-Term Memory (LSTM) multiplier.

In the TVP-VAR variance-decomposition method, as in the extant papers of Diebold and Yilmaz (2012, 2014), the directional connectedness or risk spillover of a variable is measured as its contribution to the generalized forecast error variance decomposition of the other variables in the VAR system. In other words, the TVP-VAR connectedness measure is a variance-based connectedness or second moment measure. By allowing parameters to vary over time it is possible to model the changing nature of risk spillovers and to capture, to a certain extent, the nonlinear dependence between the system variables.

Spillover and connectedness analysis should also focus on the first moment spillovers, that is connectedness related to the future predicted values of the variables in the system. To this end, this paper introduces the LSTM multiplier method as a first moment connectedness measure. After fitting a LSTM model to the data, the connectedness of the transmitter variable, the source of the shocks, is measured as the difference between the predicted values of the other variables under two conditions: when a shock affects the source variable and in the absence of the shock. Conceptually, the method resembles the impulse response analysis of VAR models and focuses on the response of variables to shocks rather than on the second moments of the model forecasts. By design, the LSTM model captures nonlinear dependence better than a TVP-VAR at the expense of reduced explainability, which in the context of connectedness analysis, is not a major shortcoming. The application of both methods makes possible to measure first and second moment connectedness.

Connectedness measures were computed for cryptocurrencies price returns and the equity returns of GSIBs employing both methods. Irrespective of the method, the results show that, in general, cryptocurrencies were only weakly connected to GSIBs and had a limited impact on the equity returns of the latter. Rather, GSIBs, as a sector, had a larger impact on cryptocurrency returns. Periods during which variance-based connectedness from cryptocurrencies to GSIBs peaked, albeit remaining significantly small, tended to coincide with periods of high market distress and volatility, such as the months preceding Brexit, the start of the Covid-19 pandemic in early 2020, and the early stages of the Russia-Ukraine war in 2022.

The results indicate that cryptocurrencies have not yet reached the stage where they pose significant risks to financial system. Given that past trends cannot predict future outcomes reliably, concerns raised by academics and policy institutions closely monitoring cryptocurrencies and digital finance should not be ignored. The limited connection between the crypto ecosystem and traditional banking systems offers authorities a chance to enhance and update regulatory and supervisory frameworks. This way, they can effectively handle potential risks arising from the ongoing integration of crypto and traditional financial systems.

The following sections of this paper provide a concise review of the relevant literature (section II), a description of the data (section III) followed by an overview of the different connectedness approaches used (section IV). Afterwards, the paper analyzes the results (section V) and finally, draws the conclusions from the findings (section VI).

II. Related literature

Crypto assets, including cryptocurrencies, have failed to fulfill their early promise to address weaknesses in traditional finance. During 2022 and 2023, major players in the crypto space failed spectacularly leading to the collapse of several crypto assets and supporting platforms. Arner and others (2023) attributed these failures to the financialization of the crypto system, which has brought about several of the problems typically associated with traditional finance such as conflict of interests, information asymmetries, centralization and interconnection, and agency and operational risks.

Gorton and Zhang (2023) remarked that, despite the hype, crypto lending platforms are not much different than traditional banking: the business model of the platforms is to borrow short and to lend long. Hence, as banks, crypto platforms are highly exposed to liquidity risk and vulnerable to runs, risks that are exacerbated in the absence of a crypto lender of last resort.

The risk of runs on cryptocurrencies and crypto platforms materialized during the Crypto Winter of 2022-23. As documented by Liu, Makarov and Schoar (2023), some of the runs were precipitated by concerns about the viability of the affected cryptocurrencies and platforms. The Crypto Winter raised concerns that shocks in the crypto system might disrupt the traditional financial system. Connections between these systems have been growing as traditional financial firms increase their exposure to crypto assets, driven partly by growing demand for crypto asset investing by high net worth individuals and institutional investors (Choi 2023).

Despite growing interest in crypto, banks and other institutional investors seem to have behaved cautiously. Auer and others (2022) found that major banks currently maintain relatively low levels of exposure to cryptocurrencies. Exposures were higher for banks headquartered in countries with greater innovation capacity. However, retail and institutional investors conducted operations mainly in the "shadow crypto financial system" of lightly regulated crypto exchanges.

Research on the connections between various crypto assets among themselves or other assets is rapidly accumulating so the review is restricted to a limited set of studies that employ similar methodologies to ours or present results relevant to this study. Several of these studies use variations of the Diebold and Yilmaz (2012, 2014) methodology. In the original Diebold-Yilmaz method, the connectedness of a variable is proportional to its contribution to the variance decomposition of the forecast errors of other variables in a VAR system. This method has been extended to use models other than VAR, such as FAVAR, LASSO, DCC-GARCH, QVAR, and GVAR among others (Gabauer and others 2023). In particular, Antonakakis and others (2020) introduced a generalized approach using a TVP-VAR. The TVP-VAR method offers a more accurate estimation of time-varying coefficients, improved robustness against outliers, and eliminates the need for rolling window sizes used in the original Diebold-Yilmaz framework.

A large number of studies focused exclusively on connectedness among major cryptocurrencies. For instance, Antonakakis and others (2019) examined contagion between cryptocurrencies during 2015-18 using a TVP-FAVAR connectedness approach and found that cryptocurrencies connectedness is stronger in periods of increased market uncertainty and highly volatile prices. Zieba, Kokoszczynski, and Sledziewska (2019) looked at the interdependencies among 78 cryptocurrencies during 2015-18. The minimum spanning tree method was used to assign cryptocurrencies to separate clusters. Once the clusters were identified, separate VAR models were fitted to each of them. Granger causality tests and impulse response functions served to identify the dominant sources of shocks. Contrary to other studies, their results showed that Bitcoin did not have a major impact on other cryptocurrencies.

Hasan and others (2022), using price return data and trading volume data, analyzed liquidity connectedness among the six major cryptocurrencies by first applying the Diebold-Yilmaz method to obtain the variance decomposition, and then decomposing it into low and high frequency components as suggested by Barunik and Krehlik (2018). Liquidity connectedness was stronger in the short run than in other frequencies and Bitcoin played a major role as a source of spillovers. Using a similar empirical framework, Kumar and others (2022) found that return and volatility connenctedness among cryptocurrencies, as well as with other asset classes, increased during the COVID-19 period. Cui and Maghyereh (2022), using intraday price data, analyzed higher moment connectedness among cryptocurrencies both in the time and frequency domains using the TVP-VAR approach and the Barunik and Krehlik methods respectively. Thety found that variance connectedness was stronger than that of other moments, especially at lower frequencies.

Several studies examined linkages between cryptocurrencies and other assets. Among them, Apostolakis (2023) studied the volatility transmission between spot price of Bitcoin and its price in futures markets using diverse techniques, including the standard Diebold-Yilmaz methodology. His findings suggest that the Bitcoin spot market was the dominant transmitter of volatility shocks to the futures markets. Within a GARCH framework, Nur and Korkmaz (2022) noted that there were minimal volatility spillovers between Bitcoin and the Saint Louis Fed financial stress index, a widely monitored measure of aggregate financial sector risk. This result suggests the financial system and cryptocurrencies were disconnected during the study period, which covered the years 2011 to 2021. Zhang and others (2022), applying the Diebold-Yilmaz time domain and Barunik-Krehlik frequency domain methods, found evidence that COVID-19 media coverage had a major impact on crude oil, gold, and Bitcoin markets.

A widely held belief is that some crypto assets might serve as safe haven assets. However, Yuyama and others (2023) did not find empirical support for this assertion. Using DCC-GARCH and moving average models, they established that correlations between crypto assets and equities had increased over time, a trend partly driven by increased exposures of traditional investors to crypto assets. Correlations were higher during crisis periods such as the Covid-19 pandemics, the Russia-Ukraine war, and during the Crypto Winter.

VAR-based connectedness measures assume a linear dependence between the variables in the system but are still able to capture nonlinearities partially since coefficients are allowed to change over time, as done in the TVP-VAR framework or by using rolling window estimates in an otherwise static VAR. Non-linear dependence, however, could be important. In the context of connectedness analysis, an ideal model-based measure should fulfill two criteria. First, it should capture any existent non-linear dependence between the variables. Second, to be consistent with the variance decomposition framework of TVP-VAR measures, the measure should quantify the long-term impact of a short-term shock.

LSTM models satisfy both criteria. First introduced by Hochreiter and Schmidhuber (1997), a LSTM is a type of recurrent neural network that allows information from the input variables to accumulate over time via hidden cells. LSTMs have emerged as a promising approach for sequential data analysis (van Houdt and others 2020), including time series analysis and forecasting (Lim and Zohren 2021; Benidis and others 2022).

There is an increasing number of LSTM applications in economics and finance that span diverse areas such as economic forecasting (Hopp 2021), economic growth prediction (Park and Yang 2022), financial crisis prediction (Tolo 2020), financial time series analysis (Sezer and others 2020, Khosravi and Ghazani 2023), cryptocurrencies price forecasting (Khedr and others 2021, Pour and others 2022, Nasirtafreshi 2022, Gajamannage, Park, and Dilhani 2023), stock market index prediction (Bhandari and others 2022), stock selection (Zhang and others 2018), and algorithmic long/short trading strategies (Michańków and others 2022). Despite their versatility, LSTMs have not yet been employed to explore economic and financial connectedness, a gap this study addresses.

III. Data

The data sample covered the period from August 11, 2015 until October 20, 2023. Daily log-returns of the two major cryptocurrencies, Bitcoin and Ethereum, were computed using data from CoinGecko, and for the 29 GSIBs (FSB 2022), using data from Bloomberg. Table 1 lists the GSIBs included in the analysis and their name abbreviations and Table 2 presents the summary statistics of the log returns of the cryptocurrencies and the GSIBs. Cryptocurrencies' returns are roughly two to three times more volatile than those of banks. To accomodate different time zones, the price quotes of banks headquartered in Europe and the United States were lagged by one day.

Table 1. Cryptocurrencies and GSIBs: Abbreviations

Cryptocurrencies			
BTC	Bitcoin	ETH	Ethereum
GSIBs			
JPM US	JPMorgan Chase and Co.	BAC US	Bank of America Corp.
C US	Citigroup	WFC US	Wells Fargo and Co.
HSBA LN	HSBC Holdings PLC	3988 HK	Bank of China Limited
BARC LN	Barclays PLC	BNP FP	BNP Paribas SA
DBK GR	Deutsche Bank AG	GS US	The Goldman Sachs Group
601398 CH	Industrial and Commercial Bank of China Ltd	8306 JP	Mitsubishi UFJ Financial Group Inc.
1288 HK	Agricultural Bank of China Ltd	BK US	Bank of New York Mellon Group
939 HK	China Construction Bank Corp.	CSGN SW	Credit Suisse Group AG
ACA FP	Credit Agricole SA	INGA NA	ING Groep NV
8411 JP	Mizuho Financial Group	MS US	Morgan Stanley
RY CN	Royal Bank of Canada	SAN SM	Banco Santander SA
GLE FP	Societe Generale SA	STAN LN	Standard Chartered PLC
STT US	State Street Corp.	8316 JP	Sumitomo Mitsui Financial Group Inc.
TD CN	Toronto Dominion Bank	UBS US	UBS Group AG
UCG IM	UniCredit SpA		

IV. Methodology and model estimation

We evaluate connectedness between cryptocurrencies and GSIBs using two different approaches. The first one is the Antonakakis-Chatziantoniou-Gabauer (ACG) TVP-VAR connectedness method, in which the connectedness, or spillover, from one variable to another variable is directly proportional to the importance of the former in explaining the variance of the forecast error of the latter. The second approach is the Long Short-Term Memory multiplier (LSTMM), in which the connectedness of a variable is measured as the difference in the predicted values of other variables when the former is subject to a shock or not. Both methods are described in detail next.

A. TVP-VAR connectedness measures

The ACG TVP-VAR model is built upon the generalized forecast error variance decomposition (GFEVD) of Koop and others (1996), and Pesaran and Shin (1998). It further refines and extends the original framework of Diebold and Yilmaz (2012, 2014).[1]

[1]See Gabauer and others 2023 for a complete description of the method.

Table 2. Log Returns, Cryptocurrencies and GSIBs: Summary Statistics

	mean	min	max	sdev
BTC	0.0021998	-0.4337144	0.2870991	0.0450597
ETH	0.0033062	-0.5630799	0.4073331	0.0686111
JPM US	0.0003546	-0.1621058	0.1656203	0.0176540
BAC US	0.0001954	-0.1672046	0.1637858	0.0201140
C US	-0.0001723	-0.2144141	0.1653812	0.0213486
HSBA LN	-0.0000715	-0.1059862	0.1008125	0.0168768
WFC US	-0.0001558	-0.1727786	0.1357072	0.0202874
3988 HK	-0.0002056	-0.1090227	0.0713293	0.0127695
BARC LN	-0.0004130	-0.2682187	0.1462627	0.0244675
BNP FP	-0.0000440	-0.2077742	0.1601192	0.0214540
DBK GR	-0.0005029	-0.1896182	0.1315280	0.0257336
GS US	0.0001803	-0.1358806	0.1619513	0.0185078
601398 CH	-0.0000891	-0.1047197	0.0967333	0.0124454
8306 JP	0.0000673	-0.0878510	0.1265355	0.0178395
1288 HK	-0.0000971	-0.0947121	0.0749092	0.0138385
BK US	-0.0000275	-0.1566932	0.1451088	0.0178397
939 HK	-0.0001616	-0.1211106	0.0600468	0.0140356
CSGN SW	-0.0015441	-0.8156695	0.1741522	0.0299138
ACA FP	-0.0000796	-0.1890078	0.1309347	0.0210827
INGA NA	-0.0000936	-0.2241363	0.1870075	0.0225411
8411 JP	-0.0001091	-0.1089742	0.0814207	0.0147981
MS US	0.0002976	-0.1696028	0.1804034	0.0201565
RY CN	0.0001642	-0.1315806	0.1313494	0.0132665
SAN SM	-0.0002545	-0.2383315	0.1705869	0.0228486
GLE FP	-0.0003923	-0.2469484	0.1637491	0.0252880
STAN LN	-0.0001970	-0.1387903	0.1516729	0.0231201
STT US	-0.0000786	-0.2098111	0.2014639	0.0216581
8316 JP	0.0000235	-0.1118053	0.0988941	0.0163685
TD CN	0.0001779	-0.1455822	0.1570028	0.0141414
UBS US	0.0000324	-0.1702666	0.1259075	0.0194654
UCG IM	-0.0001732	-0.2882671	0.1460723	0.0279494

Source: Authors' calculations.

