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Connectedness between central bank digital currency index, financial stability and digital assets[☆]

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ABSTRACT

This study examines the interconnectedness between central bank digital currencies (CBDC) index, digital assets and financial stability. First, we use the CBDC index as a measure of financial stability and examine its connectedness with other known measures of financial stability used in the literature. Secondly, we analyse the connectedness of CBDC index with digital assets such as cryptocurrencies and non-fungible tokens and various measures of financial stability. By analysing index returns of CBDC data and applying various connectedness measures to CBDC index, cryptocurrencies, stablecoins and NFTs, we gain insights into the relationships among these assets within a framework. The findings reveal a significant level of connectedness between CBDCs index, digital assets and financial stability. Our analysis shows a weak positive connectedness between CBDCs index and digital assets, indicating that movements in the CBDC index are not closely related to the performance of various digital assets and have a very small contribution to the changes in the returns of digital assets. Furthermore, the study finds bidirectional connectedness between CBDCs and other financial stability measures, suggesting that changes in CBDC performance can influence the overall stability of the financial system, and vice versa. This highlights the importance of carefully considering the design and implementation of CBDCs to ensure they support financial stability objectives.

1. Introduction

> *"Digital currency may re-define currency. Although the main function of currency is still there, it will redefine currency, just like Apple redefines mobile phones [as] not just being a phone".*

Jack Ma, the co-founder of the e-commerce group, Alibaba (Blockchain News, 2020).

Technology and innovation are two key critical components of the Fourth Industrial Revolution which has attributed to the emergence and boom of digital assets such as cryptocurrencies, non-fungible tokens (NFTs), digital payment systems such as mobile

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payments, the development of new products such as Kindle, blockchain technology, digital trading platforms, and so forth. In recent times, due to the explosive boom of digital money, several central banks in the world are considering and exploring their options for introducing a central bank digital currency (CBDC, hereafter).

Nine out of ten of the world's central banks are creating a digital version of their currencies; The Bahamas has the Sand Dollar, Nigeria has the eNaira and China is close to launching the digital renminbi, or e-CNY (Financial Times, 2022a). The Hong Kong Monetary Authority (HKMA) is currently working with the People's Bank of China and other central banks on the "mBridge" project to enable them to swap assets instantaneously (Financial Times, 2022b). In Europe, the Banque de France and the Swiss National Bank are collaborating on Project Jura, a foreign exchange CBDC pilot (Financial Times, 2022b). Carapella and Flemming (2020) document the lack of a universally acceptable definition of CBDC and state that, broadly, the literature considers CBDC as a means of payment that can pay interest and that does not necessarily need to be held in an account at a commercial bank.

If CBDCs were to be introduced, one critical aspect that would need to be considered is its implication on a country's fiscal and monetary policies (Agur, Ari and Dell'Ariccia, 2022; Chen and Silko, 2022; Elsayed and Nasir, 2022; Hoang, Ngo and Vu, 2025). In their systematic literature review, Hoang, Ngo and Vu (2023) conclude that the financial stability of a country can be affected by the introduction of CBDC. They suggest that central banks must research and develop strategies to maintain financial stability considering CBDC. Elsayed and Nasir (2022) argue that, although central banks are more stable than commercial banks, the introduction of CBDC may initially be disruptive to the economy. Kumhof and Noone (2021) recommend that the introduction of CBDC should be based on four core principles that would ensure financial stability. The literature, however, defines several measures of financial stability and uncertainty that might have a significant predictive power of the stability of the financial system. In this study, we aim to address the primary research question of whether Central Bank Digital Currencies, a measure of financial stability, have any impact on digital assets. This investigation involves exploring the interconnectedness between CBDCs and various measures of financial stability, economic uncertainty, as well as the returns and risks associated with digital assets. In this context, previous studies use uncertainty measures based on economic policy (Demir et al., 2018; Fang et al., 2019; Ji et al., 2019; Wang et al., 2020) and Twitter (Wu et al., 2021; Aharon et al., 2022; Elsayed, Gozgor and Lau, 2022), geopolitical risk (Aysan et al., 2019; Al Mamun et al., 2020) and VIX (Bouri et al., 2017) as indicators of financial stability. These studies document these factors as significant drivers of transmission effects among cryptocurrencies. For instance, Ji et al. (2019) examine the spillover effect of six cryptocurrencies and the economic policy uncertainty as an important indicator of this transmission. Elsayed et al. (2022) provide evidence for the return and price volatility transmission effects of Bitcoin, traditional financial assets and financial stability measures, such as economic policy uncertainty, Twitter-based economic uncertainty and VIX. Using TVP-VAR, dynamic connectedness and network analysis, they conclude that economic policy uncertainty is the only driving factor that causes an increase in volatility in Bitcoin, noting that they could not find a significant relation for the Twitter-based economic uncertainty. On the other hand, Aharon et al. (2022) examine the nexus between the performance of four major cryptocurrencies and economic and market uncertainty measured through Twitter-based indicators by utilising various methods, such as Granger causality, predictability and quantile regressions. They find a strong causal relation between cryptocurrency returns and economic and market uncertainty based on Twitter.

The emergence of digital assets has totally changed the world of investing. Cryptocurrencies are an asset class that is unregulated and extremely volatile and is not recognised as legal tender in most countries. Meanwhile, another digital asset class that is growing in popularity is the non-fungible token (NFT) market. Given the significance of these digital assets, this study also examines the connectedness between digital assets such as cryptocurrencies, non-fungible tokens and stablecoins.

Recent literature can be classified into two broader research areas. The first focuses on the transmission effect among the cryptocurrency market and traditional assets (Bas, Malki and Sivaprasad, 2024; Koutmos, 2018; Ji et al., 2019; Yi, Xu and Wang, 2018). However, there is no consensus on the findings of these studies. Grobys et al. (2021) find that Bitcoin volatility is a fundamental driver that influences the volatility of stablecoins, as was evident in the recent downturn in the cryptocurrency market. However, none of these studies examine the transmission effects and connectedness across CBDC index, cryptocurrencies, and NFTs, and financial stability. This is important in the sense that the underlying basis for all these assets is 'digital'.

The second area of research extends the shortcomings of the former by examining the connectedness and interdependencies between CBDC index and digital assets. For example, Wang et al. (2023) use the TVP-VAR model to examine the connectedness between the CBDC attention index and the cryptocurrency market. Similarly, Helmi, Catik and Akdeniz (2023) analyse the impact of the CBDC uncertainty and attention indices on various financial markets, including VIX, S&P500, cryptocurrency policy uncertainty index, and Bitcoin price. In addition, Ayadi, Ghabri and Guesmi (2023) examine the relation between cryptocurrencies, stablecoins, and CBDC attention and uncertainty indices using a cross-quantilogram model.

These studies offer, however, very limited insights into the nature and strength of the connectedness between CBDCs and digital assets. This includes a limited set of digital assets – which mainly focuses on one class of digital assets – and a narrow definition of financial stability captured by the CBDCs. Our study, therefore, extends the literature by analysing the connectedness and transmission effects amongst CBDC index and broader measures of financial stability and digital assets.

To fill this research gap, this study first undertakes a quantitative analysis using the CBDC index created by Wang et al. (2022), namely, the CBDC Uncertainty Index, as a measure of financial stability. We examine its connectedness with various known measures of financial stability (such as Global Systemic Risk Index, Global Financial Conditions Index, TED spread and the Volatility Index) and measures of economic uncertainty (including Special Drawing Rights, Geopolitical Risk Index, Twitter Economic Uncertainty Index). We use the CBDC index as a measure of financial stability because CBDC can potentially impact financial stability through money supply (Chen and Siklos, 2022), the solvency of commercial banks and reshape the international monetary system (Brunnermeier and Landau, 2022; Minesso, Mehl and Stracca, 2022). Kim and Kwon (2022) note that CBDC is risk free as it acts as both as a means of payment and a store of value and, thus, can enhance financial stability. We use Wang et al.'s (2022) CBDC uncertainty index created by as the authors empirically show how it has an impact on the VIX, FTSEAll-World Index and the FTSE World Government Bond Index, which are other measures of financial stability. The authors conclude that this can be interpreted that CBDC has an impact on the economy and society. Moreover, uncertainty measures can explain the risk premium of financial assets (Dunbar, 2023) and their impact on the economy (Bloom, 2009). Yarovaya et al. (2022) show how the CBDC Uncertainty Index captured the volatility and the uncertainty in the digital assets during the Covid-19 pandemic. Thus, this study also uses the index as it captures the inherent uncertainties in the economic system, aligning with the concept of financial stability. Next, we analyse the network connectedness of the CBDC index measure of financial stability with digital assets such as cryptocurrencies, stablecoins, and NFTs and financial stability.

We make several contributions to the literature. First, within the financial stability literature, we provide the first evidence of using the CBDC index as a measure of financial stability and analyse its connectedness with other measures of financial stability. Recent studies by Karau (2023) and Yousaf and Goodell (2023) highlight the role of CBDC in shock transmissions and its potential effect on financial stability. Since the literature shows that CBDC is associated with financial stability (Andolfatto, 2020; Kim and Kwon, 2022), it is important to examine the connectedness of CBDC index with other measures of financial stability. Second, we enhance our understanding of the connectedness of CBDC by analysing the returns and volatility transmissions across CBDC index, digital assets, namely cryptocurrencies, stablecoins, NFTs, and other measures of financial stability. The findings will serve as a guide to policymakers, and the investment community alike on how the digital assets market and other global indicators are interconnected. Third, we apply network connectedness analysis using machine learning methods to deal with high-dimensional data and variable sections. We employ the adaptive elastic net Lasso and Ridge regressions allowing for both sparsity and shrinkage effects. Fourth, CBDC is an emerging area which has a paucity of research despite its potential benefits to society, firms and policymakers. More broadly, we contribute to the literature on UNSDGs on digitalisation and efforts to build a resilient and financially inclusive global community by considering the potential benefits of CBDCs in all aspects of life and the economy.

Our findings show, first, there is bidirectional connectedness between CBDC index and financial stability. Changes in the performance of CBDC index can influence the overall stability of the financial system, and vice versa. This highlights the importance of considering the implications of CBDC design and implementation on financial stability objectives. In contrast, CBDCs, while they seem to be interconnected with digital assets, this relationship is actually very weak. This suggests that movements in CBDCs have only a small impact on the value and volatility of digital assets. Finally, the findings indicate varying levels of connectedness among different digital assets. Cryptocurrencies demonstrate a high degree of positive connectedness with CBDCs and other digital assets, indicating potential spillover effects within the digital asset ecosystem. Stablecoins, on the other hand, exhibit a relatively lower level of connectedness, potentially acting as a buffer against shocks in the digital asset space. NFTs fall in the middle, showing a moderate level of connectedness and representing a distinct segment within the broader digital asset landscape.

The remainder of the paper is organised as follows: Section 2, provides a detailed discussion of the materials and methods including the rationale behind our sample-selection procedure, and Section 3 provides the econometric methodology. Section 4 presents the empirical results and Section 5 provides the discussion and concluding remarks.

2. Materials and methods

We use data capturing two dimensions. This includes measures of financial stability, economic uncertainty, and measures of digital assets performance. There are several sources of instability in the market that reflect part of the environment within which digital assets are traded. We employ five indices to capture various sources of financial instability including the Central Bank Digital Currency Index (CBDC) developed by Wang et al. (2022), Financial Conditions Index (FCI), Global Systemic Risk (SRISK), Global TED Spread (TED) and Volatility Index (VIX). We also capture the sources of economic uncertainty using three measures including the US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR[1] (ER), Twitter-based economic uncertainty index (TWEETS) as developed by Baker et al. (2021), and the Geopolitical Risk Index (GPR) developed by Caldara and Iacoviello (2022).

The CBDC uncertainty index is generated from the analysis of 600 million news stories related to CBDC obtained from LexisNexis News & Business (Wang et al., 2022). The index provides insights into the perceived level of uncertainty or risk associated with CBDC initiatives or developments, enabling a better understanding of public opinion and market sentiments about CBDC over time. The Twitter-based economic uncertainty index quantifies economic uncertainty by analysing the usage of words in tweets related to economic uncertainty on the social media platform Twitter (Baker et al., 2021). The index provides insights into public opinion and sentiment about economic uncertainty. On the other hand, the Geopolitical Risk Index is a metric to quantify geopolitical risk by analysing the number of articles in eleven national and international newspapers about geopolitical factors, including tensions between nations, nuclear concerns, war risks, and terrorist threats (Caldara and Iacoviello, 2022).

The second dimension of the data involves three classes of digital currencies. We employ eight cryptocurrency market measures (Bitcoin, Ethereum, Ripple, Litecoin, Dash, Nem, Stellar, Monero), three stablecoins market measures (DAI, True USD, USD Coin) and two non-fungible tokens market measures (MANA and STACKS) The choice of cryptocurrencies is based on those with a market value of over $1 billion as of December 2022. In addition, the choice of stablecoins and NFTs is based mainly on the availability of longer

[1] The Special Drawing Right (SDR) is an international reserve asset created by the International Monetary Fund (IMF) to supplement member countries' official reserves. The SDR serves as a unit of account and is used in international transactions and financial operations. The value of the U. S. dollar in terms of the SDR is determined by the reciprocal of the sum of the dollar values of specified quantities of the SDR basket currencies. The SDR basket is a weighted average of several major currencies, including the U.S. dollar, euro, Chinese yuan, Japanese yen, and British pound. Further details on the calculations can be found in https://www.imf.org/external/np/fin/data/rms_five.aspx.

series. The starting year and month of the sample are, therefore, based on the earliest date from which NFTs series are being observed. This yields a sample spanning from 21 November 2019 to 31 December 2022. Table 1 gives an overview of the series in the data and their sources.

All digital currency data are obtained as price indices in their raw form. Since we aim to measure connectedness in the returns and risk series, the returns of each stock are computed as the change of the natural logarithm of prices (i.e. $r_{it} = \Delta(lnP_{it})$, for stock i and over $t = 1, 2, \cdots, T$). The risk series is obtained by estimating a GARCH (1,1) specification for each stock return series. In this context, the risk is based on the following model:

$$r_{it} = \mu_i + \varepsilon_{it} \tag{1A}$$

$$\sigma_{it}^2 = \omega_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2 + v_{it} \tag{1B}$$

where ε_{it} $(0, \sigma_{it}^2)$, v_{it} $iid(0, \sigma_{iv}^2)$, $\omega_i > 0$, $\alpha_i, \beta_i \geq 0$, $\alpha_i + \beta_i < 1$ for stock i and over $t = 1, 2, \cdots, T$.

3. Methodology

3.1. Measures of connectedness

In this work we apply the generalised variance decomposition approach proposed by Diebold and Yilmaz (2012). The concept of connectedness, as proposed by Diebold and Yilmaz (2009; 2012; 2014), assesses the shares of forecast error variation of different stock returns series in response to a shock occurring in other stock returns. This concept is modelled in Vector Autoregressive, VAR, set up.

Suppose there are n endogenous variables, $y'_t = (y_{1t}, y_{2t}, \cdots, y_{nt})$, the general form of this dynamic model can be expressed as:

Table 1
Data Definitions and Sources.