Let x_t be a k dimensional vector collecting the daily log returns of the two main cryptocurrencies, Bitcoin and Ethereum, and the set of banks analyzed. We assume that:

$$\mathrm{x}_t = \mathrm{B}_t \mathrm{x}_{t-1} + \mathrm{u}_t, \qquad \mathrm{u}_t \sim N(0, \mathrm{S}_t) \tag{1}$$

$$vec(\mathrm{B}_t) = vec(\mathrm{B}_{t-1}) + \mathrm{v}_t, \qquad \mathrm{v}_t \sim N(0, \mathrm{R}_t) \tag{2}$$

where u_t and v_t are error terms, B_t are $k \times k$ matrices collecting the time-varying VAR coefficients, S_t are the $k \times k$ time-varying variance-covariance matrices, and R_t are $k^2 \times k^2$ dimensional matrices. The above TVP-VAR model has an equivalent TVP-VMA representation:

$$\mathrm{x}_t = \sum_{j=0}^{\infty} \mathrm{A}_{jt} \mathrm{u}_{t-j}. \tag{3}$$

Pairwise directional connectedness (PDC). From the TVP-VMA representation it is possible to obtain the unscaled GFEVD for a H-step forecast horizon:

$$\psi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (\iota'_t \mathrm{A}_t \mathrm{S}_t \iota_{\mathrm{j}})^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} \iota_j \mathrm{A}_t \mathrm{S}_t \mathrm{A}'_t \iota_i}, \tag{4}$$

where ι_i corresponds to a zero vector with unity in the i-th position. After scaling we can compute the *pairwise directional connectededness measure, PDC*, $\tilde{\psi}^g_{ij,t}$:

$$\tilde{\psi}^g_{ij,t}(H) = \frac{\psi^g_{ij,t}(H)}{\sum_{j=1}^{k} \psi^g_{ij,t}(H)}, \tag{5}$$

that satisfies $\sum_{j=1}^{k} \tilde{\psi}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\psi}^g_{ij,t} = k$. The $\tilde{\psi}^g_{ij,t}$ measure captures the influence of the variable j on variable i. If $\tilde{\psi}^g_{ij,t} = 0$, variable j has not influence on variable i. If $\tilde{\psi}^g_{ij,t} = 1$, variable j is the only variable that influences variable i. Notice that $\tilde{\psi}^g_{ii,t}$ measures the influence of past values of variable i on itself.

Pairwise net transmitters (PNT). For a pair of variables i and j, we define i as a net transmitter if $\tilde{\psi}^g_{ji,t}(H) - \tilde{\psi}^g_{ij,t}(H) > 0$, or in other words, the influence of i on j is greater than the other way around. The *pairwise net transmitter (PNT)* measure counts the number of variables for which i is a net transmitter:

$$PNT_{it}(H) = \sum_{j=1, j\neq i}^{k} 1\{\tilde{\psi}^g_{ji,t}(H) - \tilde{\psi}^g_{ij,t}(H) > 0\}, \tag{6}$$

where 1 is the indicator function.

Total directional connectedness TO and FROM others (TO, FROM). The total influence on and response of any variable (cryptocurrency or bank) in the network to shocks originating elsewhere in the network is measured using total directional connectedness measures, which are obtained summing across the individual PDC measures. The first such measure is the *total directional connectedness to others (TO)*, which captures the total influence of one unit on the rest of the network. The TO measure is computed as:

$$TO_{it}(H) = \sum_{j=1, i\neq j}^{k} \tilde{\psi}^g_{ji,t}(H). \tag{7}$$

The second measure is the *total directional connectedness from others (FROM)*, which captures the how much shocks in the network influence unit i:

$$FROM_{it}(H) = \sum_{j=1, i\neq j}^{k} \tilde{\psi}^g_{ij,t}(H). \tag{8}$$

Net connectedness (NET). The net connectedness measure is simply the difference between the TO and FROM measures:

$$NET_{it}(H) = TO_{it}(H) - FROM_{it}(H). \tag{9}$$

Total connectedness index (TCI). At the network level, it is possible to compute the *total connectedness index (TCI)* as:

$$TCI_t(H) = \frac{\sum_{j=1,i\neq j}^{k} TO_{it}(H)}{k} = \frac{\sum_{j=1,i\neq j}^{k} FROM_{it}(H)}{k}. \tag{10}$$

The TCI aggregates the individual connectedness of the currencies and banks both as sources and recipients of spillovers.

TVP-VAR estimation. The TVP-VAR measures were estimated using a one-day lag, as recommended by the Bayesian Information Criterion applied to various pairwise combinations of time series. Additionally, four different forecasting horizons were considered: 20, 60, 120, and 250 days, roughly corresponding to 1 month, 3 months, 6 months, and 1 year periods measured in business days. Results were robust to the choice of the forecasting horizon so only those corresponding to the 20-day horizon are discussed here.[2]

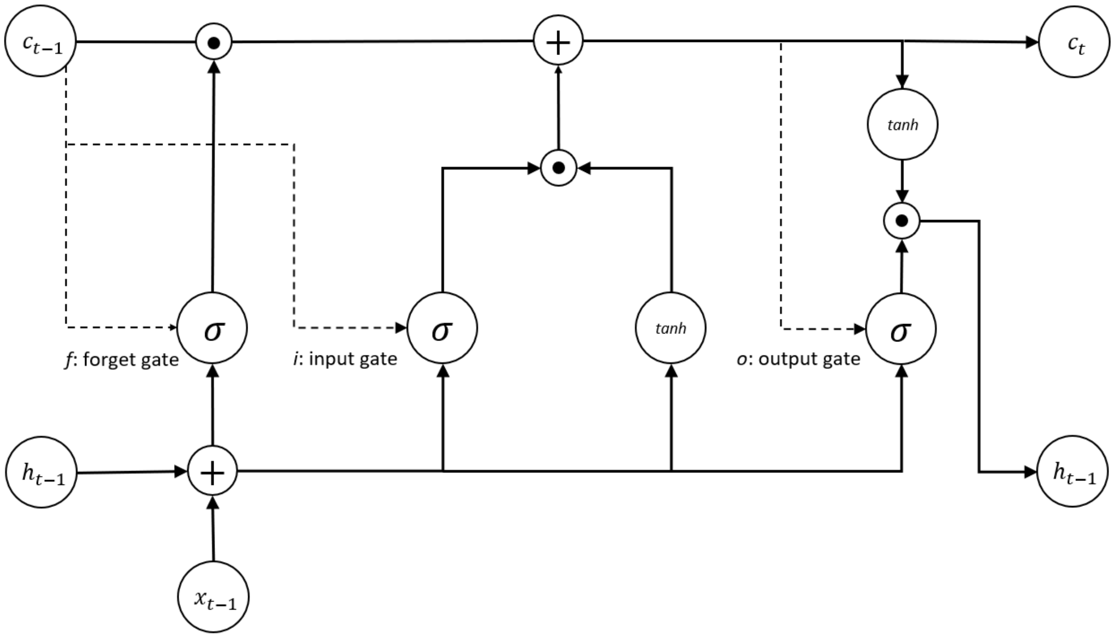
B. The LSTM multiplier

The TVP-VAR, thanks to its time-varying parameters, can capture nonlinear dependence to a certain extent. However, deep learning models developed to deal with sequential data might be better able to capture nonlinear dependence between the variables, including potential interaction effects. This paper introduces the concept of the LSTMM. The multiplier quantifies the difference between the n-periods ahead predictions a multi-time step LSTM makes when a single variable in the system remains unchanged and when it is subject to a shock. A concise description of the LSTM block, the LSTM model, and the definition of the LSTMM follow.

LSTM Block. Each stage in a multi-step LSTM model comprises several LSTM blocks.[3] The LSTM model captures potential long-term dependencies in time series data since information flows from one LSTM stage to the next through the cell and hidden states. The short-run impact of current observations is computed within the LSTM block. Our analysis uses the vanilla LSTM block of Greff and others (2007) which is shown in Figure 1.[4]

[2]All calculations were performed using the `R` package `ConnectednessApproach` (Gabauer 2022).
[3]See Hochreiter and Schmidhuber (1997), which introduces the LSTM model; Goodfellow and others (2016) for a concise introduction; Staudemeyer and Morris (2019) for a comprehensive tutorial; and Olah (2015) for a short and intuitive introduction to LSTMs.
[4]For a more detailed explanation see van Houdt and others (2020).

Figure 1. LSTM Block



Source: Authors.

The block comprises three gates that determine what information is used to update the hidden state, h, and the cell state, c. At time $t-1$, the LSTM block uses the information of the hidden state h_{t-1} and the observation x_t to update the block input, z:

$$z_t = \tanh\left(W_z x_t + R_z h_{t-1} + b_z\right), \tag{11}$$

where W_z and R_z are weight matrices and b_z is the bias coefficient. The input gate, i, combines the current input x_{t-1} and the information in the cell value from the last iteration, c_{t-1}:

$$i_t = \sigma\left(W_i x_t + R_i h_{t-1} + p_i \odot c_{t-1} + b_i\right), \tag{12}$$

where W_i and R_i are weight matrices, p_i is a weight vector, b_i is the bias vector, $\odot$ is the Hadamard point-wise multiplication operator, and σ is the sigmoid function. The forget gate, f, evaluates what information should be removed from the previous cell state c_{t-1} using the information from the current observation x_t, the hidden state, h_{t-1}, and the cell state c_{t-1}:

$$f_t = \sigma\left(W_f x_t + R_f h_{t-1} + p_f \odot c_{t-1} + b_f\right), \tag{13}$$

where W_f and R_f are weight matrices, p_f is a weight vector and b_f is the bias vector. With the computed values of the block input, the forget gate, and the input gate, the LSTM block updates the value of the cell state, c_t:

$$c_t = z_t \odot i_t + c_{t-1} \odot f_t, \tag{14}$$

which in turn, combined with the current input, x_t, and previous step hidden state, h_{t-1} yields the output gate:

$$o_t = \sigma\left(W_o x_{t-1} + R_o h_{t-1}\right) + p_o \odot c_t + b_0, \tag{15}$$

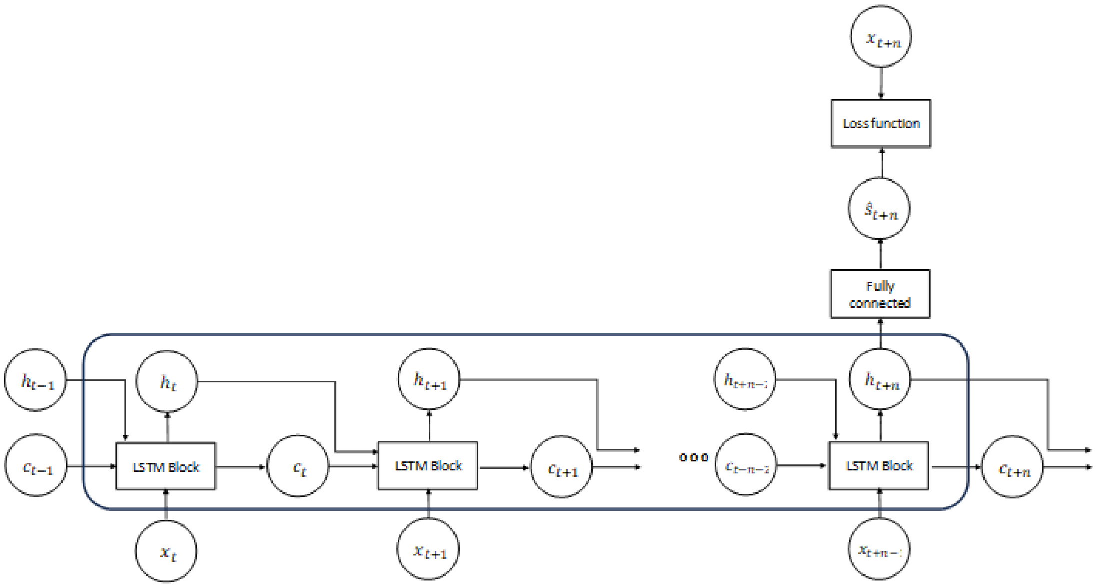
where W_o, R_o, and p_o are the matrix and vector weights, and b_o is the bias vector. Finally, the hidden state is updated to h_t using the information delivered by the output gate :

$$h_t = \tanh(c_t \odot o_t). \tag{16}$$

Additionally, the new hidden state h_t could be passed to a regression layer, typically a fully connected layer, to predict x_{t+1} as $\hat{s}_{t+1}$.

The multi-time step LSTM model. Figure 2 shows a single stage of the time unfolded multi-time step single layer LSTM model. The architecture of the LSTM network comprises a LSTM layer with n LSTM blocks. Let $x_j = [x_{j,1}, \ldots, x_{j,k}]^T$ be the vector collecting the observed values of the k variables in the system at time j. For a sequence of n time-ordered observations, $x_j, \quad j = t, \ldots, t+n-1$, the LSTM model attempts to predict the value of x_{t+n}. Note the similarity of the information set with that of a VAR model with n lags, that also assumes that only the past n realizations of the variables serve to predict their current values. The main difference with the VAR regarding the information set is that each stage of the LSTM could carry information, which is contained in c_{t-1} and h_{t-1}, to the next stage.

Figure 2. Multi-Step LSTM Network



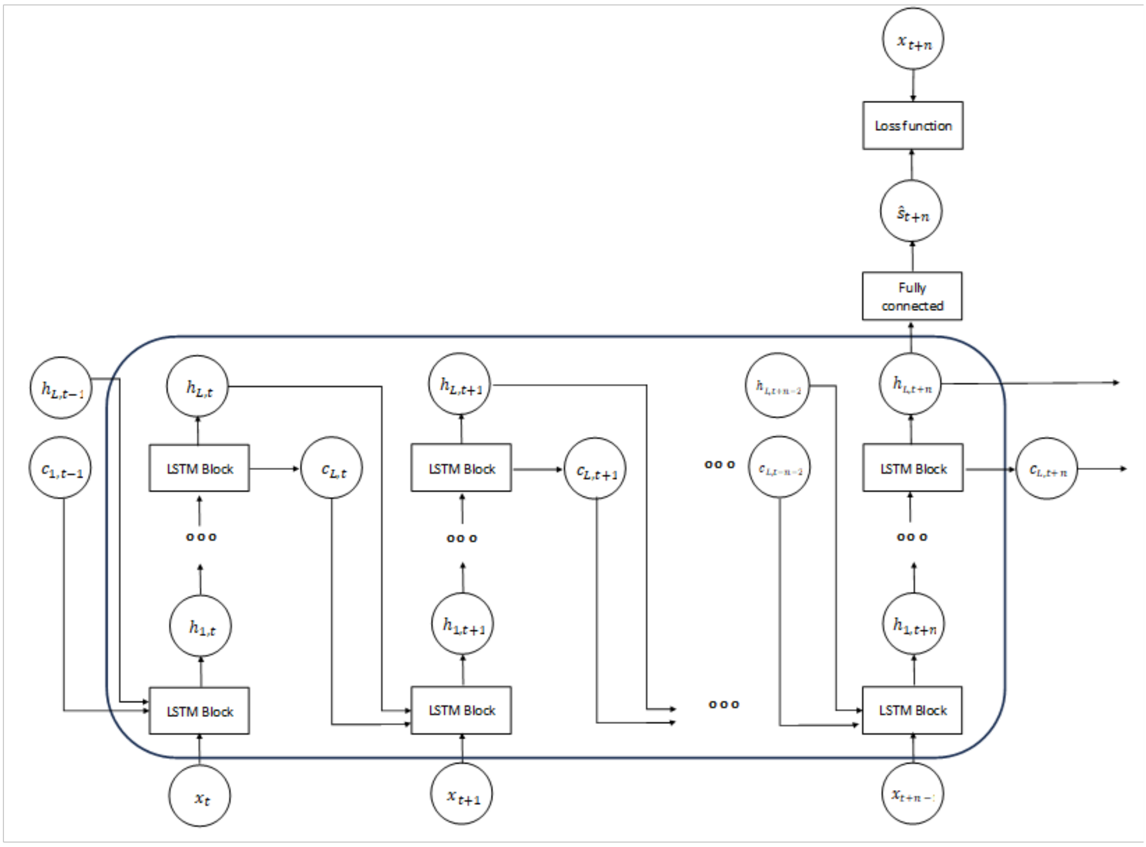
Source: Authors.

To make a prediction, the LSTM model uses as an initial input the state information from the previous stage and summarized in $[c_{t-1}, h_{t-1}]$, where c is the cell (or memory) state and h is the hidden state. The cell state preserves past information the LSTM model considers useful for making predictions once it filters and passesit to the hidden state. The LSTM block receives the previous state information and combines it with new information from the observation x_t. Based on the new information, the LSTM block decides what past information to retain, what new information to add, and how much of the updated information should be passed to the hidden state.

in case a prediction is needed. In this case, the hidden state information is passed to a fully connected (dense) layer to generate the prediction $\hat{s}_{t+1}$.

The computation cycle is repeated in each of the remaining $n-1$ steps. In the last step n, the information in the hidden state h_{t+n} is passed to a fully connected (dense) layer to generatge the prediction $\hat{s}_{t+n}$. The prediction is them compared to the observed value of x_{t+n}, and a loss metric is computed using a pre-specified loss function, the root mean squared error (RMSE). The training of the model, a.k.a. parameter estimation, is performed using multiple samples, i.e. blocks of n observations and the parameters are computed by minimizing the cumulative loss over the sample predictions. Since only the n-period ahead prediction matters, the predictions in earlier periods, $\hat{s}_{t+i}, \quad i = 1, \ldots, n-1$, do not matter in the loss calculation but are used in the computation of the LSTMM.

Figure 3. Multi-Step Multi-Layer LSTM Network



Source: Authors.

The single layer LSTM model could be expanded by stacking successive LSTM layers on top of each other. In this case, in each of the time steps of the hidden state of the first LSTM layer are the inputs to the next LSTM layer and so on. At the end of a given time step, the cell and hidden states are updated and passed to the next time step. When the last time-step is reached, the hidden state of the last layer is fed into a fully connected layer to generate the prediction $\hat{s}_{t+n}$ (Figure 3).

The LSTM Multiplier (LSTMM). The computation of the LSTMM for variable i requires constructing baseline and shock input sequences for the LSTM model using a closed-loop method. Let the baseline input sequence be $x^B_{t:t+n-1} = [x_t, \hat{s}_{t+1}, \hat{s}_{t+2}, \dots, \hat{s}_{t+n-1}]^T$. In period t, the state n periods earlier, $[c_{t-n}, h_{t-n}]$, is set to $[0, 0]$, which together with the sequence $\{x_{t-n+1}, x_{t-n+2}, \dots, x_t\}$, is input into the LSTM to generate $\hat{s}_{t+1}$. The LSTM now generates $\hat{s}_{t+2}$ using as inputs the state $n-1$ periods earlier, $[c_{t-n+1}, h_{t-n+1}]$, which is set to $[0, 0]$, and the sequence $\{x_{t-n+2}, x_{t-n+3}, \dots, x_t, \hat{s}_{t+1}\}$. The process is repeated until it generates the last element in the baseline input sequence. With this sequence the LSTM yields the n-step ahead prediction s^B_{t+n}:

$$s^B_{t+n} = \mathrm{LSTM}(x^B_{t:t+n-1}). \tag{17}$$

Similarly, let the shock input sequence, when only variable i is affected, be $x^C_{i,t:t+n-1} = [x_t + \Delta_i, \tilde{s}_{t+1}, \tilde{s}_{t+2}, \dots, \tilde{s}_{t+n-1}]^T$, where $\Delta_i = [0, \dots, \delta_i, \dots, 0]$ is a shock vector, δ_i is the shock to variable i, and $\tilde{s}_{t+i}$ are the intermediate outputs calculated sequentially in a similar manner as for the baseline input sequence. The n-step ahead prediction when variable i experiences the shock δ_i is $s^C_{k,t+n}$:

$$s^C_{i,t+n} = \mathrm{LSTM}(x^C_{i,t:t+n-1}). \tag{18}$$

We now define the LSTMM of variable i at time t as the vector-valued variable LSTMM(i, t):

$$\begin{aligned} \mathrm{LSTMM}(i,t) &= |s^C_{i,t+n} - s^b_{t+n}| \oslash \Omega \\ &= [\mathrm{LSTMM}(i,1,t), \mathrm{LSTMM}(i,2,t), \dots, \mathrm{LSTMM}(i,k,t)]^T \end{aligned} \tag{19}$$

where $\Omega = [\sigma_1, \sigma_2, \dots, \sigma_k]^T$ is the vector collecting the standard deviation of the forecast errors of each variable, $\oslash$ is the element-wise division operator, and k is the number of variables in thesystem. The j-th element in LSTMM(i, j, t) is the value of the LSTMM from variable i to variable j. In contrast to the TVP-VAR connectedness measure, in any given time period t the LSTMM values is a function of the observation x_t since the nonlinear interactions between the variables might depend on their current values.

Estimation of the LSTMM. The estimation of the LSTMM required fitting a LSTM to the daily log return data described in section 3 and specifying the shocks to the variables in the system. The hyperparameters of the LSTM were the number of time steps, the size of the hidden state (or number or neurons), the number of layers in the LSTM, and the dropout rate. The last hyperparameter forces the LSTM to drop out the input of a subset of the neurons from one layer to the next and helps to prevent model overfitting.

While the number of time steps was set equal to 20 days to be consistent with the TVP-VAR forecast horizon, the LSTM was fitted for different values of the other hyperparameters. The number of neurons was allowed to vary from 1 to 5 neurons per variable, taking values in $[31, 62, \dots, 155]$, the number of layers could be either 1, 2, or 3, and the dropout rate could take any of the values in $[0.3, 0.4, 0.5]$.

Standard five-fold cross-validation was used to select the hyperparameters, using mean squared error as the loss metric. Given the number of time steps, n, the data observations were partitioned into overlapping subsequences with length equal to the number of steps. It was assumed that the prediction *one* step ahead only depended on the previous n observations, so short time-step sample were considered i.i.d. realizations of the same underlying data generating process, justifying the use of the standard cross-validation procedure. To be consistent with the assumption that only the information in the past n observations mattered, the initial values of the cell and hidden states in each sample were set equal to zero. The final architecture of the LSTM was 1 neurons per variable for a total of 31 neurons, using one layers of LSTM.

Once the hyperparameters were fixed, the forecast errors of the LSTM were computed for each of the variables. The LSTMM of a source variable, i.e. the variable experiencing the shock, was computed assuming a shock equal to one percent of the standard deviation of the forecast errors 20 days ahead. The chosen shock value mirrors to a certain extent the calculation of the impulse response function in a VAR system.

V. Results

The results, either from the TVP-VAR or the LSTM analyses, suggest there have been no major spillovers from cryptocurrencies to the GSIB system. Rather, the latter does impact cryptocurrencies on aggregate despite the fact that the effect of any individual GSIB is small. Nevertheless, there have been short periods during which cryptocurrencies did have a large impact on banks. We discuss these results in detail below.

A. TVP-VAR connectedness

The estimated TO and FROM measures assess how variables influence each other, whether it be a cryptocurrency or a single GSIB. The discussion focuses first on the impact the cryptocurrencies have had on the GSIB sector by summing up the pairwise TO measures of the former on each GSIB bank. The impact of a cryptocurrency on the GSIB sector, or its total connectedness or spillovers, can be normalized to values in [0,1]. Total connectedness would be equal to 1 (or 100 percent) if the cryptocurrency fully explains the forecast variance of the GSIBs and equal to 0 if it explains none of it.

The left panel of Figure 4 shows the total connectedness from Bitcoin and Ethereum to GSIBs. Connectedness from cryptocurrencies to the GSIB sector has been relatively small, seldom exceeding 4 percent when averaged across all GSIBs, for each cryptocurrency (Table 3). Periods during which connectedness peaked, albeit remaining significantly small, tend to coincide with periods of high market distress and heightened volatility, such as in late 2015, when equity and commodity markets were upset by concerns about economic growth in China and Greece's debt negotiations stalled; the start of the COVID-19 pandemic in 2020; the beginning of the war between Russia and Ukraine, and the Crypto Winter 2022.

The GSIBs, on aggregate, have had a larger impact on the cryptocurrencies. The connectedness of the GSIB sector to a cryptocurrency, or spillover, is computed as the sum of the cryptocurrency's FROM GSIB measures. The total spillover of the GSIB sector to a cryptocurrency could take values in [0,1], with the value 1 (100 percent) corresponding to the case when the GSIB sector explains all of the forecast variance of the cryptocurrency, and 0 if it explains none. The right panel in Figure 4 shows that in periods of high economic uncertainty the GSIB sector can explain as much as 90 percent of a cryptocurrency. It is noteworthy that during the Crypto Winter, when the media focused on the risk of spillovers from the crypto space to the broader financial system, spillovers from the banking sector dominated those from cryptocurrencies. Lastly, regardless of the direction of spillovers, cryptocurrencies and GSIBs began to decouple from each other in early 2023.

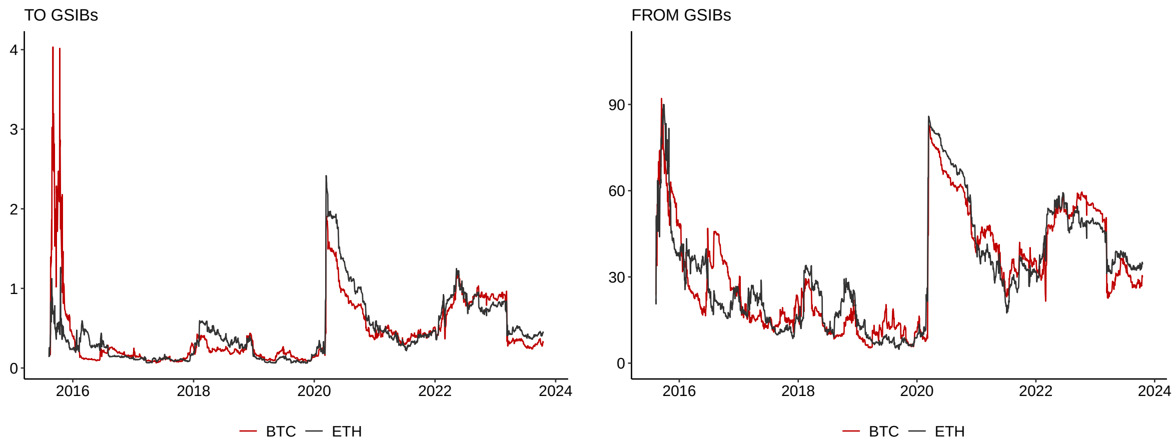
Table 3. TO Connectedness Measures: Summary Statistics, Full Sample (Percent)

	Sample statistics			
Cross-section statistics, daily	Mean	Minimum	Maximum	Standard deviation
A: Bitcoin to GSIBs				
Minimum	0.10	0.00	1.43	0.16
Mean	0.44	0.06	4.03	0.44
Maximum	1.23	0.20	10.45	1.12
B: Ethereum to GSIBs				
Minimum	0.10	0.00	1.26	0.16
Mean	0.45	0.06	2.42	0.39
Maximum	1.14	0.17	5.38	0.71
C: GSIBs to Bitcoin				
Minimum	0.12	0.00	1.31	0.14
Mean	1.11	0.18	3.18	0.66
Maximum	2.65	0.38	15.61	1.32
D: GSIBs to Ethereum				
Minimum	0.10	0.00	0.97	0.13
Mean	1.12	0.17	3.10	0.67
Maximum	3.06	0.38	31.25	2.39
E: GSIBs to other GSIBs				
Minimum	0.06	0.00	0.42	0.06
Mean	2.99	2.80	3.29	0.08
Maximum	19.79	7.85	30.27	2.96
F: Between cryptocurrencies				
Bitcoin To Ethereum	19.44	0.04	36.93	10.35
Ethereum To Bitcoin	19.60	0.10	36.43	10.54

Source: Authors' calculations.
Note: TO connectedness measures the percent contribution of the source variable to explain the 20-day forecast variance decomposition of the target variable. Columns 2 to 5 in Panels A to E report the full sample summary statistics of the daily cross-section GSIB's statistics.

Connectedness between cryptocurrencies can exhibit large fluctuations (Figure 5). Connectedness increased gradually from a very low level during periods of rising cryptocurrency prices and dropped sharply during major price correction periods such as the start of the COVID-19 pandemic. At that time, connectedness to GSIBs greatly exceeded that between cryptocurrencies (Figure 4, right panel). These results are consistent with those of ther studies, which found that cryptocurrencies price correlations move opposite to the degree of uncertainty in the markets (Nakagawa and Sakemoto 2022) and that connectedness rose again in the aftermath of the COVID-19 period (Kumar and others 2022).

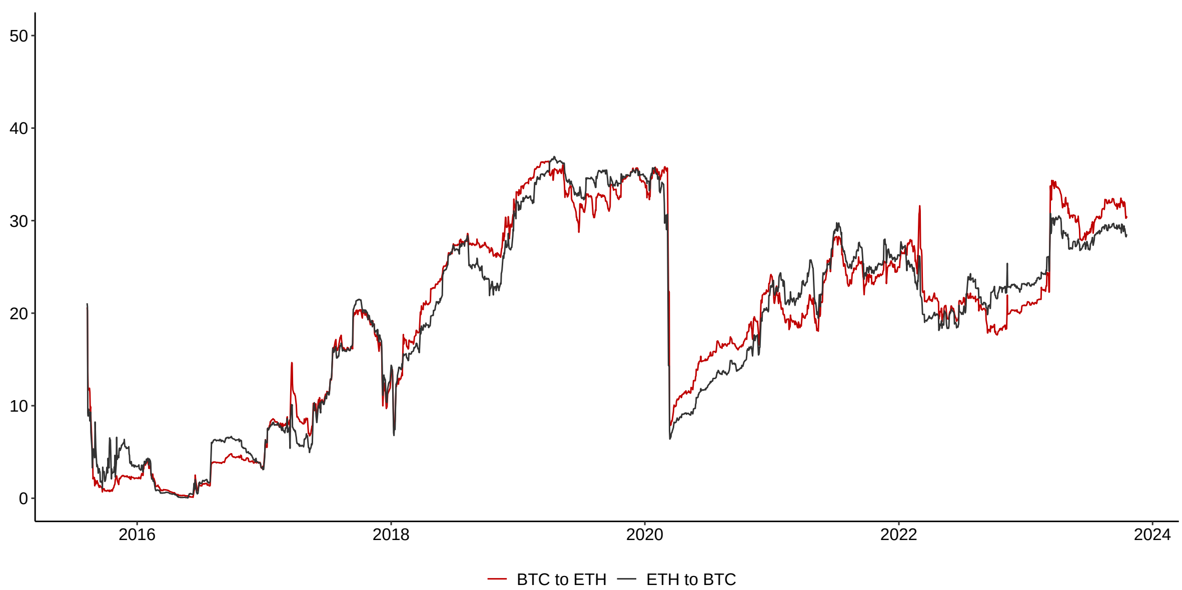
Figure 4. TO and FROM Connectedness of Cryptocurrencies and GSIBs (Percent of variance)



Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Lower connectedness in periods of high uncertainty is also consistent with the perception in crypto markets that Bitcoin is akin to a safe asset or "digital gold" while Ethereum is akin to a growth, speculative stock. The fall in connectedness then reflects a flight to safety in the crypto space. Ongoing structural changes might also affect connectedness. Each cryptocurrency has its own blockchain platform and until recently, both blockchains used Proof-of-Work. Ethereum has switched to Proof-of-of-Stake validation which favors validators with larger stakes in the cryptocurrency (Sergeenkov and Bochan 2023).