Variable	Symbol	Measure	Source
Central Bank Digital Currency	CBDC	Index expressed as a cyclical series. The cyclical series is obtained using the Hodrick-Prescott filter.	https://sites.google.com/view/cryptocurrency-indices/the-indices/cbdc-indices?authuser = 0
Financial Conditions Index	FCI	Index	Bloomberg
Systemic Risk[a]	SRISK	Index expressed in natural logarithms	The Volatility Laboratory of the NYU Stern Volatility and Risk Institute (https://vlab.stern.nyu.edu).
TED Spread	TED	Index	Bloomberg
Volatility Index	VIX	Index	https://fred.stlouisfed.org/tags/series?t = vix
Economic Uncertainty Measures			
Exchange Rates	ERUS	Rate	https://www.imf.org/external/np/fin/data/rms_five.aspx
Twitter-based Economic Uncertainty	Twitter	Index	https://www.policyuncertainty.com/twitter_uncert.html
Geopolitical Risk Index	GPR	Index	https://www.matteoiacoviello.com/gpr.htm
Cryptocurrency			
Bitcoin	BTC	Price Index	https://coinmetrics.io/
Ethereum	ETH	Price Index	https://coinmetrics.io/
Ripple	XRP	Price Index	https://coinmetrics.io/
Litecoin	LTC	Price Index	https://coinmetrics.io/
Dash	DASH	Price Index	https://coinmetrics.io/
Nem	XEM	Price Index	https://coinmetrics.io/
Stellar	XLM	Price Index	https://coinmetrics.io/
Monero	XMR	Price Index	https://coinmetrics.io/
Stablecoins			
DAI	DAI	Price Index	https://uk.investing.com/
True USD	TUSD	Price Index	https://uk.investing.com/
USD Coin	USDC	Price Index	https://uk.investing.com/
Non-Fungible Tokens			
MANA	MANA	Price Index	https://nonfungible.com/
STACKS	STX	Price Index	https://nonfungible.com/

Note: Table 1 presents the variables, their symbols, measure and data sources used in the analysis. The variables are categorised into five groups: Financial Stability Measures, Economic Uncertainty Measures, Cryptocurrency, Stablecoins, and Non-Fungible Tokens. Financial Stability Measures include the Central Bank Digital Currency (CBDC) index, Financial Conditions Index (FCI), Systemic Risk (SRISK), TED Spread, and Volatility Index (VIX). The CBDC index is expressed as a cyclical series obtained using the Hodrick-Prescott filter, while the SRISK index is expressed in natural logarithms. Economic Uncertainty Measures consist of Exchange Rates (ERUS), Twitter-based Economic Uncertainty, and Geopolitical Risk Index (GPR). These indices capture various aspects of economic and geopolitical uncertainty. The Cryptocurrency category includes price indices for major cryptocurrencies such as Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Dash (DASH), Nem (XEM), Stellar (XLM), and Monero (XMR). Stablecoins are cryptocurrencies designed to maintain a stable value relative to a reference asset. The stablecoins included in the table are DAI, True USD (TUSD), and USD Coin (USDC). Non-Fungible Tokens (NFTs) are unique digital assets that represent ownership of a specific item or piece of content. The NFTs included in the table are MANA and STACKS (STX).
[a]Refer to Appendix 9 for further details on how the SRISK is constructed.

$$\boldsymbol{y}_t = \boldsymbol{c} + \sum_{i=1}^{p} \Phi_i \boldsymbol{y}_{t-i} + \boldsymbol{u}_t \tag{2}$$

where the maximum number of lags is p (i.e. the optimal lag length). The term $\boldsymbol{c}' = (c_1, c_2, \cdots, c_n)$ is a $1 \times n$ vector of constants, and $\Phi_1, \Phi_2, \cdots, \Phi_p$ are $n \times n$ coefficients matrices. The error term $\boldsymbol{u}'_t = (u_{1t}, u_{2t}, \cdots, u_{nt})$ is a $1 \times n$ vector with zero mean, and a variance – covariance matrix, Σ, is an $n \times n$ symmetric – and possibly non-diagonal – matrix.

The VAR (p) model allows for reverse causality and interdependence across all variables. The structure of this model, in which every endogenous variable is regressed on its own lagged values and the lags of the other variables in the system, allows the coefficients matrices, Φ_i, to include all the information about the interactions and connectedness between these variables. Furthermore, all the series in the vector $\boldsymbol{y}_t$ are assumed to be covariance stationary. This requires that the roots of the characteristic equation (i.e. $|\Phi(z)|$), lie outside the unit circle. Using the lag operator, L, and combined with the stationarity assumption of the model in (2), the VAR(p) can be written as a function of moving averages of infinite order, or MA(∞). In other words:

$$\boldsymbol{y}_t = \Theta(L)\boldsymbol{u}_t \tag{3}$$

where $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \cdots$ is the infinite lag polynomial that can be computed recursively from $\Phi(\boldsymbol{L}) = \boldsymbol{I}_N - \Phi_1 \boldsymbol{L} - \Phi_2 \boldsymbol{L}^2 - \cdots - \Phi_p \boldsymbol{L}^p = [\Theta(L)]^{-1}$. The term Θ_0 does not need to be diagonal and captures the contemporaneous features of connectedness, while the terms $\Theta_1, \Theta_2, \cdots$ capture the dynamics of connectedness. The measure of connectedness based on this structure is best obtained using variance decompositions.

The literature on econometrics offers various methods of variance decompositions. In the context of connectedness, Diebold and Yilmaz (2012) employ Cholesky factorisation, which depends on the ordering of variables. In the context of Cholesky decompositions, the first variable in the system is affected contemporaneously only by its own shocks. The second variable in the system is affected contemporaneously by the first and second variables' innovations, and so on. Although Diebold and Yilmaz (2014) argue that the total connectedness is robust to the ordering of variables, this does not rule out the possibility that the connectedness is sensitive to the order assigned to variables in the VAR system. To overcome this issue, one can use generalised variance decomposition, as proposed by Pesaran and Shin (1998), which do not rely on variable ordering and treats each variable as the first variable in the ordering. In other words, correlated shocks are allowed while accounting for their historical correlation. Formally, for the h-step generalised variance decomposition matrix

$$D_t^{gH} = \left[d_{ij,t}^{gH}\right] \tag{4}$$

has the elements

$$d_{ij,t}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e'_i \Theta_{h,t} \Sigma_t e_j\right)^2}{\sum_{h=0}^{H-1} \left(e'_i \Theta_{h,t} \Sigma_t \Theta'_{h,t} e_j\right)^2} \tag{5}$$

where σ_{jj}^{-1} j-th diagonal element of the covariance matrix Σ_t, e_j is section vector with j-th element unity and zeros elsewhere, Θ_h is $n \times n$ of moving average coefficients at lag length h.

$d_{ij,t}^{gH}$ refers to the contribution of the j-th variable to the variance of the forecast error of the element i at horizon h. Since the shocks under the generalised variance decomposition are not necessarily orthogonal, the row sums of $d_{ij,t}^{gH}$ are not necessarily equal to one (i.e. forecast error variance contribution does not necessarily sum to one). Therefore, the generalised connectedness index and its other variations are based on the normalised $d_{ij,t}^{gH}$, which is defined as:

$$\widetilde{d_{ij,t}^{gH}} = \frac{d_{ij,t}^{gH}}{\sum_{j=1}^{N} d_{ij,t}^{gH}} \tag{6}$$

whereby definition $\sum_{j=1}^{N} \widetilde{d_{ij,t}^{gH}} = 1$ and $\sum_{i,j=1}^{N} \widetilde{d_{ij,t}^{gH}} = N$). Using the definition in (6), we can compute the following measures of connectedness:

Total Connectedness Index (TCI): This captures the interconnectedness among different variables and defined as:

$$C_t^{g\mathrm{H}} = \frac{\sum_{i,j=1, i \neq j}^{N} \widetilde{d_{ij,t}^{gH}}}{\sum_{j=1}^{N} \widetilde{d_{ij,t}^{gH}}} \times 100 \tag{7}$$

The directional spillover from all variables j to variable i:

$$C_{i \leftarrow j}^{g\mathrm{H}} = \frac{\sum_{j=1, i \neq j}^{N} \widetilde{d_{ij,t}^{gH}}}{\sum_{i=1}^{N} \widetilde{d_{ij,t}^{gH}}} \times 100 \tag{8}$$

The directional spillover from all variables i to variable j:

$$C_{i\to j}^{\mathrm{gH}} = \frac{\sum_{j=1,i\neq j}^{N}\widetilde{d_{ij,t}^{gH}}}{\sum_{i=1}^{N}\widetilde{d_{ij,t}^{gH}}}\times 100 \tag{9}$$

3.2. Estimation of high dimension VARs

In this study, we propose a novel approach to estimate large forecast error variance decompositions in a VAR model. These provide valuable insights into the contribution of each variable to the overall forecast error variance, thus shedding light on the interdependencies and interactions within the system.

To tackle the challenges posed by high-dimensional data and variable selection, we employ the adaptive elastic net lasso and ridge regression framework. This approach combines the λ_1 (lasso) and λ_2 (ridge) regression methods, allowing for both sparsity and shrinkage effects. By leveraging these regression techniques, we can effectively handle many variables and mitigate the risk of overfitting.

The estimation procedure involves minimising the following objective function:

$$\widehat{\beta} = \mathrm{argmin}_{\beta}\left\{\frac{1}{T}\sum_{t=1}^{T}|Y_t - X_t\beta|^2 + \lambda_1\sum_{j=1}^{k}|\beta_j| + \lambda_2\sum_{j=1}^{k}|\beta_j|^2\right\} \tag{10}$$

where $\widehat{\beta}$ represents the estimated coefficient matrix, while Y_t and X_t denote the vector of endogenous variables and the design matrix consisting of lagged variables, respectively. The terms λ_1 and λ_2 are tuning parameters that control the level of regression, with the former promoting sparsity and the latter encouraging shrinkage.

By incorporating the adaptive elastic net lasso and ridge regression into the estimation of the VAR model, we can simultaneously achieve variable selection and regression (Ma et al., 2022; Castren, Kavonius and Rancan., 2022; Chuliá, Garrón and Uribe, 2023). This not only enhances the interpretability of the model but also improves its forecasting performance, particularly when dealing with high-dimensional datasets. Moreover, we link the estimated VAR model to connectedness measures, which provide a comprehensive understanding of the interdependencies and spillover effects within the system. By integrating these connectedness measures, we gain insights into the transmission mechanisms and interconnectedness among the variables in the VAR model.

3.3. Network connectedness

We apply return and risk network connectedness to understand the spillover effect among digital assets and stability measures. The adjacency matrix in network theory is the variance decomposition matrix in the spillover methodology. The degree of a node refers to the number of connections it has with other nodes according to the network theory.

$$D_i = \sum_{j=1}^{N} A_{ij} \tag{11}$$

where A_{ij} represents the adjacency matrix A constructed based on the spillover table. The elements of pairwise directional connectedness, C_{ij} represent the strength of connections between nodes. The row sums of the adjacency matrix (node in-degrees) give us the total directional connectedness 'From', $C_{i\leftarrow j}$. Similarly, the column sums of the adjacency matrix (node out-degrees) represent the total directional connectedness 'To', $C_{i\to j}$. These 'From' and 'To' degrees together form the set of edges in the network (Diebold and Yilmaz, 2014).

3.4. Other empirical considerations

The VAR model and proposed measure of connectedness require that the variables within the system are covariance stationary. Thus, we need to test whether this is the case for the return series. One common approach to test for non-stationarity is to apply unit root tests such as the Augmented Dickey and Fuller (1981) test (ADF), the Phillips and Perron (1988) test (PP), and/or stationarity tests such as Kwiatkowski et al. (1992) (KPSS). In the context of this paper, we apply two tests: the ADF and KPSS tests. When the null of unit root is rejected by the ADF test, this does not necessarily imply stationarity. Thus, applying the KPSS test will help in confirming the conclusion of the ADF test if the null cannot be rejected.

Furthermore, the variables in the VAR system may exhibit different orders of integration, including both I(0) and I(1) variables. The choice of the VAR model is supported by the seminal work of Toda and Yamamoto (1995), which demonstrates the validity of estimating VARs formulated in levels and testing general restrictions on the parameter matrices, even in the presence of integrated or cointegrated processes.

Toda and Yamamoto's (1995) methodology enables us to apply a standard lag selection procedure to the VAR model, irrespective of the order of integration of the variables. This is possible because the standard asymptotic theory remains valid, as long as the order of integration does not exceed the true lag length of the model. In other words, we can determine an appropriate lag length, denoted as "k", using well-established lag selection criteria. Once the lag length "k" is determined, we proceed to estimate a (k + dmax)th -order VAR model, where "dmax" represents the maximal order of integration that we suspect might be present in the underlying processes.

Importantly, Toda and Yamamoto (1995) propose disregarding the coefficient matrices of the last dmax lagged vectors in the model, treating them as zeros. This allows us to focus on the meaningful relationships captured by the first k coefficient matrices.

4. Empirical results

4.1. Primary results

Figs. 1–6 illustrate the dynamic behaviour of all variables reported in Table 1. In addition, the statistical properties outlined in Table 2 offer insights into the characteristics of various financial stability measures (including the Central Bank Digital Currency (CBDC), Financial Conditions Index (FCI), Global Systemic Risk (SRISK), Global TED Spread (TED), Volatility Index (VIX)) and economic uncertainty measures (including the US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ERUS), Twitter-based economic uncertainty index (TWEETS), and Geopolitical Risk Index (GPR)). Additionally, the table encompasses data on the return and risk series for prominent cryptocurrencies (such as Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), Ripple (XRP), Dai (DAI)) stablecoins (including True USD (TUSD), USD Coin (USDC)) and NFTs (Decentraland (MANA), and Stacks (STACKS)).

Examining the measures of stability, CBDC index stands out with a mean of 0 and a narrow standard deviation of 0.009, indicating relatively low volatility compared to other variables. This index, representing Central Bank Digital Currency, exhibits minimal fluctuation between its minimum and maximum values of −0.024 and 0.033, respectively. In contrast, VIX, representing market volatility, displays a significantly higher mean of 24.258 with a larger standard deviation of 8.727, signifying greater market fluctuation and uncertainty. The VIX values range from a minimum of 1.272 to a maximum of 6.291.

Moving to the FCI, it has a mean of 0.026 and a standard deviation of 1.228. FCI, representing the overall financial health of the global economy, shows a considerable range between its minimum and maximum values of −6.3 and 1.4, respectively. Global Systemic Risk has a mean of 15.407 with a standard deviation of 0.156, showcasing relatively stable characteristics. SRISK values range from a minimum of 14.479 to a maximum of 15.632. The Global TED Spread exhibits a mean of 20.079 and a substantial standard deviation of 20.187, reflecting wide market variability. TED values range from −7.462 to 124.803.

The US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR has a mean of 1.385 with a narrow standard deviation of 0.045, indicating relatively stable exchange rates. Twitter-based economic uncertainty has a mean of 5.138 and a standard deviation of 0.501, suggesting moderate variability in economic uncertainty based on Twitter data. Geopolitical Risk Index has a mean of 4.466 with a standard deviation of 0.614, indicating moderate geopolitical risk.

The Cryptos group, comprising major cryptocurrencies, demonstrates varying levels of mean returns and standard deviations. Bitcoin displays a positive mean return of 0.001, indicative of a relatively stable performance, with a standard deviation of 0.039. Ethereum (ETH) exhibits a slightly higher mean return of 0.002 and a standard deviation of 0.051, signifying comparable stability. DASH and LTC present mean returns close to zero, suggesting relatively stable performance, while XEM, XLM, XMR, XRP and DAI share a similar trend. Notably, these cryptocurrencies exhibit distinct levels of variability in returns as indicated by their standard deviations.

Within the stablecoins group, True USD (TUSD) and USD Coin (USDC) aim to provide stability and low volatility. Both stablecoins maintain mean returns close to zero, with TUSD having a slightly higher standard deviation of 0.001 compared to USDC's 0.001, emphasising their focus on preserving value.

The NFTs group, represented by Decentraland (MANA) and Stacks (STACKS), presents distinctive characteristics. MANA stands out with a positive mean return of 0.002 and a higher standard deviation of 0.078, indicating potential for positive returns but also higher inherent risk. In contrast, STACKS displays a mean return close to zero with a standard deviation of 0.074, suggesting relatively stable performance.