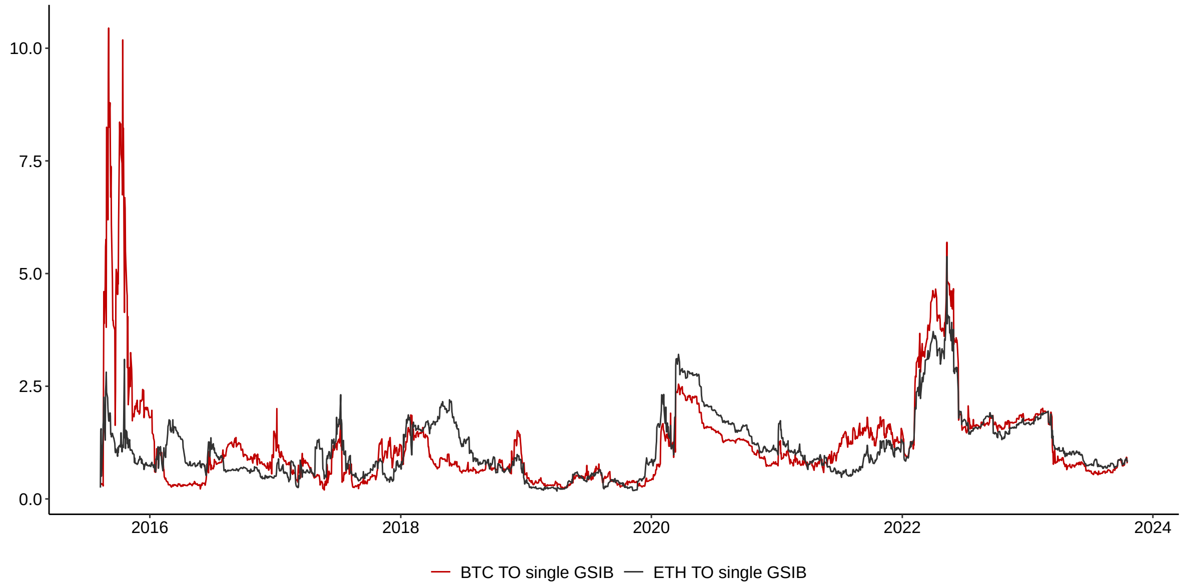
Figure 5. Cryptocurrency Connectedness (Percent of variance)



Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Cryptocurrencies' connectedness to the GSIB sector has been relativley small. Sectoral results, however, could be deceiving since they do not suffice to evaluate vulnerabilities at the single GSIB level. Under certain scenarios or historic episodes, a single GSIB or a few of them could be highly exposed to cryptocurrencies while most of the other GSIBs are only weakly connected.[5] Figure 6, which plots cryptocurrencies maximum pairwise TO connectedness to a single GSIB, shows this is not the case most of the time. Neverthless, in periods of high uncertainty, some GSIBs might experience larger than usual spillovers from cryptocurrencies (Table 3).

Figure 6. Cryptocurrencies Maximum Conectedness to a Single GSIB (Percent of variance)



Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

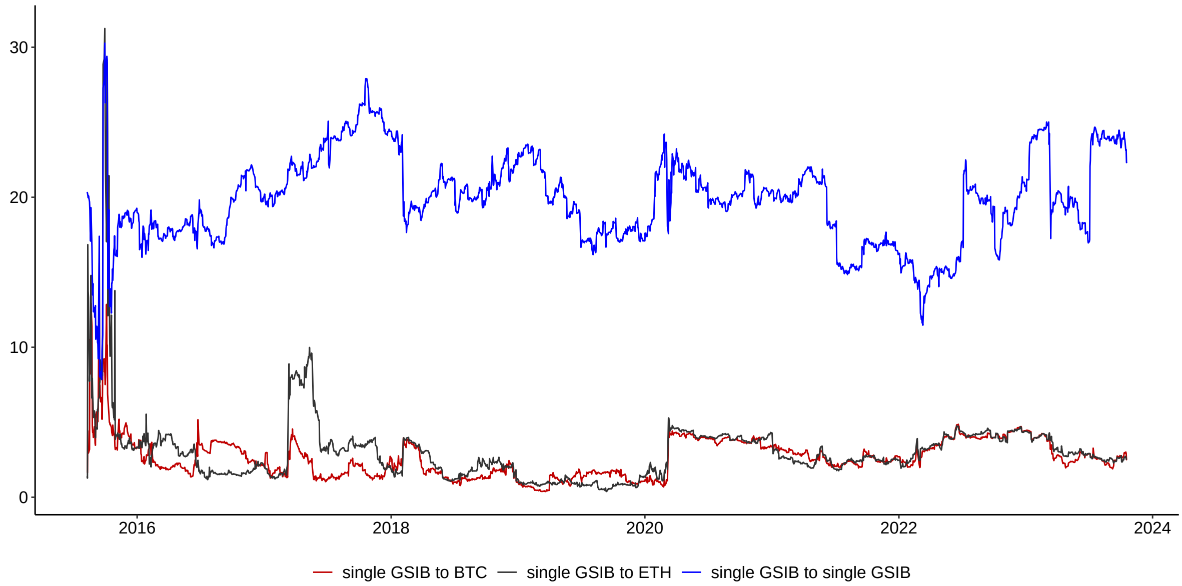
The analysis focuses now on the maximum connectedness measure flowing from individual GSIBs to cryptocurrencies and to other GSIBs. As in the case of cryptocurrencies, this measure is derived from the GSIBs' pairwise TO connectedness measures. When a cryptocurrency is the spillover target, the maximum connectedness correspond to the TO measure of the GSIB that influences the currency the most. When other GSIBs are the main targets, the maximum connectedness singles out the pairwise TO measure with the highest value, that is, it picks the two GSIBs more strongly connected, one as the spillover source and the other as the spillover recipient.

Figure 7 shows that, despite the large influence GSIBs on aggregate have on cryptocurrencies (see Figure 4, right panel), at the individual GSIB level connectedness is small. As it was the case with the other connectedness measures analyzed above, GSIBs influence on cryptocurrencies peaked in the second half of 2015 and has faded away since then. The maximum pairwise connectedness between GSIBs has remained relatively stable, taking values between 15 to 30 percent. Typically, the maximum connectedness has occurred between GSIBs headquartered in the same region, arguably driven by regional common factors.

[5]For instance, if a cryptocurrency explains 100 percent of the variance of a particular GSIB but none of the variance for the remaining GSIBs, the cryptocurrency aggregate TO measures will have a value of 1. This value is also consistent with a very different case where the cryptocurrency explains just 3 percent of the variance of each GSIB.

From a systemic risk assessment, it is also important to determine which cryptocurrency or specific GSIB serves as the primary transmitter (or source) of shocks. Table 4 shows the summary statistics of the TO, FROM, NET, and PNT measures calculated over the study sample from 2015 to 2023. GSIBs with large investment bank operations were the primary transmitters. Among them, US firms ranked first followed closely by European firms. Any of these firms had a major influence over more than 20 other firms as well as on the cryptocurrencies. Snapshots of the connectedness measures at different time periods suggest that the full sample rankings have remained unchanged over time. For instance, Table 5 shows that in October 2023, US and European GSIBs were the most important net transmitters, underscoring their ongoing importance as sources of systemic risk.

Figure 7. Maximum Connectedness of a Single GSIB to Cryptocurrencies and other GSIBs (Percent of variance)



Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Table 4. TVP-VAR Connectedness Measures: Summary Statistics

	TO (in percent)				FROM (in percent)			
	mean	min	max	sdev	mean	min	max	sdev
BTC	32.33	2.71	123.8	14.49	51.84	16.58	93.25	17.69
ETH	32.64	6.7	77.95	14.38	51.83	18.58	92.81	18.25
JPM US	110.92	85.19	140.03	7.74	90.25	86.57	94.86	1.7
BAC US	111.16	77.24	131.47	5.99	90.23	86.28	96.97	1.82
C US	110.44	86.77	141.85	7.39	90.15	86.43	94.92	1.67
HSBA LN	71.51	35.76	106.41	13.91	86.88	78	93.57	3.53
WFC US	91.91	61.14	137.5	12.99	88.12	79.04	94.76	2.98
3988 HK	68.95	41.96	113.29	12.25	71.56	56.97	95.29	5.79
BARC LN	87.63	33.19	163.44	19.72	88.13	75.75	94.62	4.2
BNP FP	104.77	78.23	202.69	8.15	90.24	86.16	95.12	1.9
DBK GR	97.49	58.36	159.96	9.79	89.1	80.76	94.25	2.33
GS US	100.03	78.83	136.84	8.18	89.23	83.45	94.83	2.16
601398 CH	25.41	6.68	184.21	11.7	49.73	24.12	92.61	12.47
8306 JP	77.16	45.99	131.37	7.45	83.43	72.18	97.48	3.64
1288 HK	63.68	39.03	108.67	11.65	70.18	52.18	93.85	6.76
BK US	91.05	44.15	116.45	12.95	87.91	75.15	95.88	3.86
939 HK	68.94	34.6	129.91	14.97	71.57	53.27	94.79	5.89
CSGN SW	78.18	14.25	452.59	32.16	85.49	47.38	95.24	9.3
ACA FP	94.81	61.81	300.57	12.81	89.37	81.44	95.95	2.59
INGA NA	99.44	59.9	171.22	11.16	89.57	80.76	94.94	2.39
8411 JP	65.12	34.83	136.75	7.58	81.18	70.31	96.89	4.12
MS US	107.86	77.74	137.24	8.97	89.92	85.75	95.81	1.8
RY CN	75.67	50.85	112.23	12.59	86.15	72.91	95.91	4.25
SAN SM	97.84	74.43	174.56	9.03	89.41	83.58	94.37	2.19
GLE FP	99.52	60.98	157	12.26	89.64	81.82	94.95	2.54
STAN LN	72.81	52.32	94.91	11.04	87.05	77.65	95.03	3.4
STT US	92.85	66.14	189.16	9.04	88.12	78.7	94.59	2.88
8316 JP	74.81	53.46	146.17	9.39	82.95	71.1	97.14	4.12
TD CN	73.65	35.74	112.24	18.13	84.99	64.85	96.74	6.43
UBS US	100.95	76.38	139.69	7.65	89.25	82.76	94.88	2.22
UCG IM	81.02	47.79	202.12	11.32	87.09	74.74	94.45	3.42

Source: Authors' calculations.

Table 4. TVP-VAR Connectedness Measures: Summary Statistics (continued)

	NET (in percent)				PNT			
	mean	min	max	sdev	mean	min	max	sdev
BTC	-19.5	-52.64	59.76	11.44	4.58	0	24	3.1
ETH	-19.19	-78.33	0.23	11.42	4.57	0	21	3.23
JPM US	20.67	-6.9	50.68	8.15	26.58	8	30	3.34
BAC US	20.93	-19.73	40.63	6.09	26.87	11	30	3.2
C US	20.3	-6.6	50.93	7.78	26.04	12	30	3.65
HSBA LN	-15.37	-45.57	17.35	11.25	8.33	1	22	4.7
WFC US	3.79	-19.5	47.78	10.99	17.52	4	30	4.87
3988 HK	-2.6	-47.19	36.45	11.93	10.77	0	27	6.07
BARC LN	-0.51	-44.28	73.98	16.07	14.93	1	29	7.45
BNP FP	14.52	-10.07	111.68	7.62	23.09	8	30	5.11
DBK GR	8.39	-25.12	70.28	8.92	19.16	3	30	5
GS US	10.8	-15.75	45.27	7.3	21	10	28	4.06
601398 CH	-24.32	-74.98	132.79	10.33	4.5	0	30	3.72
8306 JP	-6.28	-51.49	42.57	6.82	11.07	2	27	3.67
1288 HK	-6.49	-39.05	28.87	10.27	9.26	1	25	5.28
BK US	3.14	-37.96	25.51	9.96	17.12	2	30	4.86
939 HK	-2.63	-44.51	48.2	13.49	10.57	0	27	6.38
CSGN SW	-7.31	-58.91	366.61	27.74	11.1	0	30	5.46
ACA FP	5.44	-22.18	215.17	11.24	17.74	5	30	5.32
INGA NA	9.86	-21.04	79.78	9.74	20.27	5	30	5.37
8411 JP	-16.06	-61.72	50.76	7.38	7.63	2	27	3.4
MS US	17.94	-15.69	44	8.89	24.83	8	30	4.2
RY CN	-10.48	-41.27	17.81	9.78	9.66	0	24	4.37
SAN SM	8.43	-16.38	83.52	8.34	18.79	7	30	4.98
GLE FP	9.88	-22.75	64.82	10.41	20.63	4	30	6.54
STAN LN	-14.24	-41	3.58	8.98	8.18	0	21	3.58
STT US	4.74	-13.83	98.93	7.28	17.87	6	27	3.6
8316 JP	-8.14	-37.32	58.57	7.75	10.26	3	28	3.65
TD CN	-11.35	-43.95	22.36	12.57	9.36	0	24	5.3
UBS US	11.7	-14.66	48.65	6.7	21.01	5	30	3.96
UCG IM	-6.07	-28.88	114.08	8.85	11.73	2	28	3.15

Source: Authors' calculations.

Table 5. Cryptocurrencies and GSIBs TVP-VAR Connectedness, October 2023

	BTC	ETH	JPM US	BAC US	C US	WFC US	HSBA LN	3988 HK
BTC	48.16	19.60	1.33	1.35	1.45	0.84	1.27	0.40
ETH	19.44	48.17	1.12	1.15	1.46	0.79	1.10	0.53
JPM US	0.39	0.38	9.75	7.80	7.12	2.09	6.00	0.78
BAC US	0.43	0.37	7.80	9.77	7.21	2.13	6.19	0.71
C US	0.47	0.46	7.17	7.26	9.85	2.16	5.78	0.83
HSBA LN	0.35	0.39	2.98	3.03	3.06	13.12	2.59	2.36
WFC US	0.44	0.40	7.18	7.44	6.89	2.15	11.88	0.79
3988 HK	0.39	0.29	1.50	1.41	1.57	0.91	1.39	28.44
BARC LN	0.38	0.44	3.07	3.08	3.11	4.37	2.39	0.98
BNP FP	0.34	0.38	2.85	2.71	2.87	3.34	2.14	0.90
DBK GR	0.51	0.50	3.70	3.78	3.85	2.94	2.98	0.69
GS US	0.49	0.50	6.91	6.94	6.69	1.93	5.43	0.80
601398 CH	0.73	0.58	0.97	0.96	1.09	0.57	1.09	8.05
8306 JP	0.37	0.45	3.39	3.41	3.01	1.72	3.07	1.22
1288 HK	0.44	0.33	1.30	1.29	1.51	1.02	1.32	17.23
BK US	0.46	0.47	6.35	6.66	6.33	2.06	5.33	0.79
939 HK	0.50	0.31	1.45	1.39	1.54	1.01	1.33	17.48
CSGN SW	0.48	0.55	3.18	3.24	3.43	3.08	2.59	1.12
ACA FP	0.45	0.47	2.81	2.76	2.84	3.30	2.08	0.92
INGA NA	0.39	0.45	2.74	2.70	2.85	3.72	2.14	0.99
8411 JP	0.36	0.47	2.94	2.89	2.57	1.59	2.72	1.01
MS US	0.54	0.52	6.81	6.87	6.60	1.97	5.19	0.81
RY CN	0.51	0.54	4.62	4.38	4.59	2.30	3.78	1.09
SAN SM	0.37	0.37	2.69	2.62	2.84	3.81	2.20	1.04
GLE FP	0.35	0.43	2.72	2.63	2.77	3.32	2.17	0.92
STAN LN	0.41	0.44	2.86	2.81	2.87	6.06	2.36	2.07
STT US	0.47	0.47	6.08	6.33	6.02	2.04	4.95	0.86
8316 JP	0.46	0.52	3.16	3.28	2.89	1.77	2.81	1.15
TD CN	0.51	0.53	4.53	4.37	4.55	2.37	3.84	0.84
UBS US	0.55	0.54	4.25	4.22	4.35	2.70	3.60	0.91
UCG IM	0.35	0.46	2.43	2.41	2.50	3.45	2.08	0.67
TO	32.33	32.64	110.92	111.16	110.44	71.51	91.91	68.95
Including Own	80.50	80.81	120.67	120.93	120.30	84.63	103.79	97.40
NET	-19.50	-19.19	20.67	20.93	20.30	-15.37	3.79	-2.60
PNT	2.00	2.00	29.00	30.00	28.00	4.00	16.00	10.00

Source: Authors' calculations.
Note: Any given column j reports:
(1) PDCs, influence of variable j listed in the column to variables i listed in the row;
(2) TO, the sum of j's PDC measures;
(3) NET, j's net influence over all variables;
(4) PNT, the number of variables which j dominates.
All measures in percent except NPT.