The Augmented Dickey Fuller and Kwiatkowski-Phillips-Schmidt-Shin tests provide valuable insights into the stationarity properties of the variables. Notably, both CBDC and GPR exhibit significant negative ADF test results, implying stationarity. On the other hand, the US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ERUS) and Twitter-based economic uncertainty index (TWEETS) show ADF results not significantly different from zero, indicating potential non-stationarity. The KPSS tests corroborate these findings, with ERUS and TWEETS showing significant positive values, signifying non-stationarity. In contrast, CBDC and GPR demonstrate weaker evidence against non-stationarity, as indicated by lower KPSS test values. Moving beyond, additional variables within the dataset exhibit varying ADF and KPSS test outcomes. For instance, the Global Financial Condition Index, Global Systemic Risk, Global TED Spread, Volatility Index, and Geopolitical Risk Index all present significant negative ADF test results, suggesting stationarity. Conversely, the Twitter-based economic uncertainty index displays ADF results not significantly different from zero, indicating potential non-stationarity. KPSS tests reinforce these findings, with significant positive values for TWEETS, implying non-stationarity. This mixed evidence, encompassing a combination of I(0) and I(1) variables, prompts the application of the Toda and Yamamoto (1995) approach. This involves incorporating additional lags in the specified VAR model, facilitating a more nuanced understanding of the time-series properties and relationships among the variables for further analysis.

Table 3 presents a comprehensive pairwise correlation matrix, providing insights into the relationships among financial stability measures, economic uncertainty measures, and assets returns, as well as the correlations among the different assets themselves.

Notable associations include a negative correlation between the Financial Conditions Index and Twitter-based economic uncertainty index at −0.78, indicating a potential inverse relationship. Additionally, strong negative correlations are observed between the Volatility Index and several cryptocurrencies, such as Dash, Ethereum, and Ripple. On the other hand, positive correlations are found between the US dollar exchange rate and certain cryptocurrencies, such as Ethereum and Litecoin and between Stellar and Ripple.

Moving on to Table 4, which focuses on the risk series, it allows for an exploration of the correlations between financial stability and

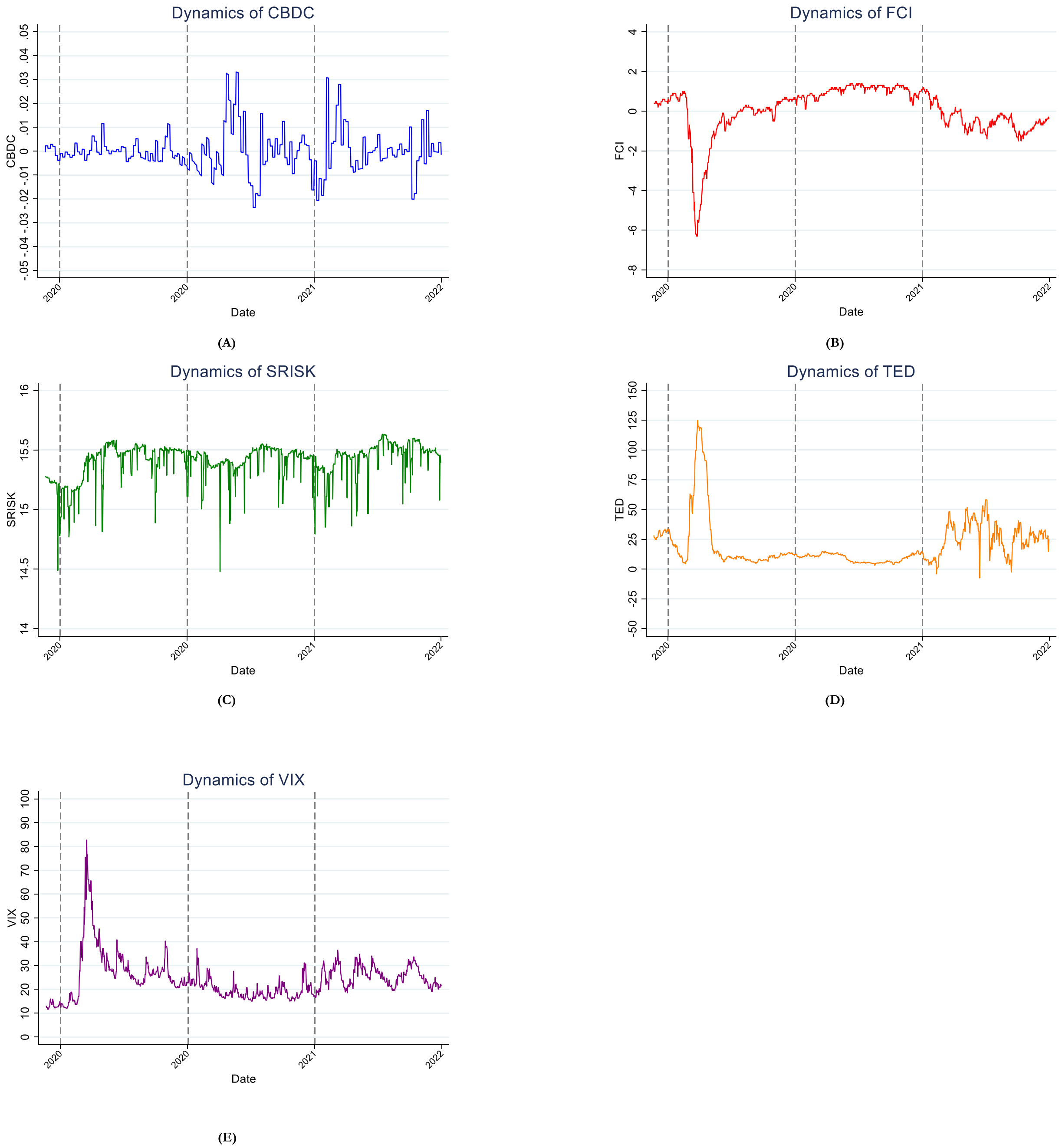

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Fig. 1. Dynamics of Financial Stability Measures**. Notes: (A)** Dynamics of CBDC. This figure presents the time series of the Central Bank Digital Currency (CBDC) index from November 2019 to December 2022. The CBDC index is a measure of the level of development and adoption of CBDCs by central banks worldwide. The vertical axis represents the index value, which ranges from −0.05 to 0.05. The horizontal axis shows the date in yearly intervals. The blue line depicts the evolution of the CBDC index over time. **(B)** Dynamics of FCI. This figure displays the time series of the Financial Conditions Index (FCI) from November 2019 to December 2022. The FCI is a gauge of the overall state of financial conditions in the economy, capturing factors such as interest rates, credit availability, and market volatility. The vertical axis represents the index value, ranging from −8 to 4. The horizontal axis shows the date in yearly intervals. The red line illustrates the progression of the FCI over time. **(C)** Dynamics of SRISK. This figure shows the time series of the Systemic Risk (SRISK) measure from November 2019 to December 2022. SRISK quantifies the expected capital shortfall of a financial institution in the event of a severe market downturn, providing an assessment of the institution's vulnerability to systemic risk. The vertical axis represents the SRISK value, ranging from 14 to 16. The horizontal axis shows the date in yearly intervals. The green line portrays the evolution of SRISK over time. **(D)** Dynamics of TED. This figure presents the time series of the TED spread from November 2019 to December 2022. The TED spread is the difference between the three-month Treasury bill rate and the three-month London Interbank Offered Rate (LIBOR), serving as a measure of credit risk and liquidity in the financial system. The vertical axis represents the TED spread value, ranging from −50 to 150 basis points. The horizontal axis shows the date in yearly intervals. The orange line depicts the progression of the TED spread over time. **(E)** Dynamics of VIX. This figure displays the time series of the CBOE Volatility Index (VIX) from November 2019 to December 2022. The VIX is a measure of the market's expectation of stock market volatility over the next 30 days, derived from S&P 500 index option prices. It is often referred to as the "fear index" or the "fear gauge." The vertical axis represents the VIX value, ranging from 0 to 100. The horizontal axis shows the date in yearly intervals. The purple line illustrates the evolution of the VIX over time. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

economic uncertainty measures and asset risk.

Table 4 provides insights into potential associations among risk series variables. Notable correlations include a negative correlation between the Central Bank Digital Currency Index and the Volatility Index at −0.87, indicating a potential inverse relationship between CBDC and market volatility. Additionally, positive correlations are observed between the Geopolitical Risk Index and several cryptocurrencies, such as Bitcoin, Ethereum, and Litecoin. For example, the GPR, BTC pair exhibits a positive correlation of 0.56, suggesting a potential association between geopolitical risk and Bitcoin's risk. Similarly, GPR, LTC has a positive correlation of 0.53, indicating a potential positive relationship between geopolitical risk and Litecoin's risk.

However, it is important to interpret these correlations cautiously, as correlation does not imply causation. While the correlations presented in Tables 3 and 4 offer insights into the potential relationships between different measures and assets, they do not provide a definitive explanation for the observed associations. Other factors and underlying dynamics within the cryptocurrency market should be considered to obtain a more comprehensive understanding.

4.2. Connectedness of returns and volatility

In this section we report the estimation results of spillovers and interconnectedness among financial stability, economic uncertainty measures and digital assets. We apply adaptive elastic net estimator using both ridge and lasso regression to report important insights into the dynamics of the network.[2] Thus, we report two sets of estimates for each case: a set of estimates based on ridge regularisation and another set of estimates based on lasso regression. All spillover estimates are reported in Tables 5 – 8.

In addition, all tables report further metrics in the spillover table, such as "FROM", "TO". "Inc.Own", "NET", "NPT" and the ratio "cTCI/TCI", provide further insights into the dynamics of the network and its implications. The "FROM" and "TO" columns in the spillover table represent the source and destination variables, respectively. These columns identify the specific stability measures and digital assets involved in the spillover effects. Understanding the directionality of spillovers is crucial for comprehending the transmission mechanisms and the potential lead-lag relationships within the network.

The "Inc.Own" row represents the influence of each variable on the overall connectedness of the network. Higher values in this column indicate variables that contribute more significantly to the overall interconnectedness of the network. In the context of stability measures and digital assets, higher values in the "Inc.Own" row suggest that certain variables have a stronger impact on the overall connectedness of the network, potentially acting as key drivers of interconnectedness.

The "NET" row provides insights into the net effect of each variable on the overall network. Positive values in this column indicate variables that strengthen the overall connectedness of the network, while negative values suggest variables that weaken the connectedness. Analysing the "NET" column enables us to identify which stability measures and digital assets exert a positive or negative influence on the overall interconnectedness, providing valuable information for risk management and portfolio optimisation strategies.

The "NPT" row represents the net predictive ability of each variable in relation to the other variables in the network. Higher values in this column indicate variables with stronger predictive power, implying that they are more influential in forecasting the behaviour of other variables in the network. Understanding the predictive power of stability measures and digital assets allows for more accurate risk assessments and forecasting of market trends.

[2] The lag length of the VAR model is k+ dmax = 2 – as proposed by Toda and Yamamoto (1995) – where dmax is the maximum integration order, which is found to be 1 based on the ADF and KPSS tests. The optimal lag length, *k,* is identified using Hatemi-J (2003) information criterion (HJC). HJC is found to perform better than standard AIC and BIC under both stable and unstable VAR with and without autoregressive conditional heteroskedastic volatility (Hatemi-J, 2008).

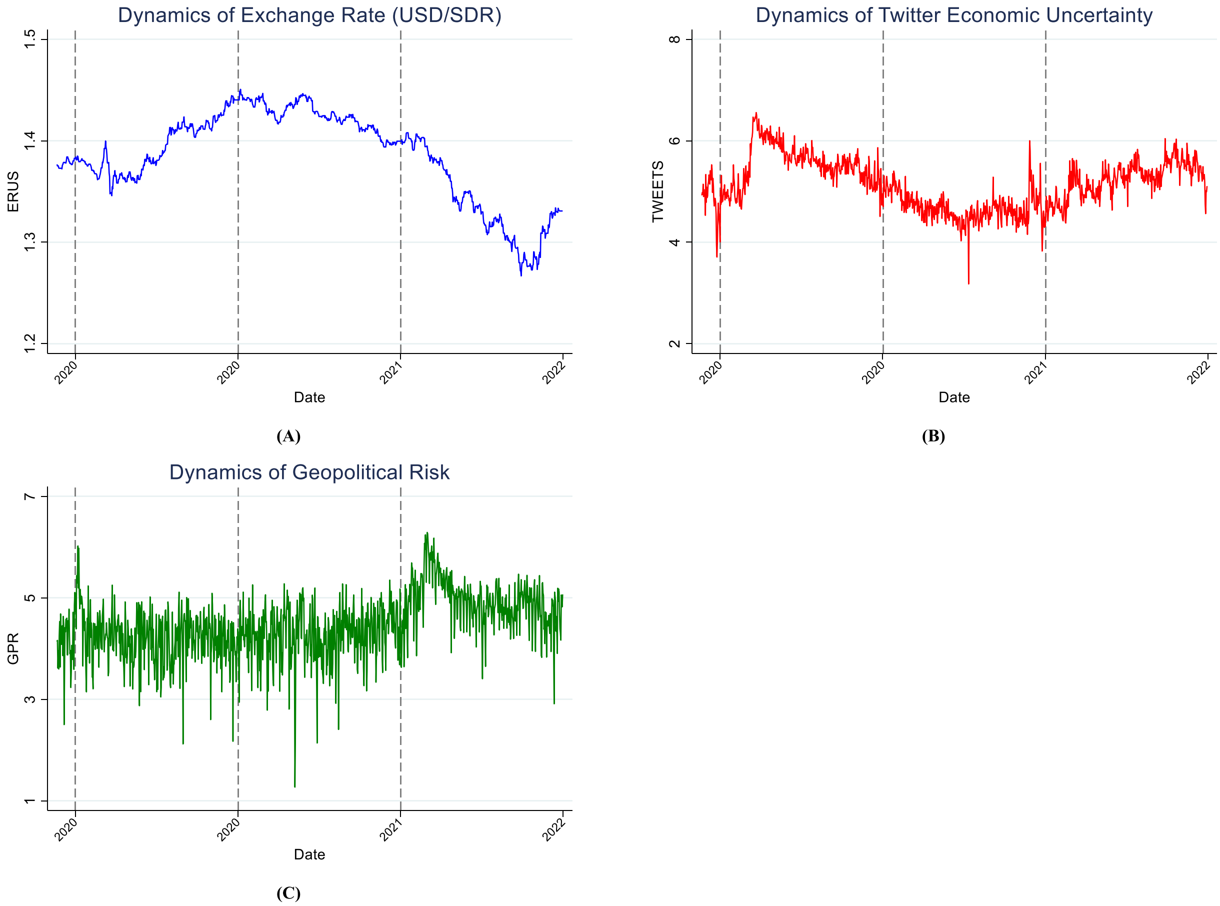


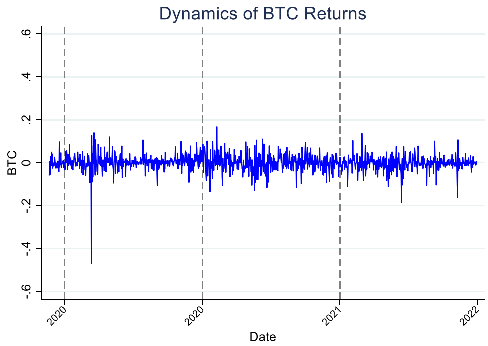
Fig. 2. Dynamics of Macro Risk Factors. **Notes: (A)** Dynamics of Exchange Rate (USD/SDR). This figure presents the time series of the exchange rate between the US dollar (USD) and the Special Drawing Rights (SDR) from November 2019 to December 2022. The SDR is an international reserve asset created by the International Monetary Fund (IMF) to supplement member countries' official reserves. The vertical axis represents the exchange rate value, ranging from 1.2 to 1.6 USD per SDR. The horizontal axis shows the date in yearly intervals. The blue line depicts the evolution of the USD/SDR exchange rate over time. **(B)** Dynamics of Twitter Economic Uncertainty. This figure displays the time series of the Twitter Economic Uncertainty index from November 2019 to December 2022. The Twitter Economic Uncertainty index is a measure of economic uncertainty derived from the analysis of tweets containing terms related to the economy and uncertainty. It captures the public sentiment and perception of economic uncertainty expressed on the Twitter platform. The vertical axis represents the index value, ranging from 2 to 8. The horizontal axis shows the date in yearly intervals. The red line illustrates the progression of the Twitter Economic Uncertainty index over time. **(C)** Dynamics of Geopolitical Risk. This figure shows the time series of the Geopolitical Risk (GPR) index from November 2019 to December 2022. The GPR index quantifies the level of geopolitical risk and uncertainty based on the frequency of newspaper articles discussing geopolitical tensions, conflicts, and uncertainties. It provides an assessment of the global geopolitical climate. The vertical axis represents the index value, ranging from 1 to 7. The horizontal axis shows the date in yearly intervals. The green line portrays the evolution of the GPR index over time. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Finally, the ratio "cTCI/TCI" compares the conditional connectedness (cTCI) to the total connectedness (TCI). This ratio provides insights into the relative importance of direct connections between variables compared to the overall connectedness of the network. A ratio greater than 1 suggests the existence of significant direct connections between variables that cannot be explained solely by the overall connectedness of the network. This implies that certain stability measures and digital assets have distinct and influential relationships with others in the network, beyond what can be explained by general interconnectedness.

4.2.1. Returns

The spillover table (Table 5) presents the quantitative measures of spillovers, expressed as percentages, and highlights the overall connectedness and interdependencies within the network based on ridge regularisation.

Examining the spillovers from financial stability and economic uncertainty indicators, we find very limited measurable impacts on digital assets. For example, the Central Bank Digital Currency (CBDC) index to digital currency ranges between 0 % and 0.1 %. Similarly, the ranges of estimated spillovers from financial stability measures and economic uncertainty to digital assets are very small, showing little evidence of any significant impact of these global indicators. Among notable effects, the measure of global volatility



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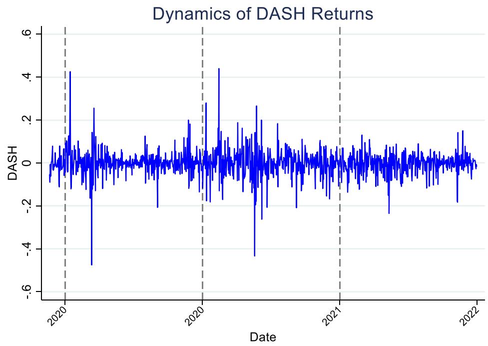

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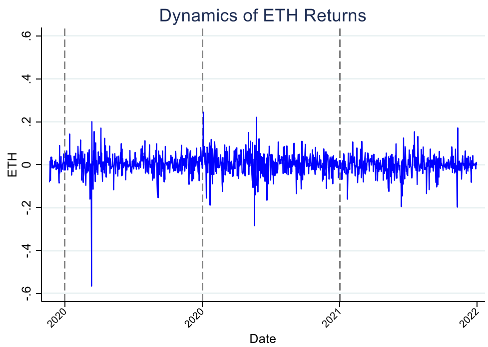

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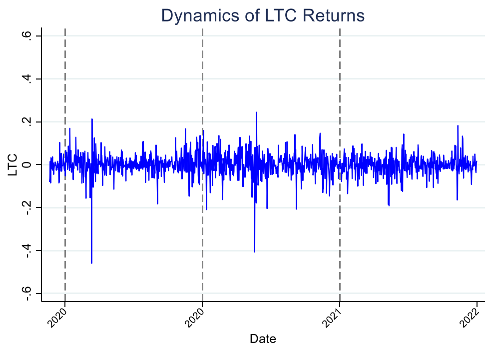

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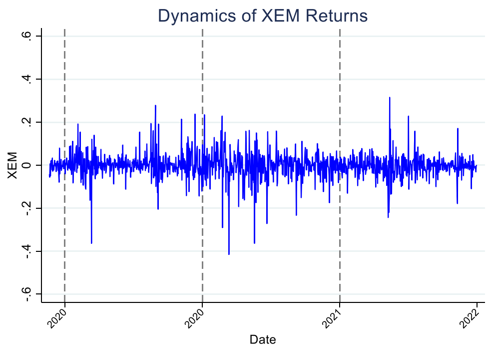

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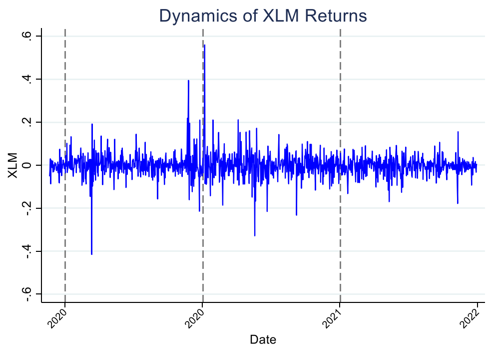

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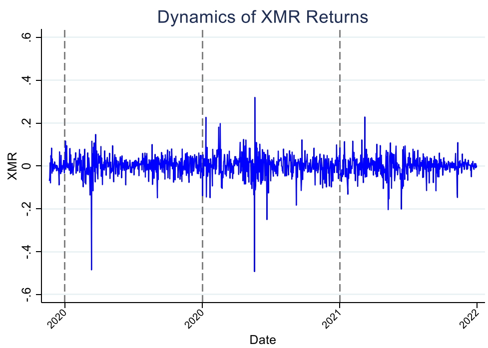

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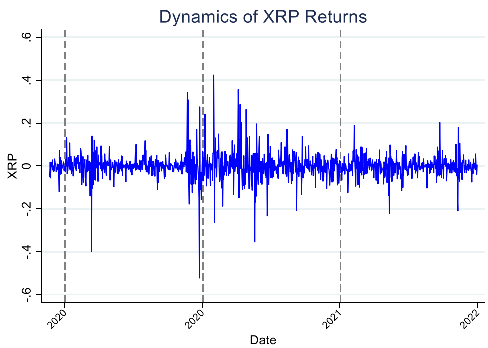

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Fig. 3. Dynamics of Cryptocurrency Returns. **Notes: (A)**: Dynamics of BTC Returns. This figure presents the time series of returns for Bitcoin (BTC) from November 2019 to December 2022. Bitcoin is a decentralized digital currency and the largest cryptocurrency by market capitalization. The vertical axis represents the return values, ranging from −0.6 to 0.6. The horizontal axis shows the date in yearly intervals. The blue line depicts the evolution of BTC returns over time. **(B)**: Dynamics of DASH Returns. This figure displays the time series of returns for Dash (DASH) from November 2019 to December 2022. Dash is a cryptocurrency that focuses on privacy and fast transactions. The vertical axis represents the return values, ranging from −0.6 to 0.6. The horizontal axis shows the date in yearly intervals. The blue line illustrates the progression of DASH returns over time. **(C)**: Dynamics of ETH Returns. This figure shows the time series of returns for Ethereum (ETH) from November 2019 to December 2022. Ethereum is a decentralized, open source blockchain platform that enables the creation of smart contracts and decentralized applications. The vertical axis represents the return values, ranging from −0.6 to 0.6. The horizontal axis shows the date in yearly intervals. The blue line portrays the evolution of ETH returns over time. **(D)**: Dynamics of LTC Returns. This figure presents the time series of returns for Litecoin (LTC) from November 2019 to December 2022. Litecoin is a peer-to-peer cryptocurrency that aims to provide faster transaction confirmation times and improved storage efficiency compared to Bitcoin. The vertical axis represents the return values, ranging from −0.6 to 0.6. The horizontal axis shows the date in yearly intervals. The blue line depicts the progression of LTC returns over time. **(E)**: Dynamics of XEM Returns. This figure displays the time series of returns for NEM (XEM) from November 2019 to December 2022. NEM is a blockchain platform that utilizes a unique consensus mechanism called Proof-of-Importance (PoI) and enables the creation of customizable assets and smart contracts. The vertical axis represents the return values, ranging from −0.6 to 0.6. The horizontal axis shows the date in yearly intervals. The blue line illustrates the evolution of XEM returns over time. **(F)**: Dynamics of XLM Returns. This figure shows the time series of returns for Stellar (XLM) from November 2019 to December 2022. Stellar is an open-source, decentralized protocol for digital currency to fiat currency transfers. The vertical axis represents the return values, ranging from −0.6 to 0.6. The horizontal axis shows the date in yearly intervals. The blue line portrays the progression of XLM returns over time. **(G)**: Dynamics of XMR Returns. This figure presents the time series of returns for Monero (XMR) from November 2019 to December 2022. Monero is a privacy-focused cryptocurrency that utilizes advanced cryptographic techniques to ensure the anonymity of transactions. The vertical axis represents the return values, ranging from −0.6 to 0.6. The horizontal axis shows the date in yearly intervals. The blue line depicts the evolution of XMR returns over time. **(H)**: Dynamics of XRP Returns. This figure displays the time series of returns for Ripple (XRP) from November 2019 to December 2022. Ripple is a real-time gross settlement system, currency exchange, and remittance network. XRP is the native cryptocurrency of the Ripple network. The vertical axis represents the return values, ranging from −0.6 to 0.6. The horizontal axis shows the date in yearly intervals. The blue line illustrates the progression of XRP returns over time. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

index, VIX, has higher spillover effects on digital assets. In this context, we estimate the spillovers from VIX to exceed 2 % for six assets including BTC, ETH, LTC, XML, DAI and MANA. This can be attributed to the VIX's role as a broad indicator of market sentiment and volatility. The VIX, often dubbed the "fear index", reflects investors' expectations for future market turbulence. In contrast, other global measures such as SRISK and CBDC, being more specific, exhibit lower spillover effects, suggesting that the VIX's widespread influence is particularly pronounced during periods of heightened market uncertainty, impacting diverse asset classes simultaneously. The unique nature of the VIX as a comprehensive sentiment gauge contributes to its greater spillover influence compared to more targeted global measures.

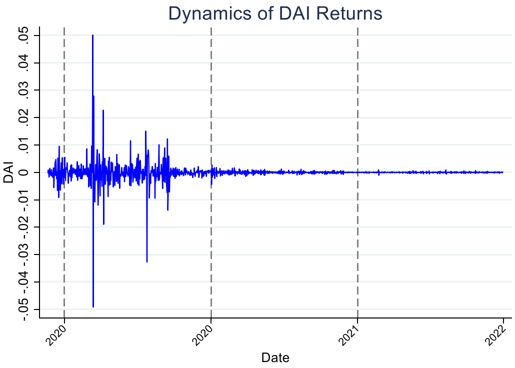
Analysing relationships within digital assets, we uncover substantial interconnectedness among dominant cryptocurrencies. We find a strong bidirectional relationship between Bitcoin and Ethereum. The spillover from Bitcoin to Ethereum stands at 12.55 %, while the reverse spillover measures 13 %, indicating significant interlinkages and the potential for volatility transmission. Bitcoin also displays pronounced effects on other major crypto assets like Litecoin (11.75 %) and Dash (9.38 %). Similarly, Ethereum is closely linked to Litecoin (12.28 %) and Ripple (9.34 %). These connections may enable price pressures to propagate across assets.

Fig. 7 depicts the network pairwise spillover between the digital assets, financial stability and economic uncertainty measures and stability. The measure of network pairwise spillover is derived from the return spillover matrix in Table 5. The characteristics of the network can be examined under five headings, such as node size, node colour, node location, link arrow sizes, and edge colour. The degree[3] of the node is used to determine the node size, suggesting the larger the degree the larger the node size is. The node colour indicates the type of asset, for instance, blue for the cryptocurrencies, yellow for the stablecoins, green for the NFTs, and red for the stability measures. The node location is set by employing the ForceAtlas2 algorithm in Gephi (Jacomy et al., 2014). This algorithm places each node into its location based on its relatedness. Basically, related nodes are positioned closer while unrelated nodes are placed at a greater distance. The thickness of the arrows represents the strength of the spillover effects, with thicker arrows indicating higher spillover magnitudes. The edge colours, dark or light grey, indicate the strength of the directional spillover. The colour dark grey indicates a strong relationship, while light grey represents a weak connection.

The network of spillover effects among digital assets, financial stability and economic uncertainty measures presents evidence of clustering. Each asset group is connected to each other strongly while, with other asset groups, the relation is weaker. For instance, financial stability measures highlight the directional flow of spillovers from one measure to another, while they are distantly related to digital assets. The cryptocurrencies and NFTs are strongly connected among and within themselves, while the stablecoins are highly related to each other but not as high as cryptocurrencies and NFTs. This visual representation enables researchers and market participants to quickly identify the dominant channels of spillovers and the key drivers of interconnectedness within stability measures.

Table 6 presents the Spillover Table, estimated using adaptive elastic net lasso regression, which provides insights into the spillover effects among digital assets and stability measures. The table displays the estimated spillover percentages between different pairs of variables, indicating the strength of the spillover effects.

[3] The degree of a node refers to the number of connections it has with other nodes.



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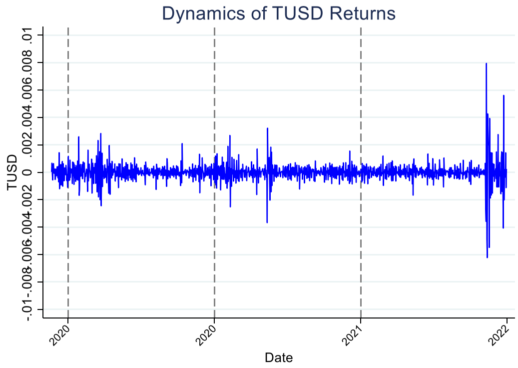

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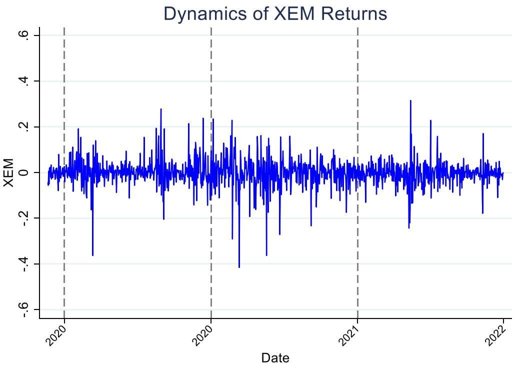

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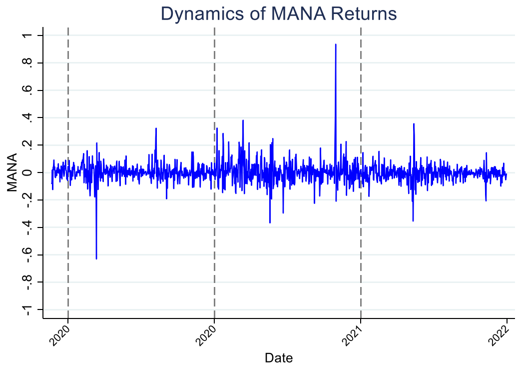

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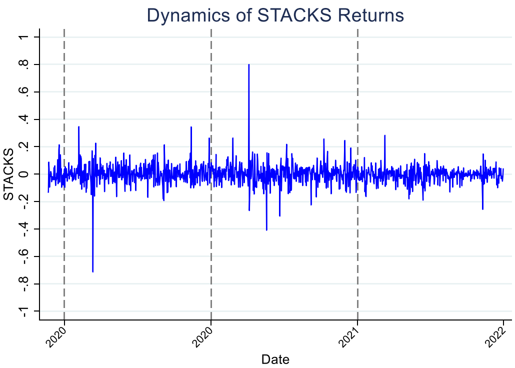