Table 5. Cryptocurrencies and GSIBs TVP-VAR Connectedness, October 2023 (continued)

	BARC LN	BNP FP	DBK GR	GS US	601398 CH	8306 JP	1288 HK	BK US
BTC	1.14	1.13	1.48	1.60	0.55	0.72	0.47	1.39
ETH	1.16	1.03	1.47	1.51	0.46	0.73	0.51	1.24
JPM US	2.47	2.69	3.37	6.30	0.27	2.18	0.60	5.38
BAC US	2.49	2.56	3.46	6.31	0.25	2.17	0.57	5.61
C US	2.56	2.70	3.53	6.15	0.33	1.97	0.69	5.39
HSBA LN	5.05	4.48	3.54	2.52	0.69	1.94	1.95	2.46
WFC US	2.31	2.34	3.24	5.93	0.26	2.26	0.63	5.35
3988 HK	0.93	1.27	1.14	1.26	4.79	2.08	16.81	1.28
BARC LN	11.87	5.62	4.36	2.67	0.35	1.62	0.87	2.50
BNP FP	4.80	9.76	4.73	2.54	0.34	1.59	0.82	2.29
DBK GR	4.09	5.16	10.90	3.59	0.28	1.79	0.69	3.10
GS US	2.33	2.59	3.55	10.77	0.21	2.15	0.58	4.96
601398 CH	0.68	0.81	0.76	0.85	50.27	1.61	7.65	1.03
8306 JP	1.92	2.16	2.52	3.04	0.60	16.57	1.15	2.57
1288 HK	0.89	1.10	1.08	1.13	4.96	1.99	29.82	1.05
BK US	2.39	2.49	3.25	5.35	0.35	2.03	0.59	12.09
939 HK	0.99	1.23	1.10	1.20	5.02	1.97	15.89	1.26
CSGN SW	4.13	5.15	4.55	2.99	0.40	1.95	1.07	2.52
ACA FP	4.72	7.14	4.75	2.45	0.30	1.58	0.92	2.22
INGA NA	5.01	6.94	4.59	2.48	0.43	1.80	0.97	2.29
8411 JP	1.79	2.23	2.12	2.67	0.61	13.49	0.91	2.33
MS US	2.34	2.65	3.46	7.13	0.26	2.12	0.63	5.24
RY CN	2.86	3.07	3.18	4.58	0.49	1.91	0.98	3.56
SAN SM	4.77	6.68	4.65	2.38	0.41	1.66	1.02	2.22
GLE FP	4.86	7.79	4.85	2.38	0.27	1.61	0.84	2.24
STAN LN	5.14	4.84	3.76	2.28	0.61	1.69	1.91	2.33
STT US	2.60	2.64	3.21	5.50	0.28	1.87	0.67	7.73
8316 JP	2.03	2.16	2.35	2.87	0.57	13.21	1.06	2.48
TD CN	3.01	2.93	3.22	4.17	0.51	2.00	0.84	3.42
UBS US	3.50	4.30	5.21	4.07	0.28	1.90	0.78	3.57
UCG IM	4.70	6.86	5.01	2.13	0.28	1.58	0.62	2.04
TO	87.63	104.77	97.49	100.03	25.41	77.16	63.68	91.05
Including Own	99.49	114.52	108.39	110.80	75.68	93.72	93.51	103.14
NET	-0.51	14.52	8.39	10.80	-24.32	-6.28	-6.49	3.14
PNT	13.00	26.00	19.00	24.00	1.00	11.00	7.00	17.00

Source: Authors' calculations.
Note: Any given column j reports:
(1) PDCs, which measure the influence of variable j listed in the column to variables i listed in the row;
(2) TO, the sum of j's PDC measures;
(3) NET, j's net influence over all varaibles;
(4) PNT, the number of variables which j dominates.
All measures in percent except NPT.

Table 5. Cryptocurrencies and GSIBs TVP-VAR Connectedness, October 2023 (continued)

	939 HK	CSGN SW	ACA FP	INGA NA	8411 JP	MS US	RY CN	SAN SM
BTC	0.40	1.24	1.30	1.12	0.71	1.67	1.26	1.10
ETH	0.54	1.23	1.28	1.16	0.78	1.74	1.24	1.02
JPM US	0.71	2.28	2.40	2.45	1.65	6.62	3.29	2.41
BAC US	0.69	2.29	2.34	2.38	1.59	6.67	3.07	2.34
C US	0.80	2.41	2.40	2.54	1.49	6.46	3.26	2.55
HSBA LN	2.40	3.30	4.04	4.71	1.44	2.70	2.32	4.68
WFC US	0.71	2.07	2.09	2.21	1.71	6.05	3.15	2.30
3988 HK	17.56	0.86	1.16	1.45	1.53	1.29	0.97	1.36
BARC LN	1.04	3.82	5.13	5.60	1.24	2.85	2.48	5.15
BNP FP	0.99	4.14	6.65	6.58	1.42	2.77	2.31	6.17
DBK GR	0.76	3.96	4.77	4.76	1.32	3.72	2.51	4.76
GS US	0.74	2.34	2.28	2.38	1.64	7.60	3.56	2.33
601398 CH	8.11	1.04	0.73	1.02	1.64	0.93	0.90	1.03
8306 JP	1.17	2.14	2.00	2.44	11.95	3.18	1.84	2.22
1288 HK	16.57	1.03	1.02	1.34	1.47	1.27	1.13	1.39
BK US	0.74	2.16	2.24	2.37	1.57	5.98	3.04	2.31
939 HK	28.43	0.94	1.16	1.47	1.57	1.37	1.18	1.39
CSGN SW	1.21	14.51	4.39	4.39	1.55	3.36	2.23	4.36
ACA FP	1.07	3.93	10.63	6.45	1.24	2.78	2.29	5.97
INGA NA	1.14	3.74	6.27	10.43	1.37	2.65	2.31	6.13
8411 JP	1.07	2.02	1.79	2.20	18.82	2.93	1.83	2.31
MS US	0.79	2.42	2.44	2.42	1.68	10.08	3.46	2.44
RY CN	1.12	2.46	2.69	2.88	1.62	4.74	13.85	2.95
SAN SM	1.09	3.82	5.98	6.27	1.46	2.67	2.38	10.59
GLE FP	0.99	4.07	6.76	6.19	1.41	2.70	2.10	6.06
STAN LN	1.97	3.41	4.28	4.93	1.38	2.64	2.61	5.05
STT US	0.71	2.27	2.44	2.45	1.44	6.03	3.18	2.58
8316 JP	1.19	2.01	1.96	2.38	12.78	3.18	1.84	2.26
TD CN	0.93	2.35	2.71	2.80	1.70	4.41	8.94	3.01
UBS US	0.98	4.63	3.82	3.80	1.50	4.53	2.91	3.73
UCG IM	0.74	3.82	6.30	6.29	1.27	2.40	2.08	6.47
TO	68.94	78.18	94.81	99.44	65.12	107.86	75.67	97.84
Including own	97.37	92.69	105.44	109.86	83.94	117.94	89.52	108.43
NET	-2.63	-7.31	5.44	9.86	-16.06	17.94	-10.48	8.43
PNT	8.00	11.00	20.00	22.00	6.00	27.00	10.00	20.00

Source: Authors' calculations.
Note: Any given column j reports:
(1) PDCs, which measure the influence of variable j listed in the column to variables i listed in the row;
(2) TO, the sum of j's PDC measures;
(3) NET, j's net influence over all varaibles;
(4) PNT, the number of variables which j dominates.
All measures in percent except NPT.

Table 5. Cryptocurrencies and GSIBs TVP-VAR Connectedness, October 2023 (continued)

	GLE FP	STAN LN	STT US	8316 JP	TD CN	UBS US	UCG IM	FROM
BTC	1.30	0.87	1.60	0.75	1.19	1.55	1.07	51.84
ETH	1.25	0.89	1.59	0.81	1.58	1.76	1.23	51.83
JPM US	2.51	1.96	5.13	1.99	3.20	3.90	1.94	90.25
BAC US	2.43	1.95	5.33	2.01	3.09	3.88	1.91	90.23
C US	2.56	1.97	5.12	1.86	3.24	4.03	2.00	90.15
HSBA LN	4.23	6.09	2.44	1.87	2.30	3.39	3.58	86.88
WFC US	2.33	1.86	4.98	2.02	3.19	3.94	1.92	88.12
3988 HK	1.03	1.01	1.32	1.93	0.81	1.28	1.01	71.56
BARC LN	5.45	4.55	2.70	1.61	2.58	3.90	4.23	88.13
BNP FP	7.41	3.62	2.47	1.52	2.20	4.10	5.28	90.24
DBK GR	5.08	3.08	3.05	1.62	2.51	5.28	4.29	89.10
GS US	2.35	1.71	5.07	2.03	3.20	4.09	1.86	89.23
601398 CH	0.70	0.72	1.17	1.64	1.09	0.82	0.74	49.73
8306 JP	2.16	1.70	2.55	12.91	1.96	2.63	1.97	83.43
1288 HK	0.89	1.29	1.16	1.84	0.80	1.40	0.91	70.18
BK US	2.37	1.87	7.76	1.94	2.92	3.86	1.86	87.91
939 HK	1.01	1.20	1.22	1.97	0.98	1.40	1.03	71.57
CSGN SW	4.88	3.13	2.65	1.78	2.11	5.34	3.65	85.49
ACA FP	6.90	3.52	2.51	1.45	2.28	4.02	5.25	89.37
INGA NA	6.21	3.86	2.42	1.70	2.23	3.92	5.13	89.57
8411 JP	2.21	1.65	2.27	14.05	1.91	2.44	1.80	81.18
MS US	2.51	1.84	5.22	2.07	3.19	4.29	2.00	89.92
RY CN	2.68	2.45	3.80	1.80	8.39	3.89	2.21	86.15
SAN SM	6.22	4.07	2.48	1.64	2.39	3.79	5.42	89.41
GLE FP	10.36	3.53	2.40	1.51	2.12	4.08	5.56	89.64
STAN LN	4.47	12.95	2.40	1.67	2.42	3.67	3.71	87.05
STT US	2.52	1.84	11.88	1.77	2.95	4.20	2.00	88.12
8316 JP	2.12	1.74	2.48	17.05	1.92	2.37	1.94	82.95
TD CN	2.70	2.41	3.52	1.88	15.01	3.77	2.24	84.99
UBS US	4.14	2.85	3.88	1.66	2.80	10.75	3.28	89.25
UCG IM	6.90	3.56	2.18	1.49	2.10	3.93	12.91	87.09
TO	99.52	72.81	92.85	74.81	73.65	100.95	81.02	2560.55
Including own	109.88	85.76	104.74	91.86	88.65	111.70	93.93	cTCI/TCI
NET	9.88	-14.24	4.74	-8.14	-11.35	11.70	-6.07	85.35/82.60
PNT	24.00	7.00	19.00	8.00	7.00	24.00	13.00	

Source: Authors' calculations.
Note: Any given column j reports:
(1) PDCs, which measure the influence of variable j listed in the column to variables i listed in the row;
(2) TO, the sum of j's PDC measures;
(3) NET, j's net influence over all varaibles;
(4) PNT, the number of variables which j dominates.
All measures in percent except NPT.

B. LSTM multiplier connnectedness

The estimated LSTMM daily time series exhibit high volatility reflecting the daily log-returns series volatility. To aid in identifying patterns, the results discussed in this section correspond to the 120-day moving average of the daily LSTMMs. The calculation of the LSTMMs of the source variable assume a shock equal to one percent of the standard deviation of its forecast error. Consequently, the LSTMM values corresponding to the target variable are also reported in percent of the standard deviation of its forecast error. Hereafter, any reference to standard deviation refers to that of the forecast error, or when returns are discussed, the discussion refers to the standardized price return.

Table 6 presents a concise summary of the main results. It reports the time average summary statistics, calculated over the data sample period, of the daily cross-section of the minimum, the maximum, and the mean values of cryptocurrencies LSTMMs on GSIBs (panels A and B), and the GSIBs LSTMMs on the cryptocurrencies and other GSIBs (panels C, D, and E respectively); as well as the LSTMMs between cryptocurrencies (panel F). Tables 7 to 9 present similar summary statistics but disaggregated by cryptocurrencies and GSIBs.

Table 6. LSTM Multipliers: Summary Statistics, Full Sample

	Sample statistics, time average			
Cross-section statistics, daily	Mean	Minimum	Maximum	Standard deviation
A: Bitcoin to GSIBs				
Minimum	0.14	0.11	0.15	0.01
Mean	0.28	0.20	0.37	0.04
Maximum	0.42	0.26	0.60	0.07
B: Ethereum to GSIBs				
Minimum	0.05	0.04	0.09	0.01
Mean	0.14	0.10	0.21	0.02
Maximum	0.23	0.18	0.33	0.03
C: Single GSIB to Bitcoin				
Minimum	0.03	0.02	0.05	0.01
Mean	0.10	0.09	0.13	0.01
Maximum	0.33	0.27	0.39	0.03
D: Single GSIB to Ethereum				
Minimum	0.05	0.03	0.10	0.02
Mean	0.17	0.14	0.21	0.01
Maximum	0.53	0.42	0.66	0.04
E: Single GSIB to other GSIBs				
Minimum	0.02	0.01	0.03	0.00
Mean	0.10	0.08	0.14	0.01
Maximum	0.36	0.24	0.54	0.06
F: Between cryptocurrencies				
Bitcoin to Ethereum	0.54	0.40	0.67	0.06
Ethereum to Bitcoin	0.19	0.15	0.26	0.02

Source: Authors' calculations.
Note: LSTMM values expressed in percent of the standard deviation of the target variable forecast error when the source variable experiences a positive one percent standard deviation shock. Columns 2 to 5 in Panels A to E report the full sample summary statistics of the daily cross-section GSIBs' statistics. Calculations based on a 120-day moving average.