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Fig. 4. Dynamics of Stablecoins and NFTs Returns. **Notes: (A)**: Dynamics of DAI Returns. This figure presents the time series of returns for Dai (DAI) from November 2019 to December 2022. Dai is a decentralized stablecoin that aims to maintain a stable value relative to the US dollar through an automated system of smart contracts on the Ethereum blockchain. The vertical axis represents the return values, ranging from −0.05 to 0.05. The horizontal axis shows the date in yearly intervals. The blue line depicts the evolution of DAI returns over time. **(B)**: Dynamics of TUSD Returns. This figure displays the time series of returns for TrueUSD (TUSD) from November 2019 to December 2022. TrueUSD is a fiat-collateralized stablecoin that is backed by US dollar reserves held in escrow accounts. It aims to provide stability and transparency in the stablecoin market. The vertical axis represents the return values, ranging from −0.01 to 0.01. The horizontal axis shows the date in yearly intervals. The blue line illustrates the progression of TUSD returns over time. **(C)**: Dynamics of USDC Returns. This figure shows the time series of returns for USD Coin (USDC) from November 2019 to December 2022. USD Coin is a fully collateralized stablecoin that is pegged to the US dollar and backed by dollar-denominated assets held in segregated accounts. It aims to provide a stable and secure digital currency for transactions. The vertical axis represents the return values, ranging from −0.01 to 0.01. The horizontal axis shows the date in yearly intervals. The blue line portrays the evolution of USDC returns over time. **(D)**: Dynamics of MANA Returns. This figure presents the time series of returns for Decentraland (MANA) from November 2019 to December 2022. Decentraland is a virtual reality platform powered by the Ethereum blockchain, where users can create, experience, and monetize content and applications. MANA is the native cryptocurrency of the Decentraland platform, used for purchasing land parcels and virtual goods. The vertical axis represents the return values, ranging from −1.0 to 1.0. The horizontal axis shows the date in yearly intervals. The blue line depicts the progression of MANA returns over time. **(E)**: Dynamics of STACKS Returns. This figure displays the time series of returns for Stacks (STACKS) from November 2019 to December 2022. Stacks is a blockchain platform that enables the creation of smart contracts and decentralized applications. It aims to provide a secure and scalable infrastructure for building and deploying blockchain-based solutions. The vertical axis represents the return values, ranging from −1.0 to 1.0. The horizontal axis shows the date in yearly intervals. The blue line illustrates the evolution of STACKS returns over time. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

One important aspect to consider is the comparison between the lasso estimates and the previously discussed ridge estimates. Lasso regression is known for its ability to perform variable selection by shrinking the coefficients of less relevant variables to zero. Therefore, the lasso estimates may exhibit some differences compared to the ridge estimates, as lasso tends to provide a more parsimonious model with a subset of significant variables.

The spillover percentages estimated using lasso regression exhibit patterns consistent with the ridge regression estimates. Both methods indicate that measures of financial stability and economic uncertainty have overall very small and limited spillover effects on digital assets. The only difference between the two sets of the estimates is the magnitude of some of the spillover estimates. Nonetheless, the conclusions are the same.

Fig. 8 displays the connectedness network among digital assets and stability measures based on return spillover estimated by the lasso VAR presented in Table 6. The size of each node represents its degree, while the node colour indicates the type of asset: blue for cryptocurrencies, yellow for stablecoins, green for NFTs, and red for stability measures. The thickness of the edge colour reflects the strength of the directional connectedness, with dark (light) grey indicating strong (weak) connectedness. In line with Fig. 7, we observe the evidence of clustering. There is a strong connection between each asset group, while the relationship with other asset groups is relatively weaker.

4.2.2. Risk

Tables 7 and 8 report the Adaptive Elastic Net with ridge and lasso regressions, respectively, of the connectedness between stability measures and risk series. Both Tables 7 and 8 provide the pairwise connectedness between different risk series variables. The values in the tables represent the strength of the spillover effects from one variable to another. Higher values indicate a stronger spillover effect, suggesting a higher level of interconnectedness between the variables.

Our estimates in Table 7 show that global measures of financial stability and economic uncertainty have very small spillovers effects on digital assets risk. These effects range between 0 and 1.23 %. Like returns, VIX demonstrates strong connectedness with other variables, reflecting its role as a volatility index. The CBDC and other financial stability measures do not seem to have a significant pairwise connectedness with other risk series variables.

Assets, however, exhibit a much stronger connectedness among each other. There are several variables which exhibit significant pairwise connectedness. For instance, BTC shows considerable spillover effects on other variables, such as DASH, ETH, LTC and XMR, indicating its influence on the overall stock risk. Similarly, DASH, ETH and the remaining assets exhibit considerable spillover effects on other assets.

Similarly, our estimates in Table 8 provide additional insights into the pairwise connectedness of risk series variables. Comparing the results with Table 7, we observe similar estimates, indicating the robustness of our previous estimates. The overall patterns of pairwise connectedness remain consistent.[4]

Figs. 9 and 10 display the network of interconnectedness among digital assets risk series, emphasising the relationships and dependencies among different assets, based on ridge and lasso regression. Nodes in the networks represent individual series, while the edges connecting them signify the strength and direction of their interconnectedness. Both figures exhibit evidence of clustering but not as strong as in Figs. 7 and 8. The risks of the digital assets are interconnected to each other, but the strongest relation is observed among the cryptocurrencies.

[4] We also estimated all these models using ridge and lasso regressions. Our findings suggest that Elastic Net estimates are consistent with those based on ridge and lasso. Results are reported in Appendices A1 – A4.

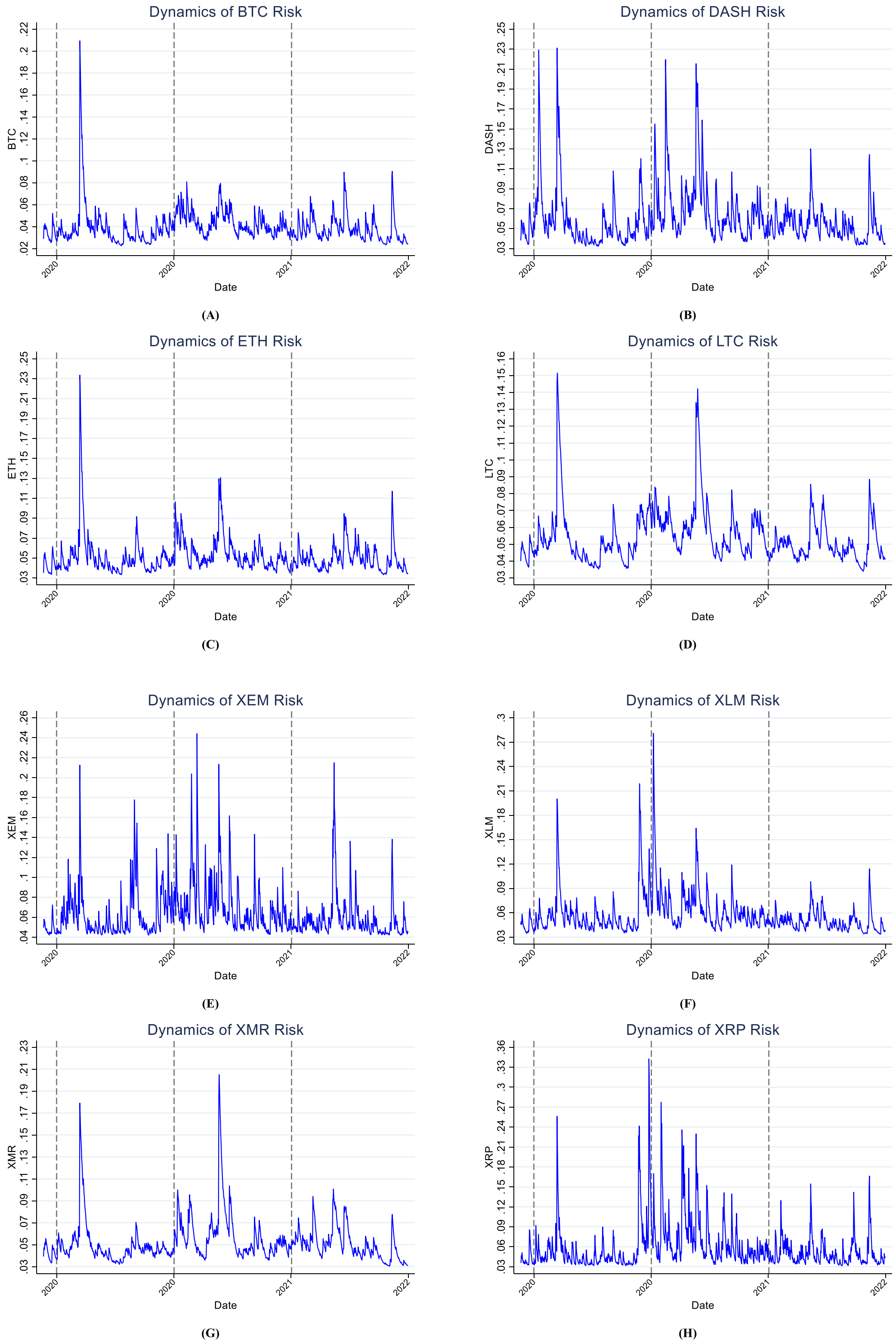

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Fig. 5. Dynamics of Cryptocurrency Risk. **Notes: (A)**: Dynamics of BTC Risk. This figure presents the time series of risk for Bitcoin (BTC) from November 2019 to December 2022. Risk is measured as the conditional volatility of BTC returns, which captures the uncertainty or variability in the cryptocurrency's price movements. The vertical axis represents the risk values, ranging from 0.02 to 0.22. The horizontal axis shows the date in yearly intervals. The blue line depicts the evolution of BTC risk over time. **(B)**: Dynamics of DASH Risk. This figure displays the time series of risk for Dash (DASH) from November 2019 to December 2022. Risk is measured as the conditional volatility of DASH returns, capturing the uncertainty or variability in the cryptocurrency's price movements. The vertical axis represents the risk values, ranging from 0.03 to 0.25. The horizontal axis shows the date in yearly intervals. The blue line illustrates the progression of DASH risk over time. **(C)**: Dynamics of ETH Risk. This figure shows the time series of risk for Ethereum (ETH) from November 2019 to December 2022. Risk is measured as the conditional volatility of ETH returns, reflecting the uncertainty or variability in the cryptocurrency's price movements. The vertical axis represents the risk values, ranging from 0.03 to 0.25. The horizontal axis shows the date in yearly intervals. The blue line portrays the evolution of ETH risk over time. **(D)**: Dynamics of LTC Risk. This figure presents the time series of risk for Litecoin (LTC) from November 2019 to December 2022. Risk is measured as the conditional volatility of LTC returns, capturing the uncertainty or variability in the cryptocurrency's price movements. The vertical axis represents the risk values, ranging from 0.03 to 0.16. The horizontal axis shows the date in yearly intervals. The blue line depicts the progression of LTC risk over time. **(E)**: Dynamics of XEM Risk. This figure displays the time series of risk for NEM (XEM) from November 2019 to December 2022. Risk is measured as the conditional volatility of XEM returns, reflecting the uncertainty or variability in the cryptocurrency's price movements. The vertical axis represents the risk values, ranging from 0.04 to 0.26. The horizontal axis shows the date in yearly intervals. The blue line illustrates the evolution of XEM risk over time. **(F)**: Dynamics of XLM Risk. This figure shows the time series of risk for Stellar (XLM) from November 2019 to December 2022. Risk is measured as the conditional volatility of XLM returns, capturing the uncertainty or variability in the cryptocurrency's price movements. The vertical axis represents the risk values, ranging from 0.03 to 0.30. The horizontal axis shows the date in yearly intervals. The blue line portrays the progression of XLM risk over time. **(G)**: Dynamics of XMR Risk. This figure presents the time series of risk for Monero (XMR) from November 2019 to December 2022. Risk is measured as the conditional volatility of XMR returns, reflecting the uncertainty or variability in the cryptocurrency's price movements. The vertical axis represents the risk values, ranging from 0.03 to 0.23. The horizontal axis shows the date in yearly intervals. The blue line depicts the evolution of XMR risk over time. **(H)**: Dynamics of XRP Risk. This figure displays the time series of risk for Ripple (XRP) from November 2019 to December 2022. Risk is measured as the conditional volatility of XRP returns, capturing the uncertainty or variability in the cryptocurrency's price movements. The vertical axis represents the risk values, ranging from 0.03 to 0.36. The horizontal axis shows the date in yearly intervals. The blue line illustrates the progression of XRP risk over time. These accompanying notes provide a clear explanation of what risk represents in the context of each cryptocurrency and how it is measured. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.2.3. Net pairwise spillovers

Following Elsayed and Helmi (2021), we extend the analysis to identify the main return and risk transmitters using the net directional spillovers reported in Tables 5, 6, 7 and 8 as NET. This offers further insights into pinpointing the key net transmitters and receivers of shocks within the interconnected financial stability and digital asset ecosystem. The net spillover value represents the difference between the shocks transmitted to versus received from all other variables, delineating whether a variable primarily serves as a transmitter or receiver.

Scrutinising the net spillover estimates for return dynamics under ridge regression in Table 5, Ethereum, Bitcoin and Dash surface as leading net transmitters of return shocks. Ethereum exhibits a sizable net value of 36.07, disseminating over 30 % more shocks than it absorbs. Bitcoin also displays a robust net transmission effect of 31.19, underscoring its pivotal role in propagating return pressures rippling through the system. The positive net contributions signal these variables function as dominant net generators of return shocks. VIX is the only measure of financial stability to act as a transmitter with net transmission of 15.27, while GPR displays a net transmission of 2.75.

In contrast, stablecoins such as Dai, USD Coin and TrueUSD reveal negative net values, establishing them as net shock absorbers. For example, Dai shows a net value of −17.06 as it helps dampen excess volatility. Similarly, the CBDC and the remaining measures of financial stability and economic uncertainty demonstrate muted net transmission activity, implying limited involvement in relaying return pressures.

The lasso regression estimates in Table 6 convey a comparable narrative, with Bitcoin and Ethereum again starring as foremost net transmitters with positive net indices. VIX, on the other hand, is estimated to have a very small net transmission compared to ridge regularisation estimates.

Table 7 presents estimates of the volatility spillover for digital stability variables under ridge regression. Inspecting the net spillover values, Ethereum (29.84), Bitcoin (37.69), and Dash (21.72) distinctly emerge as leading net transmitters of risk shocks. Their sizable positive indices signify these cryptocurrencies propagate over 20 % more volatility to the system than they receive. In contrast, stablecoins like Dai (-9.97), TrueUSD (-55.35), and USD Coin (-12.13) are net receivers, evidenced by substantial negative net spillovers. Their risk-absorbing capacity likewise extends to CBDC (-5.10) and the remaining measures of financial stability and economic uncertainty.

Table 8 – the lasso regression estimates –conveys similar conclusions, with Bitcoin (24.16), Ethereum (29.84), and Dash (4.06) as dominant net transmitters trailed closely by Litecoin and Monero. Stablecoins endure as leading net absorbers, with TrueUSD topping at −19.52 followed by Dai's −16.88. FCI and VIX are dominant transmitters of financial stability measures, while CBDC and the remaining measures of financial stability and economic uncertainty sustain muted activity.

In summary, cryptocurrencies transmit and stablecoins absorb the bulk of risk shocks across models. Isolating sources and recipients of volatility pressures through net directional positioning allows targeted stability planning and risk management in connected ecosystems.