Table 7. LSTM Multiplier TO GSIBs : Summary Statistics, Full Sample

	Sample statistics, time average			
Source of shock	Mean	Minimum	Maximum	Standard deviation
BTC	0.28	0.11	0.60	0.08
ETH	0.14	0.04	0.33	0.05
JPM US	0.12	0.02	0.26	0.06
BAC US	0.06	0.02	0.14	0.02
C US	0.11	0.02	0.28	0.05
HSBA LN	0.08	0.01	0.22	0.03
WFC US	0.09	0.01	0.17	0.03
3988 HK	0.15	0.03	0.31	0.06
BARC LN	0.10	0.02	0.28	0.06
BNP FP	0.19	0.06	0.39	0.05
DBK GR	0.06	0.01	0.11	0.02
GS US	0.11	0.03	0.30	0.05
601398 CH	0.09	0.02	0.21	0.04
8306 JP	0.10	0.02	0.21	0.04
1288 HK	0.05	0.02	0.12	0.02
BK US	0.14	0.04	0.36	0.05
939 HK	0.09	0.02	0.22	0.04
CSGN SW	0.08	0.02	0.20	0.03
ACA FP	0.22	0.06	0.54	0.08
INGA NA	0.10	0.03	0.26	0.04
8411 JP	0.11	0.02	0.32	0.06
MS US	0.05	0.01	0.14	0.02
RY CN	0.08	0.01	0.19	0.03
SAN SM	0.12	0.02	0.26	0.04
GLE FP	0.13	0.05	0.24	0.03
STAN LN	0.07	0.01	0.22	0.03
STT US	0.13	0.03	0.29	0.06
8316 JP	0.08	0.03	0.21	0.03
TD CN	0.13	0.04	0.26	0.04
UBS US	0.08	0.03	0.27	0.03
UCG IM	0.08	0.02	0.21	0.03

Source: Authors' calculations.
Note: LSTMM values expressed in percent of the standard deviation of the target variables forecast error when the source variable experiences a positive one percent standard deviation shock. Calculations based on a 120-day moving average.

Table 8. LSTM Multiplier to Bitcoin: Summary Statistics, Full Sample

	Sample statistics, time average			
Source of shock:	Mean	Minimum	Maximum	Standard deviation
ETH	0.19	0.15	0.26	0.02
JPM US	0.05	0.03	0.09	0.01
BAC US	0.12	0.10	0.14	0.01
C US	0.10	0.07	0.13	0.01
HSBA LN	0.13	0.11	0.14	0.01
WFC US	0.09	0.07	0.12	0.01
3988 HK	0.06	0.03	0.11	0.01
BARC LN	0.05	0.03	0.08	0.01
BNP FP	0.23	0.20	0.27	0.01
DBK GR	0.06	0.05	0.09	0.01
GS US	0.12	0.10	0.14	0.01
601398 CH	0.04	0.02	0.06	0.01
8306 JP	0.06	0.05	0.09	0.01
1288 HK	0.09	0.06	0.15	0.02
BK US	0.15	0.11	0.21	0.02
939 HK	0.13	0.10	0.16	0.01
CSGN SW	0.04	0.02	0.08	0.01
ACA FP	0.33	0.27	0.39	0.03
INGA NA	0.06	0.03	0.08	0.01
8411 JP	0.06	0.04	0.11	0.01
MS US	0.03	0.02	0.05	0.01
RY CN	0.09	0.05	0.12	0.01
SAN SM	0.04	0.02	0.07	0.01
GLE FP	0.28	0.27	0.30	0.01
STAN LN	0.04	0.02	0.07	0.01
STT US	0.21	0.18	0.24	0.01
8316 JP	0.16	0.14	0.17	0.01
TD CN	0.11	0.08	0.14	0.01
UBS US	0.04	0.02	0.07	0.01
UCG IM	0.06	0.04	0.11	0.01

Source: Authors' calculations.
Note: LSTMM values expressed in percent of the standard deviation of the target variables forecast error when the source variable experiences a positive one percent standard deviation shock. Calculations based on a 120-day moving average.

Table 9. LSTM Multiplier to Ethereum: Summary Statistics, Full Sample

	Sample statistics, time average			
Source of shock:	Mean	Minimum	Maximum	Standard deviation
BTC	0.54	0.40	0.67	0.06
JPM US	0.13	0.08	0.19	0.02
BAC US	0.23	0.19	0.26	0.01
C US	0.10	0.05	0.17	0.02
HSBA LN	0.18	0.15	0.21	0.01
WFC US	0.13	0.10	0.18	0.02
3988 HK	0.25	0.17	0.36	0.03
BARC LN	0.09	0.06	0.14	0.02
BNP FP	0.26	0.19	0.34	0.03
DBK GR	0.12	0.09	0.16	0.01
GS US	0.23	0.18	0.27	0.02
601398 CH	0.08	0.05	0.13	0.02
8306 JP	0.06	0.04	0.11	0.01
1288 HK	0.14	0.10	0.20	0.02
BK US	0.25	0.18	0.34	0.03
939 HK	0.14	0.11	0.19	0.02
CSGN SW	0.12	0.09	0.15	0.01
ACA FP	0.53	0.42	0.66	0.04
INGA NA	0.11	0.05	0.18	0.03
8411 JP	0.10	0.05	0.21	0.03
MS US	0.06	0.03	0.11	0.02
RY CN	0.14	0.10	0.18	0.02
SAN SM	0.08	0.05	0.12	0.02
GLE FP	0.37	0.33	0.41	0.02
STAN LN	0.07	0.03	0.16	0.03
STT US	0.30	0.27	0.33	0.01
8316 JP	0.22	0.18	0.26	0.02
TD CN	0.21	0.15	0.27	0.03
UBS US	0.06	0.03	0.11	0.02
UCG IM	0.10	0.05	0.20	0.03

Source: Authors' calculations.
Note: LSTMM values expressed in percent of the standard deviation of the target variables forecast error when the source variable experiences a positive one percent standard deviation shock. Calculations based on a 120-day moving average.

The sample statistitcs show that, in terms of equity price returns, cryptocurrencies and GSIBs have been only weakly connected on average (Table 6, panels A and B). This finding is consistent with the TVP-VAR variance decomposition connectedness measures. During the 2015-2023 period, a one percent standardized shock to Bitcoin caused, on average, a movement of one third of a percent in the GSIBs' price return as measured by the LSTMM. The mean values of the Bitcoin LSTMMs on GSIBs fluctuated in the $[0.20, 0.37]$ percent range. Bitcoin shocks appeared to influence GSIBs more than Ethereum shocks. The mean LSTMMs values of the latter on GSIBs were about half of those of Bitcoin, fluctuating in the $[0.10, 0.21]$ percent range. The maximum impact Bitcoin and Ethereum had on a single GSIB in this period were 0.60 percent and 0.33 percent respectively. Hence, while on average the LSTMM values have been small, it is not possible to ignore that from time to time, cryptocurrencies shocks could induce large GSIB equity price movements.

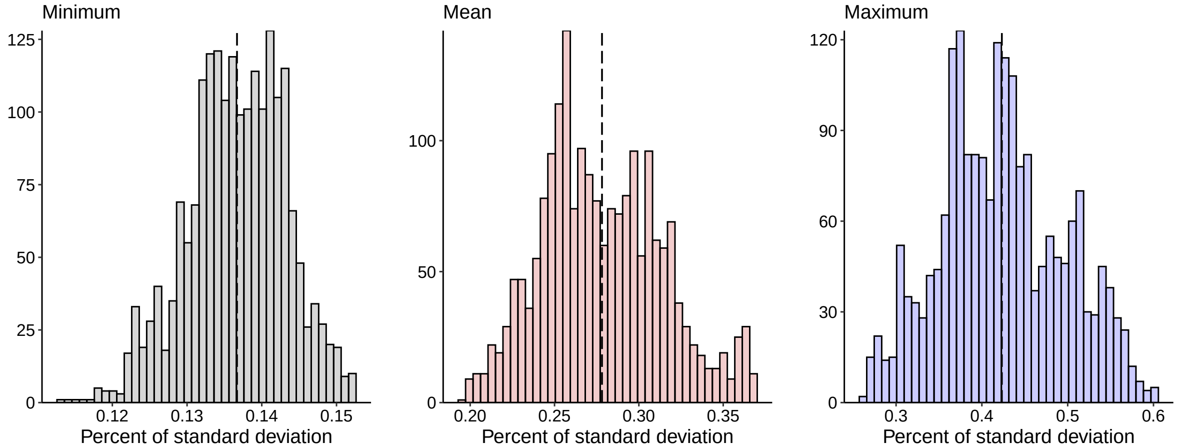
Similarly, shocks from GSIBs to cryptocurrencies and to other GSIBs have had only a minor impact on the targets, as evidenced by the low LSTMM values (Table 6, panels C, D and E). Following a one percent shock to a GSIB, Bitcoin and Ethereum would experience, on average, movements of 0.10 and 0.17 percent, with the largest movements at 0.39 percent and 0.66 percent respectively. Between GSIBs, the same shock would induce an average price return of 0.10 percent, with the maximum impact between two GSIBs equal to 0.54 percent. As it was the case, the maximum impact (or LSTMM value) corresponds to LSTMMs between GSIBs headquartered in the same geographic region.

The disaggregated results presented in Tables 7 to 9 further support the argument that there has been weak connectedness at the equity price return level between GSIBs and cryptocurrencies, a finding that mirrors those obtained at the variance decomposition level. Between GSIBs, banks headquartered in the France, and to a lesser extent in the United States, appear to be the major sources of shocks in the GSIB sector. Shocks from cryptocurrencies to GSIBs had somewhat a larger impact than those between GSIBs, but on aggregate, GSIBs have been more affected by shocks from other GSIBs (Table 7). Bitcoin has experienced larger price returns movements in response to shocks to certain banks headquartered in France and the US than to Ethereum. The opposite holds for Ethereum, which is mainly affected by Bitcoin shocks (Tables 8 and 9).

The LSTMM histograms (Figures 8 to 12) reveal common patterns which can be associated with the transmission of shocks (or connectedness) between GSIBs and cryptocurrencies. The distributions are right skewed, with a majority of the observations falling below the mean value. Hence, following the realization of a shock to either a GSIB or a cryptocurrency, most GSIBs are only minimally affected – recall that the mean LSTMM value is small. The long right tail, however, indicates that a few of the GSIBs could either be a source of large spillovers (relative to the spillovers' mean value) to other GSIBs or cryptocurrencies, or a target of them.

These results might imply that there are two main systemic risk channels in the GSIB sector. One channel is associated with the transmission and amplification of idiosyncratic shocks affecting individual firms. In this case, the presence of right tails hints that an idiosyncratic shock might have a large impact on other firm and could potentially trigger a cascade of failures (Elliott, Golub and Jackson, 2004). Spillovers from cryptocurrencies could play a role in this transmission channel. The other channel is associated with a Too-Many-to-Fail event: systemic risk could arise from the simultaneous occurrence of idiosyncratic shocks that, when accumulated, might lead to large equity price declines. Cryptocurrencies could play a systemic role since they could transmit shocks to several GSIBs at the same time. Risks, for the time being, are minimal due to weak connectedness.

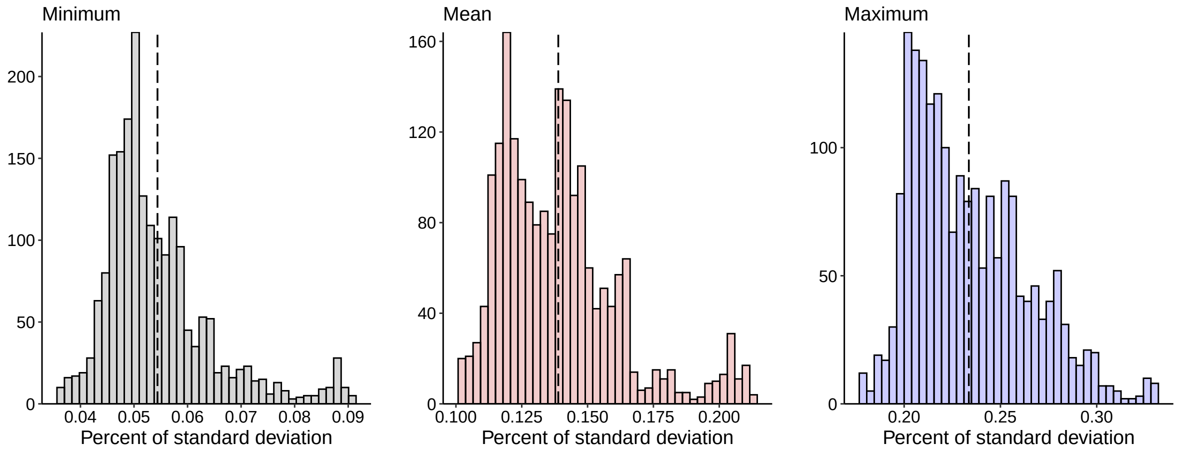
Figure 8. LSTM Multiplier Histograms: Bitcoin to GSIBs (Count)



Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Note: a dotted line corresponds to the mean of the distribution.

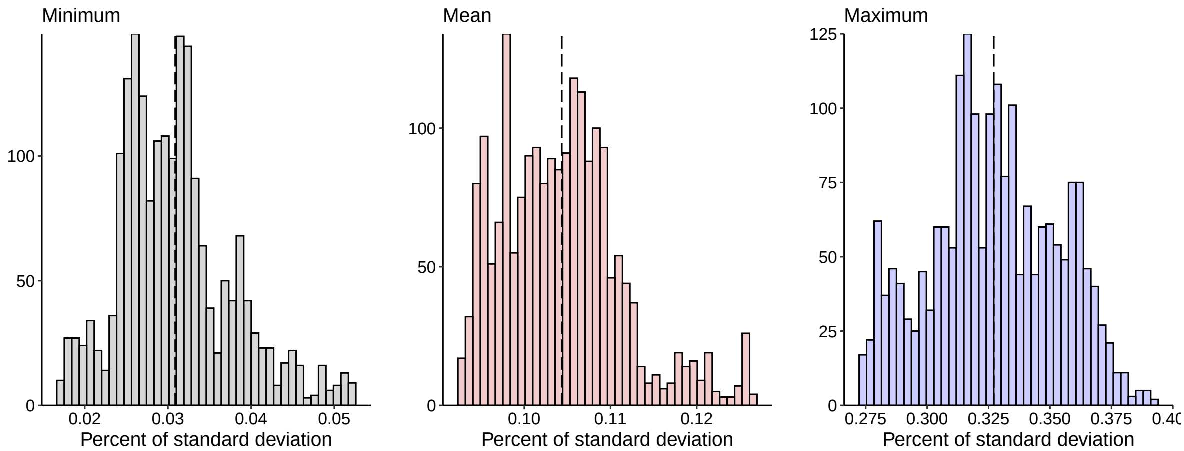
Figure 9. LSTM Multiplier Histograms: Ethereum to GSIBs (Count)



Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Note: a dotted line corresponds to the mean of the distribution.