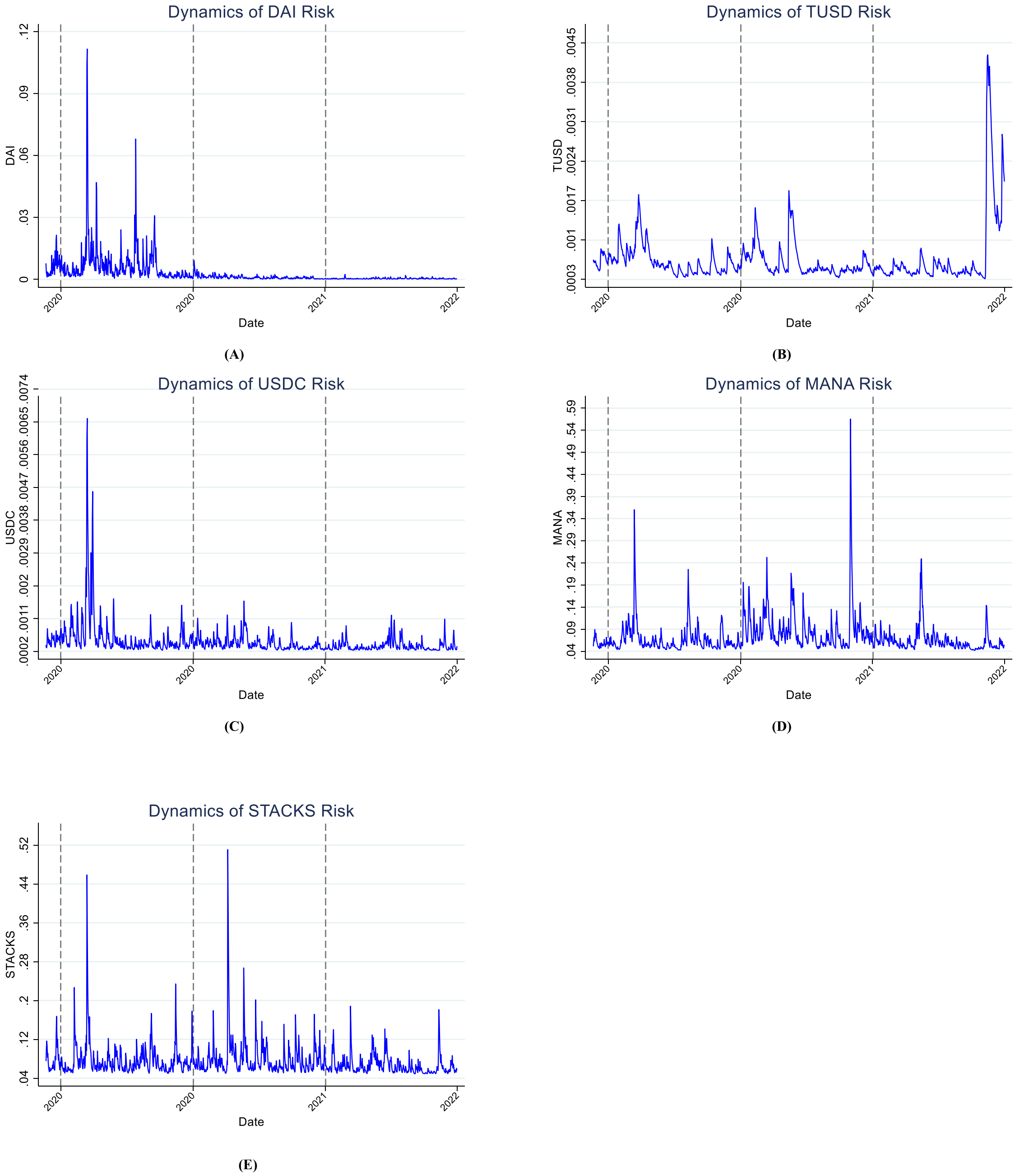

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Fig. 6. Dynamics of Stablecoins and NFTs Risk. **Notes: (A)**: Dynamics of DAI Returns. This figure presents the time series of returns for Dai (DAI) from November 2019 to December 2022. Dai is a decentralized stablecoin that aims to maintain a stable value relative to the US dollar through an automated system of smart contracts on the Ethereum blockchain. The vertical axis represents the return values, ranging from −0.05 to 0.05. The horizontal axis shows the date in yearly intervals. The blue line depicts the evolution of DAI returns over time. **(B)**: Dynamics of TUSD Returns. This figure displays the time series of returns for TrueUSD (TUSD) from November 2019 to December 2022. TrueUSD is a fiat-collateralized stablecoin that is backed by US dollar reserves held in escrow accounts. It aims to provide stability and transparency in the stablecoin market. The vertical axis represents the return values, ranging from −0.01 to 0.01. The horizontal axis shows the date in yearly intervals. The blue line illustrates the progression of TUSD returns over time. **(C)**: Dynamics of USDC Returns. This figure shows the time series of returns for USD Coin (USDC) from November 2019 to December 2022. USD Coin is a fully collateralized stablecoin that is pegged to the US dollar and backed by dollar-denominated assets held in segregated accounts. It aims to provide a stable and secure digital currency for transactions. The vertical axis represents the return values, ranging from −0.01 to 0.01. The horizontal axis shows the date in yearly intervals. The blue line portrays the evolution of USDC returns over time. **(D)**: Dynamics of MANA Returns. This figure presents the time series of returns for Decentraland (MANA) from November 2019 to December 2022. Decentraland is a virtual reality platform powered by the Ethereum blockchain, where users can create, experience, and monetize content and applications. MANA is the native cryptocurrency of the Decentraland platform, used for purchasing land parcels and virtual goods. The vertical axis represents the return values, ranging from −1.0 to 1.0. The horizontal axis shows the date in yearly intervals. The blue line depicts the progression of MANA returns over time. **(E)**: Dynamics of STACKS Returns. This figure displays the time series of returns for Stacks (STACKS) from November 2019 to December 2022. Stacks is a blockchain platform that enables the creation of smart contracts and decentralized applications. It aims to provide a secure and scalable infrastructure for building and deploying blockchain-based solutions. The vertical axis represents the return values, ranging from −1.0 to 1.0. The horizontal axis shows the date in yearly intervals. The blue line illustrates the evolution of STACKS returns over time. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5. Conclusion

The primary objective of this study has been to investigate the interconnectedness between central bank digital currencies (CBDC) index and other measures of financial stability, economic uncertainty measures and digital assets – both returns and risk. Although there is a growing literature on CBDC, most of the studies are confined to descriptive or theoretical expositions. Limited studies examine the transmission effects and connectedness across CBDC, digital assets, and financial stability. Given that CBDCs are introduced by central banks, a supreme monetary authority, we have argued that this is important and critical to investigate the connections of this introduction to a country's stability.

To fill this research gap, this study first undertook a quantitative analysis using various measures of financial stability – including CBDC, FCI, TED, SRISK and VIX– to provide comprehensive insights into the implications of the interconnectedness between stability measures and digital assets. These insights provided important implications for the global financial and macroeconomic landscape. The robustness of our findings was enhanced through the application of econometric methodologies appropriate for high dimensional data, specifically the adaptive elastic-set with ridge and lasso regression.

Our findings shed light on the complex nature of the relationships among these elements and underscore the importance of careful consideration of their implications for policy and regulation. The interconnectedness analysis revealed several significant insights, offering valuable guidance for policymakers, regulators and industry participants.

Firstly, our analysis demonstrated bidirectional connectedness between CBDC index and financial stability measures. Changes in the CBDC index performance can have a profound impact on the overall stability of the financial system, and conversely, the stability of the financial system can exert influence on CBDCs. This highlights the critical role of CBDC design and implementation in achieving financial stability objectives. It is essential for policymakers to recognise the potential spillover effects and feedback loops between CBDCs and financial stability, ensuring that CBDCs are developed and managed in a manner that minimises systemic risks.

In contrast, our study has found that financial stability and economic uncertainty measures did not exhibit a strong relationship with digital assets. This suggests that, while CBDCs – and indeed all other financial stability and economic uncertainty measures – may have an impact on financial stability, their influence on the broader digital asset ecosystem may be limited. However, given the rapid evolution of digital assets and the potential for future interactions, ongoing monitoring and analysis of these interconnections remain crucial.

Moreover, our research detected varying levels of connectedness across different digital assets. Cryptocurrencies exhibit high internal connectedness, transmitting volatility pressures among themselves. Ethereum, Bitcoin, and Dash distinctly emerge as net transmitters of both return and risk shocks based on positive net spillovers, establishing them as key propagators. But stablecoins prove more isolated with greater shock-absorbing capacity. This heterogeneity within the digital asset sphere calls for nuanced, asset-specific regulatory approaches. A one-size-fits-all governance strategy seems suboptimal given divergent network embeddedness and risk transmission profiles.

Conversely, stablecoins exhibited a relatively lower level of connectedness, indicating that they may act as a buffer against shocks in the digital asset space. This finding suggests that stablecoins have the potential to contribute to the stability of the digital asset ecosystem. Policymakers and regulators should consider implementing measures to enhance transparency, governance and risk management practices for cryptocurrencies while closely monitoring the development and adoption of stablecoins to mitigate potential risks.

NFTs, as a distinct segment within the broader digital asset landscape, demonstrated a moderate level of connectedness. This finding suggests that NFTs have the potential to disrupt traditional industries such as art and collectibles. Policymakers and regulators need to closely monitor the growth of NFTs, assessing their potential impact on market stability, investor protection and intellectual property rights.

Table 2
Statistical Properties of Data.

Variable	*N*	Mean	Std. Dev.	Min	Max	ADF	KPSS	#Lags
Measures of Financial Stability								
CBDC	1136	0	0.009	-0.024	0.033	−4.813***	0.027	14
FCI	1136	0.026	1.228	−6.3	1.4	−3.024**	0.532**	20
SRISK	1136	15.407	0.156	14.479	15.632	−3.283**	0.942***	21
TED	1136	20.079	20.187	−7.462	124.803	−3.812***	0.367*	20
VIX	1136	24.258	8.727	1.272	6.291	−3.8***	0.3*	15
Measures of Economic Uncertainty Measures								
ERUS	1136	1.385	0.045	1.267	1.451	−0.6	2.2***	10
TWEETS	1136	5.138	0.501	3.179	6.556	−2.3**	1.0***	13
GPR	1136	4.466	0.614	1.272	6.291	−3.8***	0.3*	21
Digital Assets Return Series								
BTC	1136	0.001	0.039	-0.471	0.168	−7.2***	0.40	16
DASH	1136	0	0.062	-0.475	0.439	−35.8***	0.20	0
ETH	1136	0.002	0.051	-0.566	0.245	−7.4***	0.40*	16
LTC	1136	0	0.053	-0.459	0.244	−16.1***	0.20	3
XEM	1136	0	0.061	-0.415	0.315	−7.2***	0.40*	16
XLM	1136	0	0.057	-0.415	0.559	−15.7***	0.30	3
XMR	1136	0.001	0.052	-0.492	0.319	−15.5***	0.30	3
XRP	1136	0	0.061	-0.521	0.423	−10.3***	0.10	8
DAI	1136	0	0.003	-0.049	0.05	−51.5***	0.02	0
TUSD	1136	0	0.001	-0.006	0.008	−51.0***	0.01	0
USDC	1136	0	0.001	-0.007	0.006	−56.8***	0.01	0
MANA	1136	0.002	0.078	-0.63	0.935	−6.5***	0.01	20
STACKS	1136	0	0.074	-0.712	0.799	−10.1***	0.4*	9
Digital Assets Risk Series								
BTC	1136	0.04	0.015	0.023	0.209	−7.1***	0.2	3
DASH	1136	0.06	0.028	0.032	0.231	−6.1***	0.3	9
ETH	1136	0.052	0.018	0.033	0.234	−7.0***	0.1	3
LTC	1136	0.054	0.016	0.034	0.151	−5.2***	0.2	0
XEM	1136	0.064	0.025	0.042	0.244	−5.2***	0.4	16
XLM	1136	0.057	0.025	0.034	0.281	−4.3***	0.6**	21
XMR	1136	0.052	0.02	0.031	0.205	−6.0***	0.2	0
XRP	1136	0.058	0.035	0.032	0.342	−4.4***	0.4*	22
DAI	1136	0.003	0.007	0	0.112	−3.9***	2.4***	21
TUSD	1136	0.001	0	0	0.004	−3.5***	0.3	20
USDC	1136	0	0	0	0.007	−4.4***	1.2***	16
MANA	1136	0.073	0.039	0.042	0.565	−6.3***	0.3	12
STACKS	1136	0.075	0.034	0.049	0.511	−8.7***	0.6**	8

Notes: Table 2 presents the statistical properties of the variables used in the analysis. The variables are categorised into four groups: Measures of Financial Stability, Measures of Economic Uncertainty, Digital Assets Return Series, and Digital Assets Risk Series. For each variable, the table provides the sample size (N), mean, standard deviation (Std. Dev.), minimum (Min), and maximum (Max) values. The table also reports the results of two unit root tests: the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The ADF test evaluates the null hypothesis of a unit root against the alternative of no unit root, while the KPSS test assesses the null hypothesis of stationarity against the alternative of a unit root. The optimal lag length for each variable, selected using the Modified Akaike Information Criterion, is also provided. The Measures of Financial Stability include the Central Bank Digital Currency (CBDC) index, Global Financial Condition Index (FCI), Global Systemic Risk (SRISK), Global TED Spread (TED), and Volatility Index (VIX). The Measures of Economic Uncertainty include the US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ERUS), Twitter-based Economic Uncertainty Index (TWEETS) and Geopolitical Risk Index (GPR). The Digital Assets Return Series and Digital Assets Risk Series include various cryptocurrencies, stablecoins, and non-fungible tokens such as Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), Ripple (XRP), Dai (DAI), True USD (TUSD), USD Coin (USDC), Decentraland (MANA), and Stacks (STACKS). The statistical significance of the ADF and KPSS tests is denoted by asterisks, with (***), (**), and (*) referring to significance levels of 1 %, 5 %, and 10 %, respectively.

In conclusion, this study has provided valuable insights into the interconnectedness among CBDCs, digital assets and financial stability. The bidirectional connectedness between CBDC index and financial stability, the varying levels of connectedness among different digital assets, and the importance of regulatory differentiation within the digital asset ecosystem have significant implications for policymakers and regulators who, by leveraging these insights, can develop effective policies and regulatory frameworks that balance innovation and market integrity.

CRediT authorship contribution statement

Tugba Bas: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Issam Malki:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sheeja Sivaprasad:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data

Table 3
Pairwise Correlation Matrix (Returns).

	CBDC	FCI	SRISK	TED	VIX	ER	GPR	TWEETS	BTC	DASH	ETH	LTC	XEM	XLM	XMR	XRP	DAI	TUSD	USDC	MANA	STACKS
CBDC	1.00																				
FCI	−0.03	1.00																			
SRISK	−0.06	−0.13	1.00																		
TED	0.08	−0.84	−0.02	1.00																	
VIX	0.01	−0.87	0.15	0.63	1.00																
ER	0.05	0.56	−0.16	−0.42	−0.27	1.00															
GPR	0.10	−0.11	0.04	0.13	0.06	−0.31	1.00														
TWEETS	0.04	−0.78	0.24	0.49	0.69	−0.48	−0.01	1.00													
BTC	−0.01	0.02	−0.01	−0.01	−0.07	0.05	−0.05	0.00	1.00												
DASH	0.00	0.01	−0.02	0.01	−0.07	0.02	−0.04	−0.01	0.68	1.00											
ETH	0.02	0.04	−0.01	−0.01	−0.10	0.05	−0.07	0.00	0.84	0.70	1.00										
LTC	0.00	0.03	−0.02	−0.01	−0.09	0.01	−0.05	0.00	0.81	0.76	0.83	1.00									
XEM	−0.01	0.02	0.01	−0.02	−0.06	0.03	−0.04	0.02	0.60	0.59	0.63	0.62	1.00								
XLM	−0.01	0.01	−0.02	0.01	−0.05	0.03	−0.05	0.01	0.68	0.65	0.71	0.71	0.65	1.00							
XMR	0.02	0.01	0.01	0.02	−0.08	0.01	−0.03	0.00	0.73	0.71	0.71	0.72	0.56	0.61	1.00						
XRP	−0.01	0.02	−0.04	−0.01	−0.06	0.02	−0.05	−0.01	0.61	0.61	0.65	0.67	0.59	0.75	0.56	1.00					
DAI	0.00	0.00	0.02	−0.01	0.04	0.00	0.04	−0.01	−0.24	−0.18	−0.22	−0.21	−0.13	−0.18	−0.18	−0.15	1.00				
TUSD	0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.08	0.09	0.06	0.07	0.10	0.06	0.08	0.12	0.00	1.00			
USDC	−0.01	0.00	0.00	0.01	−0.03	0.00	0.04	0.00	0.22	0.15	0.22	0.18	0.15	0.17	0.18	0.15	−0.29	0.20	1.00		
MANA	−0.02	0.06	0.01	−0.03	−0.10	0.06	−0.05	−0.05	0.56	0.53	0.57	0.56	0.50	0.53	0.53	0.49	−0.14	0.12	0.16	1.00	
STACKS	−0.01	0.04	−0.04	−0.01	−0.07	0.04	−0.06	−0.01	0.55	0.50	0.58	0.54	0.49	0.53	0.51	0.50	−0.17	0.03	0.14	0.48	1.00

Notes: Table 3 presents the pairwise correlation matrix for the returns of the variables used in the analysis. The correlation matrix provides insights into the relationships between the different variables, with values ranging from −1 to 1. A value of 1 indicates a perfect positive correlation, a value of −1 indicates a perfect negative correlation, and a value of 0 indicates no correlation. The variables included in the correlation matrix are: 1. Measures of Financial Stability: Central Bank Digital Currency Index (CBDC), Global Financial Condition Index (FCI), Global Systemic Risk (SRISK), Global TED Spread (TED), and Volatility Index (VIX). 2. Measures of Economic Uncertainty: US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ER), Twitter-based Economic Uncertainty Index (TWEETS), and Geopolitical Risk Index (GPR). 3. Digital Assets Return Series: Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), and Ripple (XRP). 4. Stablecoins: Dai (DAI), True USD (TUSD), and USD Coin (USDC). 5. Non-Fungible Tokens: Decentraland (MANA) and Stacks (STACKS). The correlation matrix allows for the identification of potential relationships between the variables. For example, a high positive correlation between two digital assets may suggest that their returns move in the same direction, while a negative correlation may indicate an inverse relationship. Similarly, correlations between digital assets and measures of financial stability or economic uncertainty can provide insights into how these assets behave under different market conditions.

Table 4
Pairwise Correlation Matrix (Risk).

	CBDC	FCI	SRISK	TED	VIX	ER	GPR	TWEETS	BTC	DASH	ETH	LTC	XEM	XLM	XMR	XRP	DAI	TUSD	USDC	MANA	STACKS
CBDC	1.00																				
FCI	−0.03	1.00																			
SRISK	−0.06	−0.13	1.00																		
TED	0.08	−0.84	−0.02	1.00																	
VIX	0.01	−0.87	0.15	0.63	1.00																
ER	0.05	0.56	−0.16	−0.42	−0.27	1.00															
GPR	0.10	−0.11	0.04	0.13	0.06	−0.31	1.00														
TWEETS	0.04	−0.78	0.24	0.49	0.69	−0.48	−0.01	1.00													
BTC	−0.01	0.02	−0.01	−0.01	−0.07	0.05	−0.05	0.00	1.00												
DASH	0.00	0.01	−0.02	0.01	−0.07	0.02	−0.04	−0.01	0.68	1.00											
ETH	0.02	0.04	−0.01	−0.01	−0.10	0.05	−0.07	0.00	0.84	0.70	1.00										
LTC	0.00	0.03	−0.02	−0.01	−0.09	0.01	−0.05	0.00	0.81	0.76	0.83	1.00									
XEM	−0.01	0.02	0.01	−0.02	−0.06	0.03	−0.04	0.02	0.60	0.59	0.63	0.62	1.00								
XLM	−0.01	0.01	−0.02	0.01	−0.05	0.03	−0.05	0.01	0.68	0.65	0.71	0.71	0.65	1.00							
XMR	0.02	0.01	0.01	0.02	−0.08	0.01	−0.03	0.00	0.73	0.71	0.71	0.72	0.56	0.61	1.00						
XRP	−0.01	0.02	−0.04	−0.01	−0.06	0.02	−0.05	−0.01	0.61	0.61	0.65	0.67	0.59	0.75	0.56	1.00					
DAI	0.00	0.00	0.02	−0.01	0.04	0.00	0.04	−0.01	−0.24	−0.18	−0.22	−0.21	−0.13	−0.18	−0.18	−0.15	1.00				
TUSD	0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.08	0.09	0.06	0.07	0.10	0.06	0.08	0.12	0.00	1.00			
USDC	−0.01	0.00	0.00	0.01	−0.03	0.00	0.04	0.00	0.22	0.15	0.22	0.18	0.15	0.17	0.18	0.15	−0.29	0.20	1.00		
MANA	−0.02	0.06	0.01	−0.03	−0.10	0.06	−0.05	−0.05	0.56	0.53	0.57	0.56	0.50	0.53	0.53	0.49	−0.14	0.12	0.16	1.00	
STACKS	−0.01	0.04	−0.04	−0.01	−0.07	0.04	−0.06	−0.01	0.55	0.50	0.58	0.54	0.49	0.53	0.51	0.50	−0.17	0.03	0.14	0.48	1.00

Notes: Table 4 presents the pairwise correlation matrix for the risk of the variables used in the analysis. The correlation matrix provides insights into the relationships between the different variables, with values ranging from −1 to 1. A value of 1 indicates a perfect positive correlation, a value of −1 indicates a perfect negative correlation, and a value of 0 indicates no correlation. The variables included in the correlation matrix are: 1. Measures of Financial Stability: Central Bank Digital Currency Index (CBDC), Global Financial Condition Index (FCI), Global Systemic Risk (SRISK), Global TED Spread (TED), and Volatility Index (VIX). 2. Measures of Economic Uncertainty: US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ER), Twitter-based Economic Uncertainty Index (TWEETS), and Geopolitical Risk Index (GPR). 3. Digital Assets Return Series: Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), and Ripple (XRP). 4. Stablecoins: Dai (DAI), True USD (TUSD), and USD Coin (USDC). 5. Non-Fungible Tokens: Decentraland (MANA) and Stacks (STACKS). The correlation matrix allows for the identification of potential relationships between the variables. For example, a high positive correlation between two digital assets may suggest that their returns move in the same direction, while a negative correlation may indicate an inverse relationship. Similarly, correlations between digital assets and measures of financial stability or economic uncertainty can provide insights into how these assets behave under different market conditions.

Table 5
Spillover Table, Stock Returns Using Net Elastic Estimator – Ridge Regression.

	CBDC	SRISK	TED	FCI	VIX	ER	TWEETS	GPR	BTC	DASH	ETH	LTC	XEM	XLM	XMR	XRP	DAI	TUSD	USDC	MANA	STACKS	FROM
CBDC	96.15	0.82	0.07	0.08	0.06	0.19	0.16	0.82	0.1	0.16	0.25	0.16	0.23	0.05	0.35	0.04	0.01	0.13	0.09	0.01	0.06	3.85
SRISK	0.09	92.84	0.94	0.13	0.43	0.09	2.7	0.27	0.12	0.31	0.11	0.14	0.04	0.14	0.09	0.15	0.12	0.14	0.26	0.06	0.83	7.16
TED	0.07	2.11	51.56	17.96	13.68	0.49	2.52	0.08	1.69	0.53	1.79	1.21	1	0.97	0.94	0.63	0.31	0.1	0.5	1.12	0.76	48.44
FCI	0.15	0.02	4.06	30.5	26.86	0.54	10.41	0.23	3.9	1.56	4.18	3.03	1.95	2.29	2.45	1.51	0.93	0.12	0.55	2.42	2.38	69.5
VIX	0.24	0.1	0.54	16.37	39.47	0.09	6.02	0.27	4.99	2.79	5.3	4.48	2.51	2.79	3.98	1.97	1.24	0.12	0.67	3.2	2.86	60.53
ER	1.03	1.53	0.62	4.23	2.17	55.39	4.31	7.88	3.62	1.29	3.71	2.15	1.97	2.23	1.9	1.25	0.24	0.08	0.26	2.11	2.02	44.61
TWEETS	0.05	1.22	0.75	9.91	8.73	0.54	67.36	1.81	1.31	0.74	1.42	1.06	0.52	0.72	0.83	0.56	0.25	0.07	0.11	0.81	1.23	32.64
GPR	0.22	0.03	0.03	0.78	0.31	1.37	1.66	90.55	0.45	0.27	0.75	0.64	0.36	0.45	0.33	0.47	0.36	0.01	0.12	0.56	0.31	9.45
BTC	0.03	0.01	0	0.74	2.37	0.13	0.02	0.04	18.31	8.35	13	12.14	6.63	8.36	9.66	6.89	1.07	0.11	0.79	5.8	5.55	81.69
DASH	0.02	0	0.05	0.31	1.5	0.05	0.02	0.03	9.38	20.58	10.06	12.01	7.1	8.79	10.45	7.57	0.68	0.19	0.43	5.71	5.06	79.42
ETH	0.05	0.01	0	0.72	2.3	0.13	0.01	0.1	12.55	8.64	17.68	12.25	6.95	8.88	8.99	7.38	0.87	0.07	0.78	5.83	5.83	82.32
LTC	0.02	0.01	0	0.52	2.04	0.05	0.02	0.08	11.75	10.34	12.28	17.72	6.81	8.95	9.14	8.07	0.76	0.07	0.53	5.64	5.18	82.28
XEM	0.06	0.01	0	0.46	1.47	0.11	0	0.03	8.62	8.21	9.35	9.15	23.79	10.08	7.51	8.38	0.4	0.25	0.49	6.04	5.59	76.21
XLM	0.02	0.03	0	0.53	1.36	0.1	0	0.05	9.15	8.56	10.07	10.13	8.5	20.05	7.47	11.42	0.64	0.08	0.52	5.62	5.68	79.95
XMR	0.04	0.01	0.02	0.5	2.29	0.08	0.02	0.04	10.99	10.57	10.59	10.74	6.57	7.76	20.81	6.42	0.68	0.12	0.61	5.76	5.41	79.19
XRP	0.02	0.04	0	0.32	1.12	0.03	0.01	0.07	8.41	8.23	9.34	10.19	7.88	12.74	6.9	22.37	0.49	0.35	0.47	5.36	5.66	77.63
DAI	0	0.09	0.03	1.43	2.83	0.01	0.01	0.21	3.98	2.25	3.36	2.93	1.15	2.19	2.22	1.51	68.36	0	4.03	1.37	2.05	31.64
TUSD	0.1	0.09	0	0.04	0.15	0	0.06	0	0.64	0.92	0.47	0.47	1.03	0.45	0.61	1.49	0.02	89	3.05	1.27	0.13	11
USDC	0.05	0.09	0.02	0.35	1.98	0.08	0	0.05	4.25	2.54	4.29	3.29	2.29	2.81	3.15	2.32	4.14	2.19	61.72	2.3	2.1	38.28
MANA	0	0	0	0.6	2.22	0.09	0.03	0.07	8.57	7.5	8.93	8.62	6.88	7.59	7.49	6.49	0.54	0.36	0.63	27.07	6.31	72.93
STACKS	0.03	0.26	0.02	0.86	1.94	0.06	0.05	0.06	8.42	6.82	9.15	8.11	6.52	7.86	7.21	7.02	0.83	0.03	0.54	6.47	27.75	72.25
TO	2.3	6.44	7.16	56.86	75.8	4.22	28.03	12.2	112.88	90.58	118.4	112.91	76.87	96.1	91.67	81.52	14.57	4.6	15.42	67.47	64.98	1140.97
Inc.Own	98.45	99.28	58.72	87.35	115.27	59.61	95.39	102.75	131.19	111.16	136.07	130.63	100.66	116.15	112.48	103.89	82.94	93.6	77.14	94.54	92.73	cTCI/TCI
NET	−1.55	−0.72	−41.28	−12.65	15.27	−40.39	−4.61	2.75	31.19	11.16	36.07	30.63	0.66	16.15	12.48	3.89	−17.06	−6.4	−22.86	−5.46	−7.27	57.05/54.33
NPT	4	3	1	5	9	0	5	5	18	16	20	19	13	17	15	14	8	7	8	12	11	

Notes: Table 5 presents the Spillover Table for stock returns using the Net Elastic Estimator with ridge regression. The table provides insights into the interconnectedness and spillover effects among various financial and economic variables, cryptocurrencies, stablecoins, and non-fungible tokens. The variables included in the analysis are: 1. Measures of Financial Stability: Central Bank Digital Currency Index (CBDC), Global Systemic Risk (SRISK), Global TED Spread (TED), Global Financial Condition Index (FCI), and Volatility Index (VIX). 2. Measures of Economic Uncertainty: US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ER), Twitter-based Economic Uncertainty Index (TWEETS), and Geopolitical Risk Index (GPR). 3. Cryptocurrencies: Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), and Ripple (XRP). 4. Stablecoins: Dai (DAI), True USD (TUSD), and USD Coin (USDC). 5. Non-Fungible Tokens: Decentraland (MANA) and Stacks (STACKS). The table presents several measures of connectedness and spillover effects: The "FROM" column represents the total spillover received by each variable from all other variables in the network. The "TO" row represents the total spillover transmitted by each variable to all other variables in the network. The "Inc.Own" row represents the incremental own-variable spillover, which measures the spillover from a variable to itself. The "NET" row represents the net spillover effect, calculated as the difference between the "TO" and "FROM" values. Positive values indicate that the variable is a net transmitter of spillovers, while negative values indicate that the variable is a net receiver of spillovers. The "NPT" row represents the number of pairwise transmissions, which counts the number of significant pairwise spillovers between variables. The table also includes the Total Connectedness Index (TCI), which measures the overall connectedness or interdependence among the variables, and the Conditional Total Connectedness Index (cTCI), which measures the connectedness after controlling for other factors or variables. The ratio of cTCI to TCI (cTCI/TCI) is provided to assess the relative importance of direct connections between variables compared to the overall connectedness of the network. The Spillover Table helps to identify the key drivers of spillovers and the most interconnected variables within the network, providing valuable insights into the transmission of shocks and the overall stability of the financial system.