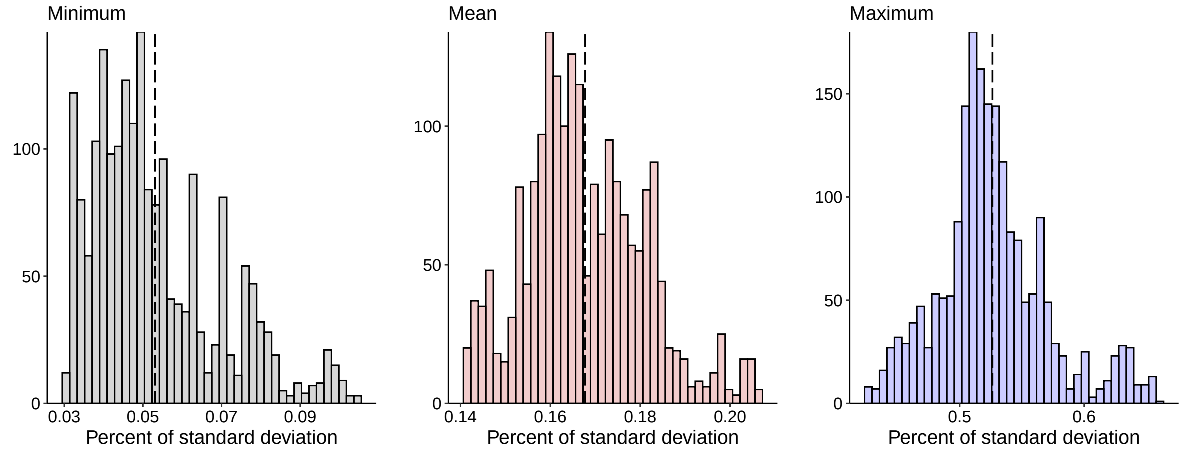
Figure 10. LSTM Multiplier Histograms: GSIBs to Bitcoin (Count)



Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Note: a dotted line corresponds to the mean of the distribution.

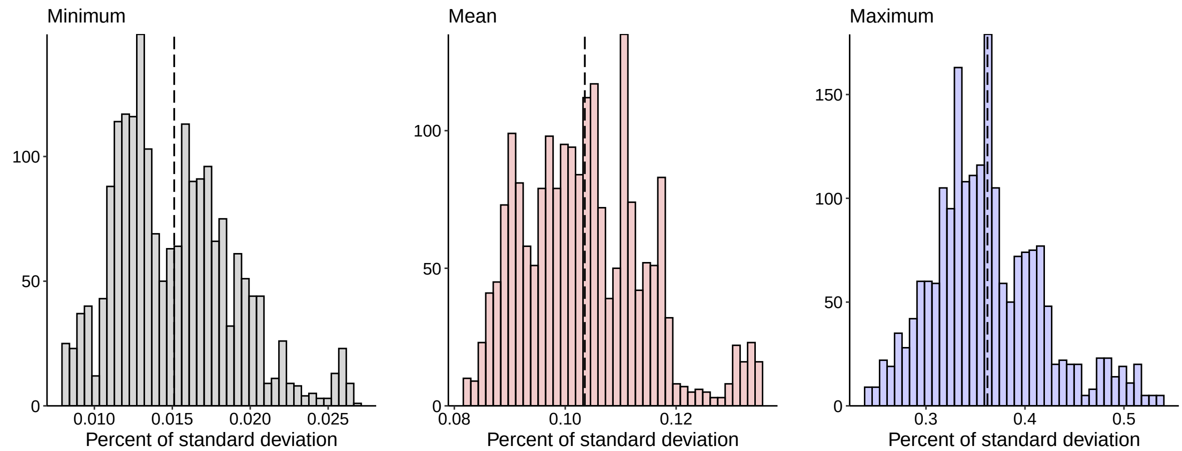
Figure 11. LSTM Multiplier Histograms: GSIBs to Ethereum (Count)



Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Note: a dotted line corresponds to the mean of the distribution.

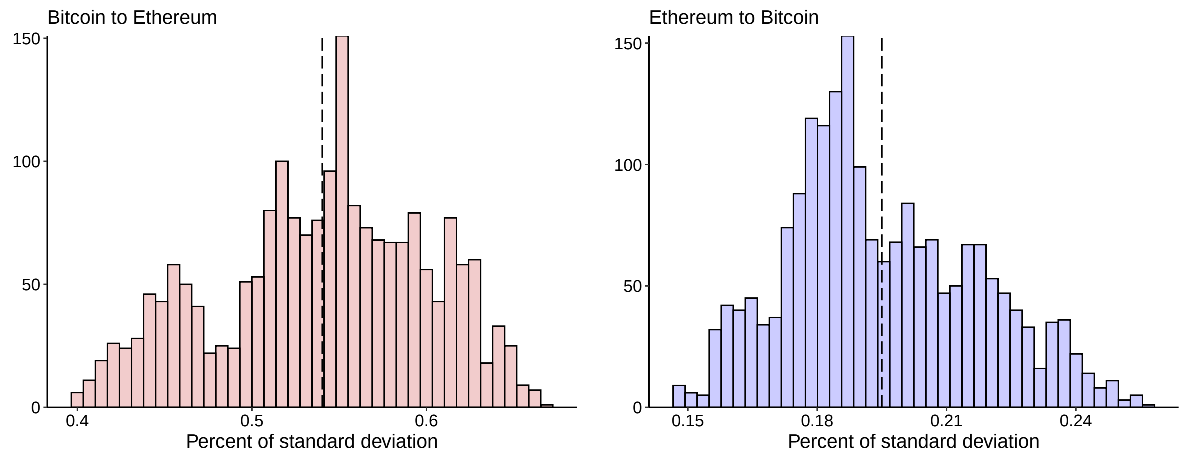
Figure 12. LSTM Multiplier Histograms: GSIBs to GSIBs (Count)



Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Note: a dotted line corresponds to the mean of the distribution.

Figure 13. LSTM Multiplier Histograms: Cryptocurrency to Cryptocurrency (Count)



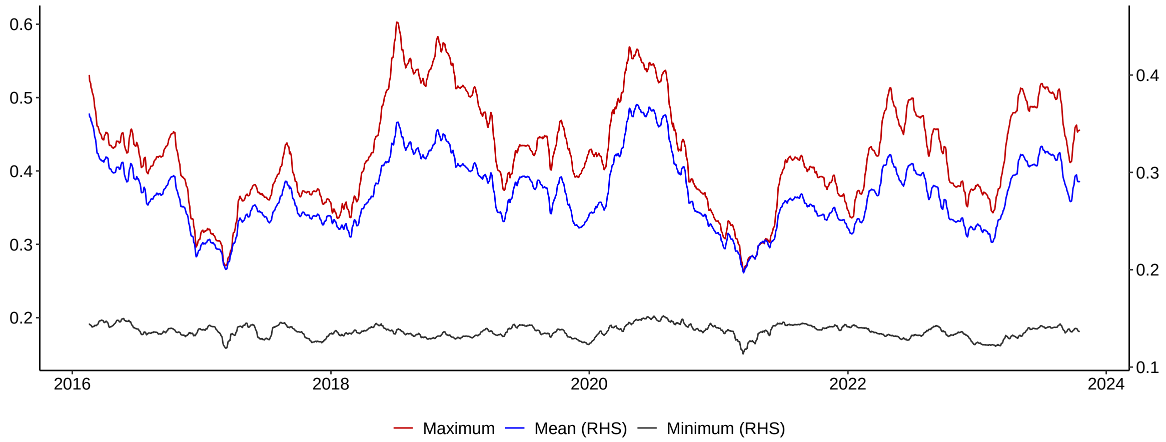
Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Note: a dotted line corresponds to the mean of the distribution.

Figures 14 to 18 show the time evolution of the mean, maximum, and minimum values of the cross-section of LSTMMs corresponding to shocks originating from the cryptocurrencies and the GSIBs. The Bitcoin and Ethereum LSTMMs exhibit similar dynamics with connectedness rising rapidly during periods of heightened volatility. Examples of such periors are the heightened risk in equity and commodity markets in 2015, the drastic price correction cryptocurrencies amid concerns about a regulatory crackdown in 2018; the start of the COVID pandemic in 2020; the Crypto Winter and the Russia-Ukraine war in 2022, and doubts about the ability of the US Federal Reserve to engineer a soft landing in 2023. The LSTMMs from GSIBs to Bitcoin and Ethereum also exhibit the same dynamics albeit with less pronounced peaks and thorughs. It is worth noting that the LSTMMs response to economic and market uncertainty is very similar to that of the TVP-VAR connectedness measures.

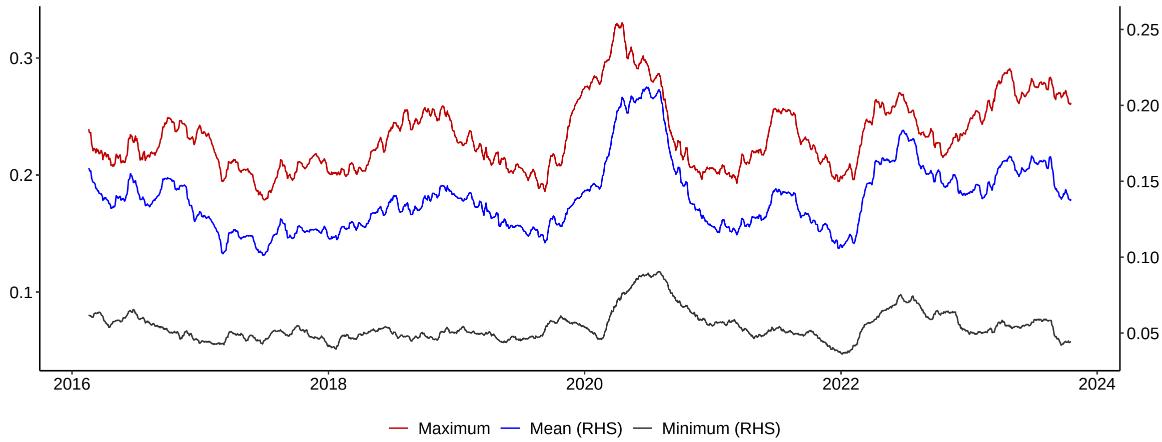
The results corresponding to the LSTM multipliers between cryptocurrencies suggest that, recently, markets might view Bitcoin as a safe asset and Ethereum as a speculative one, at least in the crypto space. Figure 19 shows both assets started to decouple in the aftermath of the Crypto Winter in 2022. Until 2021, the LSTMM from one currency to the other had a positive correlation of 0.32, with a 95 percent confidence interval of [0.27, 0.36]. From 2022 onwards, the correlation was statistically significant at 0.03 with a 95 percent confidence interval of [-0.06, 0.12]. The analysis conforms partly to the findings of Nakagawa and Sakemoto (2022) who showed that the correlation or connectedness between cryptocurrencies is stronger in calm periods. In periods of high uncertainty, the correlation weakens as investors might reduce the weight of the most speculative cryptocurrency while keeping their positions in what they consider a safe cryptocurrency.

Figure 14. LSTM Multiplier: Bitcoin to GSIBs (Percent of standard deviation)



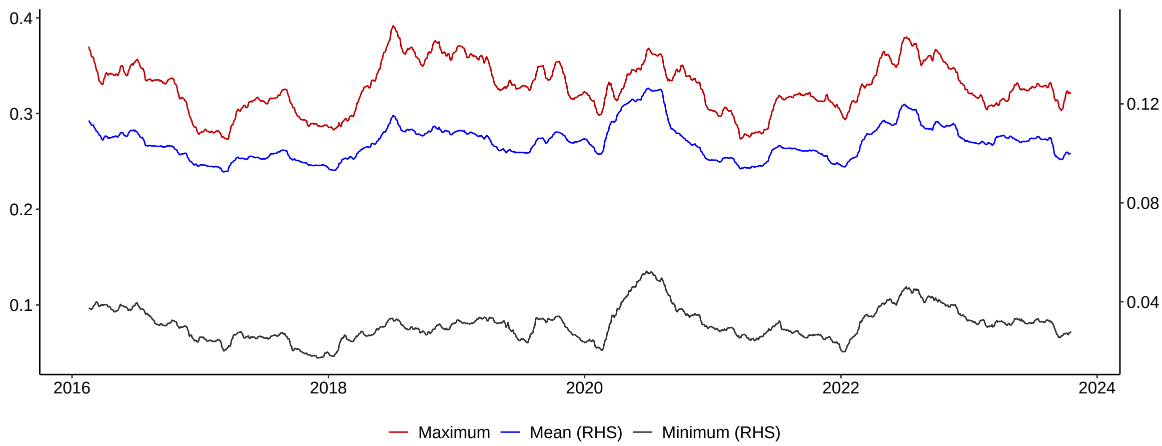
Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Figure 15. LSTM Multiplier: Ethereum to GSIBs (Percent of standard deviation)



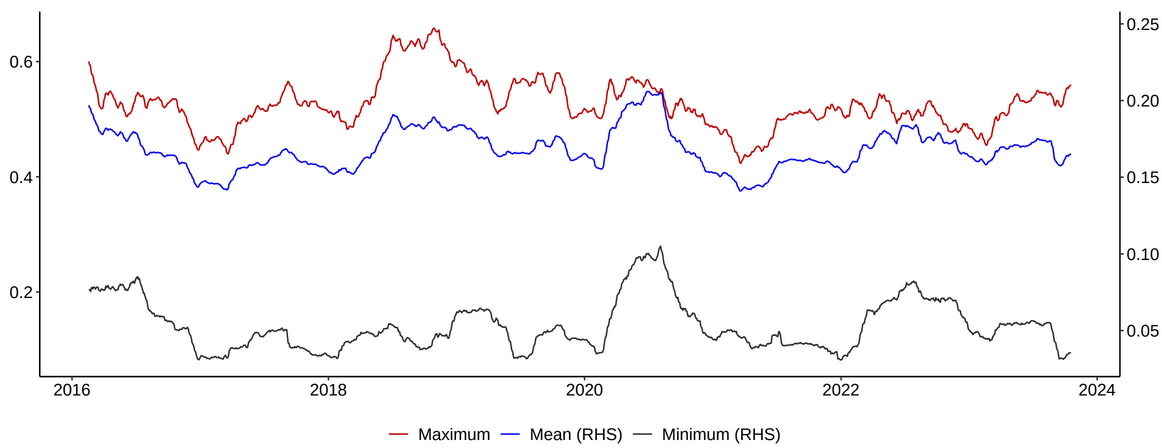
Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Figure 16. LSTM Multiplier: GSIBs to Bitcoin (Percent of standard deviation)



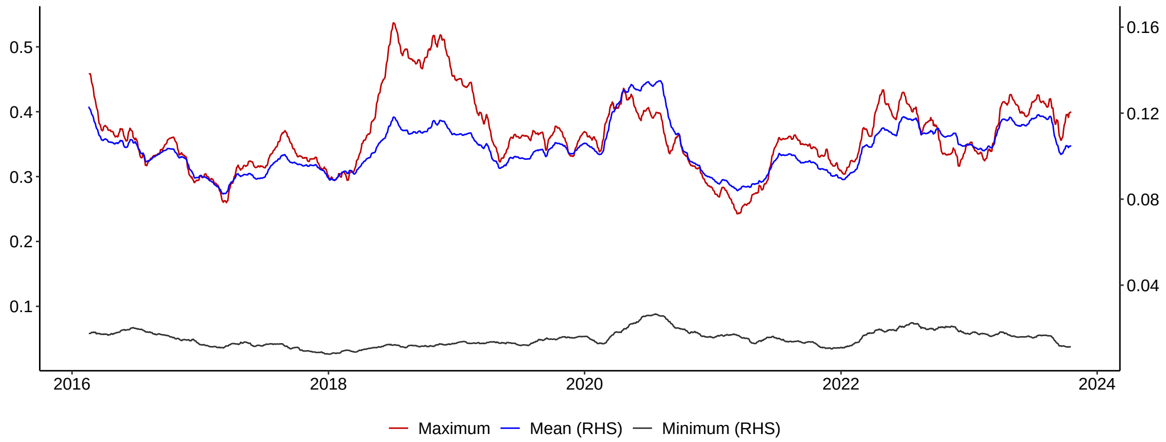
Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Figure 17. LSTM Multiplier: GSIBs to Ethereum (Percent of standard deviation)



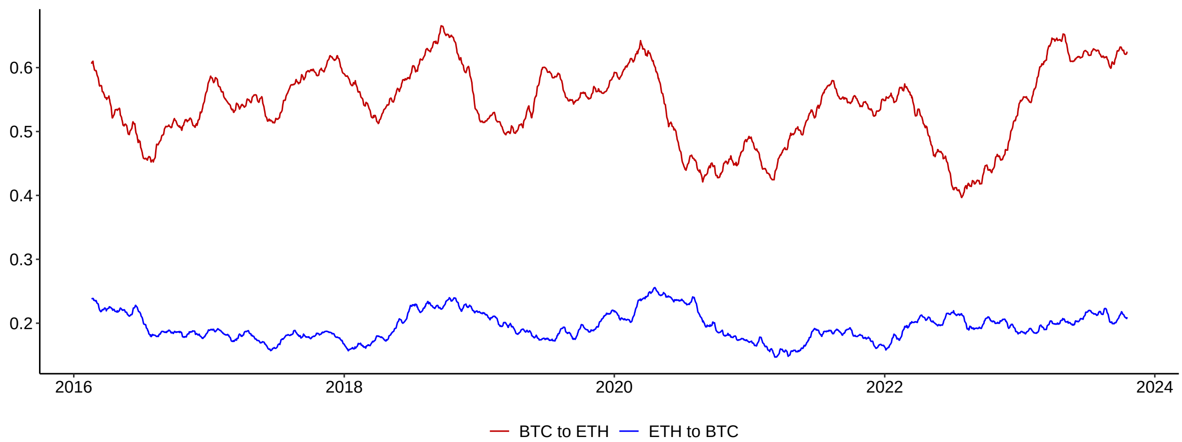
Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Figure 18. LSTM Multiplier: GSIBs to GSIBs (Percent of standard deviation)



Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

Figure 19. LSTM Multiplier: Cryptocurrency to Cryptocurrency (Percent of standard deviation)



Sources: Bloomberg Finance L.P., CoinGecko, and authors' calculations.

VI. Conclusions

The rise of cryptocurrencies and their integration into the traditional banking and financial system has raised concerns about the stability of the global financial system (FSB 2022). These concerns are compounded by the regulatory challenges in keeping up with the rapid developments in the crypto space. The "Crypto Winter" experienced between 2022 and 2023 served as a stark reminder of the system's vulnerability to liquidity risks and runs, mirroring similar vulnerabilities in the traditional financial sector.

Our findings reveal a weak connection between the crypto space and the banking system, either when connectedness is measured in terms of forecast variance decompositions (TVP-VAR connectedness) or in terms of price returns (LSTM multipliers). In the case of TVP-VAR connectedness, shocks originating from banks, both to other banks, and as a sector to cryptocurrencies, exceed the connectedness due to shocks originating from cryptocurrencies. The cryptocurrencies primarily impact one another. In the case of LSTMM connectedness, the impact of the shocks are similar regardless of the source of the shock. We also found that connectedness, either calculated using the TVP-VAR or the LSTMM, tends to rise rapidly during periods of high economic and/or market uncertainty.

Risks are limited since connectedness has been weak but historical patterns cannto reliably predict future outcomes. Knowing that the shock impact is greater during stress periods requires monitoring of market conditions carefully and further deepening our understanding of what factors drive financial connectedness. Moreover, the limited connections between crypto ecosystems and traditional finance, complemented by the cautious approach of traditional investors and financial institutions in the aftermath of the Crypto Winter, provide an opportunity to enhance the regulatory and supervisory framework governing crypto system and enhance authorities' ability to mitigate potential risks.

Specifically, the disparity in regulatory treatment between banks and crypto exchanges, along with significant data gaps, underscores the need for a proactive, comprehensive, and forward-looking approach to regulate and oversee cryptocurrency markets. This approach should strive for a more equitable playing field in terms of financial services offered by established financial institutions and intermediaries within the emerging crypto shadow financial system. Introducing more robust regulatory and supervisory oversight for the latter is crucial in achieving this objective (IMF 2023).

References

Antonakakis, Nikolaos, Ioanis Chatziantoniou, and David Gabauer. 2020. "Refined Measures of Dynamic Connectedness Based on Time-Varying Parameter Vector Autoregressions." *Journal of Risk and Financial Management* 13 (4), 84.

________. 2019. "Cryptocurrency Market Contagion: Market Uncertainty, Market Complexity, and Dynamic Portfolios." *Journal of International Financial Markets, Institutions, and Money* 61, 37-51.

Apostolakis, George. 2023. "Examining Bitcoin Price Volatility Transmission Between Spot and Futures Markets." Working Paper, University of Crete.

Arner, Douglas, Dirk Zetzsche, Ross Buckley, and Jamieson Kirkwood. 2023. "The Financialization of Crypto: Lessons from FTX and the Crypto Winter of 2022-2023." University of Hong Kong Faculty of Law Research Paper No. 2023/19.

Auer, Raphael, Marc Farag, Ulf Lewrick, Lovrenc Orazem, and Markus Zoss. 2022. "Banking in the Shadow of Bitcoin? The Institutional Adoption of Cryptocurrencies." BIS Working Paper No. 1013, Bank for International Settlements, Basel, May.

Bank for International Settlements (BIS). 2023. "The Crypto Ecosystem: Key Elements and Risks." Report submitted to the G20 Finance Ministers and Central Bank Governors, Basel, July.

Barunik, Jozef, and Tomas Krehlik. 2018. "Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk." *Journal of Financial Econometrics* 16 (2): 271–296.

Benidis, Konstantinos, Syama Rangapuram, Valentin Flunkert, Yuang Wang, Danielle Maddix, Caner Turkmen, Jan Gasthaus, Michael Bohlke-Schneider, David Salines, Lorenzo Stella, Francois-Xavier Aubet, Laurent Callot, and Tim Januschowski. 2022. "Deep Learning for Time Series Forecasting: Tutorial and Literature Survey." *ACM Computing Surveys* 55 (6): 1–36.

Bhandari, Hum N., Binod Rimal, Nawa R. Pokhrel, Ramchandra Rimal, Keshab R. Dahal, and Rajendra K.C. Khatri. 2022. "Predicting Stock Market Index Using LSTM." *Machine Learning with Applications* 9: 100320.

Brainard, Lael.2022. "Crypto-Assets and Decentralized Finance through a Financial Stability Lens." Speech at the Bank of England Conference, London, July 8.

Choi, Soon Yeong. 2023. "Entry into the Crypto Asset Business by Global Financial Firms." Working Paper, Korea Capital Market Institute.

Cui, Jinxin and Aktham Maghyereh. 2022. "Time-Frequency Co-Movement and Risk Connectedness Among Cryptocurrencies: New Evidence from the Higher Order Moments Before and During the COVID-19 Pandemic." *Financial Innovation* 8, 90.

Diebold, Francis and Kamil Yilmaz. 2014. "On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms." *Journal of Econometrics* 182 (1): 119–134.

________. 2012. "Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers." *International Journal of Forecasting* 28 (1): 57–66.

Elliott, Matthew, Benjamin Golub, and Matthew O. Jackson. 2014. "Financial Networks and Contagion." *American Economic Review* 104 (10): 3115-3153.

Financial Stability Board (FSB). 2022. "Assessment of Risks to Financial Stability from Crypto-Assets." Basel, February 16.

Gabauer, David. 2022. Package 'ConnectednessApproach'. R package version 1.0.1.

Gabauer, David, Ioannis Chatziantoniou, and Alexis Stenfors. 2023. "Model-Free Connectedness Measures." *Finance Research Letters* 54 103804.

Gajamannage, Kelum, Yonggi Park, and Jayathilake Dilhani. 2023. “Real-time Forecasting of Time Series in Financial Markets using Sequentially Trained Dual-LSTMs.” *Expert Systems with Applications* 223: 119879.

Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. 2016. *Deep Learning*, MIT Press.

Gorton, Gary and Jeffery Zhang. 2023. “Bank Runs During Crypto Winter.” Working Paper, Yale University and University of Michigan.

Greff, Klaus, Rupesh Srivastava, Jan Koutnik, Bas Steunebrink, and Jurgen Schmidhuber. 2017. “LSTM: a Search Space Odyssey.” *IEEE Transactions on Neural Networks and Learning Systems* 28 (10): 2222–2232.

Harvey, Campbell, Ashwin Ramachandran, and Joey Santoro. 2021. *DeFi and the Future of Finance*, John Wiley and Sons.

Hasan, Mudassar, Muhammad Abubakr Naeem, Muhammad Arif, Syed Jawad Hussain Shazad, and Xuan Vinh Vo. 2022. “Liquidity Connectedness in Cryptocurrency Market.” *Financial Innovation* 8, 3.

Hochreiter, Sepp and Jurgen Schmidhuber. 1997. “Long Short-Term Memory.” *Neural Computation* 9(8): 1735 - 1780.

Hopp, Daniel 2021. “Performance of LSTM Neural Networks in Nowcasting during the COVID-19 Crisis.” UNCTAD Research Paper No. 74, United Nations Conference on Trade and Development (UNCTAD), Geneva, November.

van Houdt, Greg, Carlos Mosquera, and Gonzalo Napoles. 2020. “A Review of the Long Short-Term Memory Model.” *Artificial Intelligence Review* 53: 5929–5955.

International Monetary Fund (IMF). 2023. “Elements of Effective Policies for Crypto Assets.” Policy Paper No. 2023/004, Washington, DC, February.

________. 2022. “The Rapid Growth of FinTech: Vulnerabilities and Challenges for Financial Stability.” Chapter 3 in *Global Financial Stability Report*, Washington, DC, April.

Khedr, Ahmed, Ifra Arif, Magdi EI-Bannany, Saadat Alhashmi, and Meenu Sreedharan. 2021. “Cryptocurrency Price Prediction Using Traditional Statistical and Machine-Learning Techniques: A Survey.” *Intelligent Systems in Accounting, Finance and Management* 28(1): 3–34.

Khosravi, Morteza and Majid Mirzaee Ghazani. 2023. “Novel Insights into the Modeling of Financial Time-Series through Machine Learning Methods: Evidence from the Cryptocurrency Market.” *Expert Systems with Applications* 234: 121012.

Koop, Gary, Hashem Pesaran, and Simon Potter. 1996. “Impulse Response Analysis in Nonlinear Multivariate Models.” *Journal of Econometrics* 74: 119–147.

Kumar, Ashish, Najaf Iqbal, Subrata Kumar Mitra, Ladislav Kristoufek, and Elie Bouri. 2022. “Connectedness among Major Cryptocurrencies in Standard Times and during the COVID-19 Outbreak.” *Journal of International Financial Markets, Institutions and Money* 77: 101523.

Lim, Bryan and Stefan Zohren. 2021. “Time-series Forecasting with Deep Learning: a Survey.” *Philosophical Transactions of the Royal Society A* 379:20200209.

Liu, Jiageng, Igor Makarov, and Antoinette Schoar. 2023. “Anatomy of a Run: the Terra Luna Crash.” MIT Sloan Research Paper No. 6847-23, MIT Sloan School of Management, Massachusetts.

Makarov, Igor and Antoinette Schoar. 2022. “Cryptocurrencies and Decentralised Finance (DeFi).” BIS Working Paper No. 1061, Bank for International Settlements, Basel.

Michańków, Jakub, Pawel Sakowski, and Robert Ślepaczuk. 2022. “LSTM in Algorithmic Investment Strategies on BTC and S&P500 Index”. *Sensors* 22(3): 10.3390//s22030917

Nakagawa, Kei, and Ryuta Sakemoto. 2022. "Market Uncertainty and Correlation between Bitcoin and Ether." *Finance Research Letters*: 103216.

Nasirtafreshi, I. 2022. "Forecasting Cryptocurrency Prices using Recurrent Neural Network and Long Short-Term Memory." *Data and Knowledge Engineering* 139: 102009.

Nur, Tugba and Turhan Korkmaz. 2022. "Volatility Spillover Between Bitcoin and Financial Stress Index." *The Journal of Corporate Governance, Insurance, and Risk Management* 9: 49-70.

Olah, Christopher. 2015. "Understanding LSTM Networks." Available online at https://colah.github.io/posts/2015-08-Understanding-LSTMs, accessed on November 14, 2023.

Park, Sangjin and Jae-Suk Yang. 2022. "Interpretable Deep Learning LSTM Model for Intelligent Economic Decision Making." *Knowledge-Based Systems* 248: 108907.

Pesaran, Hashem, and Yongcheol Shin. 1998. "Generalized Impulse Response Analysis in Linear Multivariate Models." *Economic Letters* 58 (1): 17-29.

Pour, Ehsan Sadeghi, Hossein Jafari, Ali Lashgari, Elaheh Rabiee, and Amin Ahmadisharaf. 2022. "Cryptocurrency Price Prediction With Neural Networks of LSTM and Bayesian Optimization." *European Journal of Business and Management Research* 7 (2): 20–27.

Sergeenkov, Andrey and Toby Bochan. "How does Ethereum Staking Work?" *CoinDesk*, February 11.

Sezer, Omer Berat, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu. 2020. "Financial Time Series Forecasting with Deep Learning: A Systematic Literature Review: 2005–2019." *Applied Soft Computing* 90: 106181.

Staudemeyer, Ralf, and Eric Rothstein Morris. 2019. "Understanding LSTM - a Tutorial into Long Short-Term Memory Recurrent Neural Networks." arXiv:1909.09586v1.

Tolo, Eero. 2020. "Predicting Systemic Financial Crises with Recurrent Neural Networks." *Journal of Financial Stability* 49: 100746.

Yuyama, Tomonori, Yusuke Ikeno, Shuran Zhang, Shin'ichiro Matsuo, and James Angel. 2023. "Can Crypto Assets Be Safe-Haven Assets During Crisis Periods." Georgetown McDonough School of Business Research Paper No. 4346079, Georgetown University, Georgetown McDonough School of Business, Washington, DC.

Zhang, Hongwei, Huojun Hong, Yaoqi Guo, and Cai Yang. 2022. "Information Spillover Effects from Media Coverage to the Crude Oil, Gold, and Bitcoin Markets during the COVID-19 Pandemic: Evidence from the Time and Frequency Domains." *International Review of Economics and Finance* 78: 267-285.

Zhang, Ru, Chenyu Huang, Weijian Zhang, and Shaozhen Chen. 2018. "Multi Factor Stock Selection Model Based on LSTM." *International Journal of Economics and Finance* 10 (8): 36 - 42.

Zieba, Damian, Ryszard Kokoszczynski, and Katarzyna Sledziewska. 2019. "Shock Transmission in the Cryptocurrency Market. Is Bitcoin the Most Influential?" *International Review of Financial Analysis* 64: 102–125.

Address: 10 Shenton Way, #15-08
MAS Building, Singapore 079117
Website: www.amro-asia.org
Tel: +65 6323 9844
Email: enquiry@amro-asia.org
LinkedIn | Twitter | Facebook | YouTube