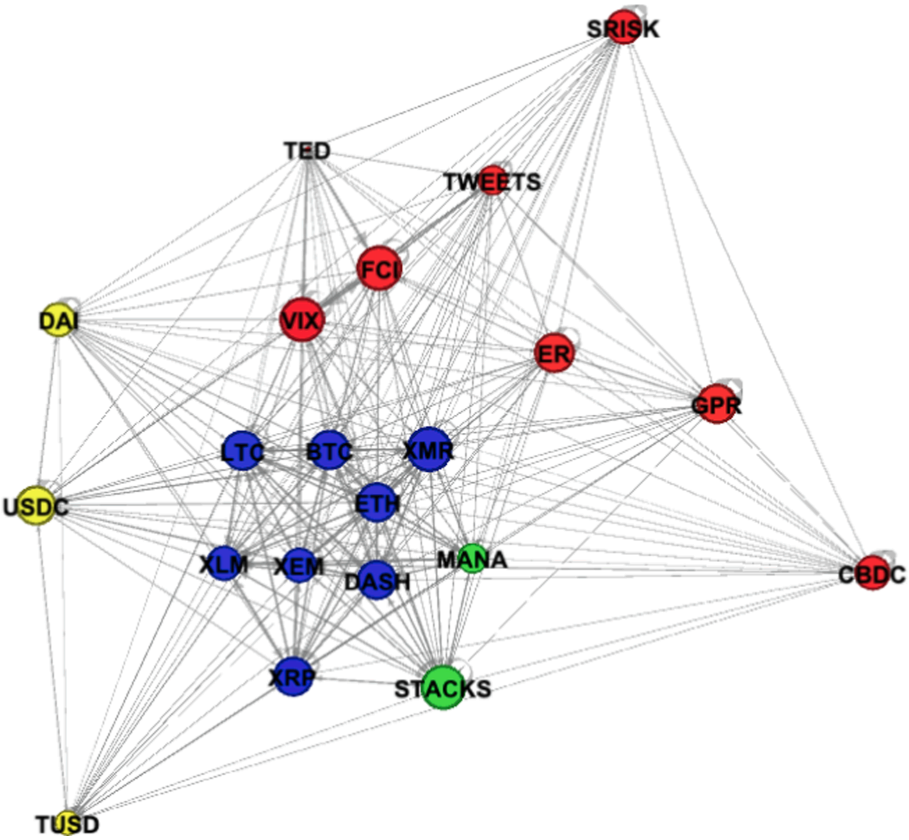

Fig. 7. Network Representation of Estimated Connectedness (Returns, Ridge Regularisation) **Notes**: This figure presents a network representation of the estimated connectedness among various assets, including cryptocurrencies, stablecoins, NFTs, and measures of financial stability, based on their returns using ridge regularisation. The nodes in the network represent individual assets, while the edges represent the strength and direction of connectedness between them. The size of the nodes indicates their degree of connectedness, with larger nodes having more connections. The colour of the nodes corresponds to the type of asset: blue for cryptocurrencies, yellow for stablecoins, green for NFTs, and red for stability measures. The thickness of the edges reflects the strength of the connectedness, with thicker edges indicating stronger connections. The network exhibits high density, with each node having between 34 and 42 connections. The clustering coefficient is 0.96, indicating a high level of local connectedness. The closeness centrality is 1.00 for most nodes, suggesting efficient information flow within the network. The harmonic centrality is also 1.00 for most nodes, with a few having values between 0.95 and 0.98. The coefficient of assortativity is −0.1059771, indicating a slight tendency for nodes with dissimilar degrees to connect. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 6
Spillover Table, Stock Returns Using Net Elastic Estimator – Lasso Regression.

	CBDC	SRISK	TED	FCI	VIX	ER	TWEETS	GPR	BTC	DASH	ETH	LTC	XEM	XLM	XMR	XRP	DAI	TUSD	USDC	MANA	STACKS	FROM
CBDC	97.56	0.09	0.1	0.02	0.01	0.35	0	0.04	0.16	0.12	0.25	0.12	0.3	0.13	0.18	0.08	0.02	0.3	0.08	0.02	0.08	2.44
SRISK	0.08	96.27	0.37	0.01	0.09	0.04	1.18	0.01	0.05	0	0.04	0.02	0.02	0.14	0.03	0.16	0.21	0.08	0.08	0	1.12	3.73
TED	0.09	0.28	80.79	14.81	2.68	0.03	0.01	0	0.17	0.07	0.17	0.12	0.1	0.13	0.09	0.06	0.05	0	0.07	0.21	0.07	19.21
FCI	0.01	0	3.2	39.46	24.95	0.73	0.56	0.01	4.36	1.65	4.14	3.27	2.25	2.54	3.22	1.64	1.96	0.01	0.84	2.76	2.44	60.54
VIX	0	0.03	0.15	16.15	38.55	0.01	0.57	0	6.06	3.33	5.88	5.15	2.61	3.27	4.51	2.42	2.76	0.05	1.53	3.84	3.12	61.45
ER	0.34	0.04	0.08	2.38	0.14	87.04	0.01	0.44	1.23	0.95	1.77	1.2	0.91	1.13	0.79	0.67	0	0.12	0.11	0.26	0.4	12.96
TWEETS	0	0.61	0.46	9.13	6.23	0.12	74.71	0.99	1.08	0.49	0.97	0.95	0.39	0.49	0.92	0.42	0.37	0.03	0.14	0.71	0.78	25.29
GPR	0.04	0.02	0	0.03	0	0.67	1.26	95.35	0.17	0.15	0.45	0.41	0.1	0.18	0.16	0.28	0.16	0.01	0.17	0.26	0.12	4.65
BTC	0.03	0.01	0	1.36	2.84	0.06	0.04	0.03	18.09	8.25	12.85	12	6.55	8.26	9.55	6.81	1.05	0.13	0.87	5.73	5.49	81.91
DASH	0.03	0	0.04	0.47	1.77	0.07	0.03	0.03	9.33	20.48	10.01	11.95	7.07	8.74	10.39	7.54	0.67	0.2	0.46	5.68	5.03	79.52
ETH	0.04	0.01	0	1.24	2.67	0.12	0.03	0.08	12.42	8.55	17.5	12.13	6.88	8.79	8.9	7.3	0.86	0.09	0.85	5.77	5.77	82.5
LTC	0.02	0	0	0.93	2.35	0.07	0.05	0.07	11.65	10.25	12.17	17.57	6.75	8.87	9.06	8	0.75	0.09	0.59	5.6	5.14	82.43
XEM	0.07	0	0	0.99	1.6	0.09	0	0.02	8.56	8.15	9.28	9.08	23.63	10.01	7.45	8.32	0.4	0.27	0.51	6	5.55	76.37
XLM	0.03	0.03	0	0.9	1.69	0.09	0.01	0.04	9.08	8.49	10	10.05	8.43	19.89	7.41	11.33	0.64	0.1	0.58	5.58	5.64	80.11
XMR	0.04	0.01	0.01	1.14	2.41	0.05	0.05	0.03	10.89	10.47	10.49	10.64	6.51	7.69	20.63	6.36	0.67	0.14	0.72	5.71	5.36	79.37
XRP	0.02	0.04	0	0.61	1.4	0.05	0.02	0.06	8.36	8.18	9.27	10.12	7.83	12.66	6.85	22.22	0.49	0.37	0.5	5.33	5.62	77.78
DAI	0.01	0.14	0.04	2.25	4.71	0.02	0.01	0.11	3.83	2.16	3.23	2.82	1.11	2.11	2.14	1.45	65.83	0	4.74	1.32	1.97	34.17
TUSD	0.27	0.07	0.01	0	0.12	0.16	0.04	0.01	0.63	0.88	0.45	0.44	1	0.43	0.59	1.49	0	88.55	3.49	1.26	0.1	11.45
USDC	0.06	0.06	0.13	0.86	2.7	0.03	0	0.12	3.25	1.52	3.28	2.28	1.47	1.98	2.35	1.53	4.87	2.67	67.7	1.74	1.4	32.3
MANA	0	0	0	1.28	2.66	0.01	0.04	0.07	8.47	7.42	8.83	8.52	6.8	7.5	7.4	6.41	0.54	0.38	0.69	26.75	6.24	73.25
STACKS	0.02	0.31	0.01	1.21	2.22	0.02	0.07	0.03	8.36	6.77	9.09	8.06	6.47	7.81	7.16	6.97	0.83	0.03	0.57	6.43	27.56	72.44
TO	1.21	1.75	4.62	55.77	63.24	2.79	3.96	2.22	108.12	87.86	112.6	109.33	73.54	92.88	89.17	79.26	17.29	5.07	17.59	64.19	61.41	1053.89
Inc.Own	98.77	98.01	85.41	95.23	101.79	89.83	78.67	97.57	126.21	108.34	130.1	126.9	97.17	112.77	109.8	101.48	83.12	93.62	85.3	90.94	88.97	cTCI/TCI
NET	−1.23	−1.99	−14.59	−4.77	1.79	−10.17	−21.33	−2.43	26.21	8.34	30.1	26.9	−2.83	12.77	9.8	1.48	−16.88	−6.38	−14.7	−9.06	−11.03	52.69/50.19
NPT	1	3	6	8	10	5	3	2	18	16	20	19	13	17	15	14	7	4	6	12	11	

Notes: Table 6 presents the Spillover Table for stock returns using the Net Elastic Estimator with lasso regression. The table provides insights into the interconnectedness and spillover effects among various financial and economic variables, cryptocurrencies, stablecoins, and non-fungible tokens. The variables included in the analysis are: 1. Measures of Financial Stability: Central Bank Digital Currency Index (CBDC), Global Systemic Risk (SRISK), Global TED Spread (TED), Global Financial Condition Index (FCI), and Volatility Index (VIX). 2. Measures of Economic Uncertainty: US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ER), Twitter-based Economic Uncertainty Index (TWEETS), and Geopolitical Risk Index (GPR). 3. Cryptocurrencies: Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), and Ripple (XRP). 4. Stablecoins: Dai (DAI), True USD (TUSD), and USD Coin (USDC). 5. Non-Fungible Tokens: Decentraland (MANA) and Stacks (STACKS). The table presents several measures of connectedness and spillover effects: The "FROM" column represents the total spillover received by each variable from all other variables in the network. The "TO" row represents the total spillover transmitted by each variable to all other variables in the network. The "Inc.Own" row represents the incremental own-variable spillover, which measures the spillover from a variable to itself. The "NET" row represents the net spillover effect, calculated as the difference between the "TO" and "FROM" values. Positive values indicate that the variable is a net transmitter of spillovers, while negative values indicate that the variable is a net receiver of spillovers. The "NPT" row represents the number of pairwise transmissions, which counts the number of significant pairwise spillovers between variables. The table also includes the Total Connectedness Index (TCI), which measures the overall connectedness or interdependence among the variables, and the Conditional Total Connectedness Index (cTCI), which measures the connectedness after controlling for other factors or variables. The ratio of cTCI to TCI (cTCI/TCI) is provided to assess the relative importance of direct connections between variables compared to the overall connectedness of the network. The Spillover Table helps to identify the key drivers of spillovers and the most interconnected variables within the network, providing valuable insights into the transmission of shocks and the overall stability of the financial system.

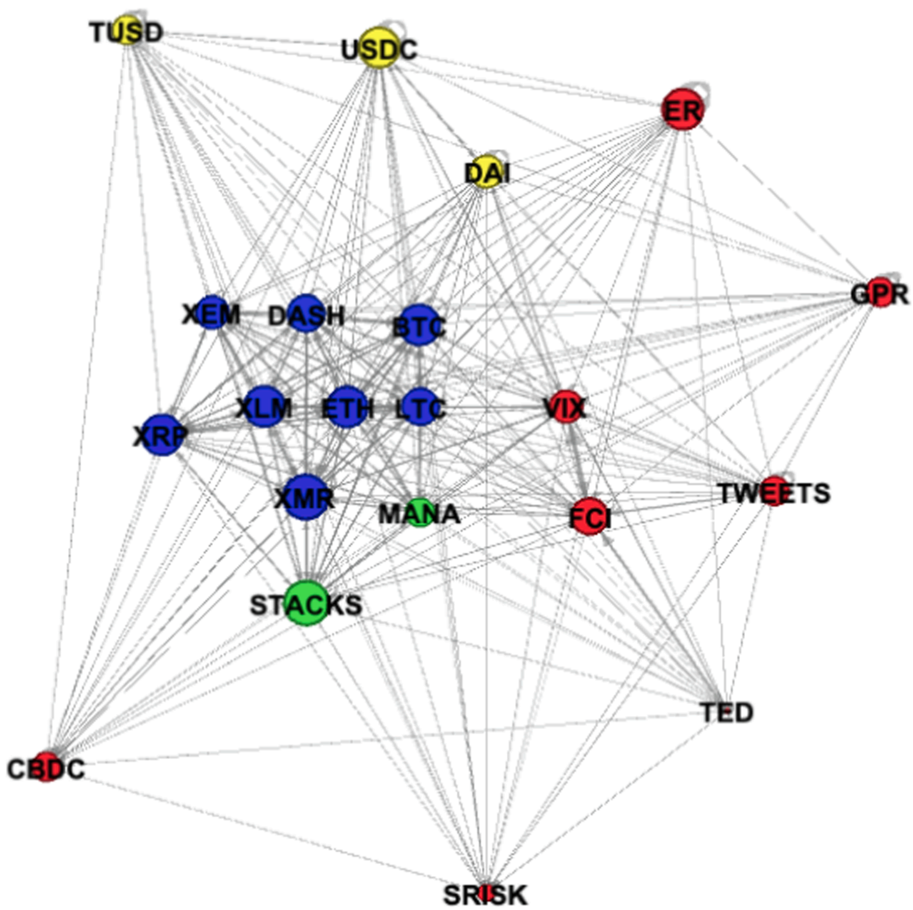

Fig. 8. Network Representation of Estimated Connectedness (Returns, Lasso Regularisation). **Notes**: This figure displays a network representation of the estimated connectedness among various assets based on their returns using lasso regularisation. The interpretation of the nodes, edges, and colours is similar to Fig. 7. The network exhibits high density, with each node having between 32 and 42 connections. The clustering coefficient ranges between 0.93 and 0.95, indicating a high level of local connectedness. The closeness centrality is 1.00 for one node, 0.95 for most nodes, and between 0.87 and 0.91 for five nodes, suggesting varying levels of information flow efficiency. The harmonic centrality is 1.00 for one node, between 0.95 and 0.98 for most nodes, and 0.93 for five nodes. The coefficient of assortativity is −0.0667007, indicating a slight tendency for nodes with dissimilar degrees to connect.

Table 7
Spillover Table, Stock Risk Using Net Elastic Estimator – Ridge Regression.

	CBDC	SRISK	TED	FCI	VIX	ER	TWEETS	GPR	BTC	DASH	ETH	LTC	XEM	XLM	XMR	XRP	DAI	TUSD	USDC	MANA	STACKS	FROM
CBDC	92.51	0.86	0.09	0.06	0.02	0.09	0.3	0.85	0.51	1.04	0.42	0.56	0.18	0.35	1.09	0.31	0.13	0.27	0.09	0.1	0.17	7.49
SRISK	0.09	91.31	0.83	0.2	0.57	0.08	2.68	0.23	0.06	0.5	0.13	0.25	0.22	0.44	0.08	0.38	0.55	0.09	0.73	0.02	0.57	8.69
TED	0.03	1.52	38.96	11.86	7.27	0.55	1.32	0.28	5.45	3.46	5.62	4.89	0.96	1.31	4.69	0.69	2.45	0.22	5.06	1.78	1.62	61.04
FCI	0.21	0.05	4.19	34.33	26.64	0.86	11.78	0.16	3.04	0.64	3.82	1.87	0.24	0.3	1.44	0.09	3.97	0.03	4.79	0.7	0.85	65.67
VIX	0.27	0.17	0.47	18.62	43.91	0.04	6.87	0.13	3.78	1.2	4.76	3.01	1.04	1.15	2.6	0.37	4.17	0.28	4.24	1.43	1.47	56.09
ER	0.4	1.01	0.47	2.8	1.45	32.8	2.37	4.3	3.64	5.42	3.82	6.59	5.24	7.56	5.47	5.98	2.67	0.35	1.62	2.7	3.33	67.2
TWEETS	0.13	1.49	0.54	10.57	8.65	0.41	68.69	1.83	0.62	1.26	0.13	0.65	0.35	0.21	1.71	0.59	1.2	0.07	0.28	0.39	0.24	31.31
GPR	0.26	0.03	0.02	0.52	0.34	1.13	1.78	90.16	0.38	0.12	0.47	0.43	0.55	0.53	0.2	0.39	1.03	0.09	0.48	0.42	0.66	9.84
BTC	0.03	0.03	0.01	0.12	0.36	0.02	0.09	0.06	17.81	8.37	13.89	11.32	5.78	7.37	10.12	5.49	3.35	0.5	4.34	5.11	5.85	82.19
DASH	0.14	0.41	0	0.04	0.06	0.04	0.18	0.11	8.93	20.79	10.02	11.47	6.7	8.6	11.43	6.67	1.63	0.61	2.46	4.81	4.89	79.21
ETH	0.03	0.03	0.01	0.07	0.21	0.01	0.01	0.03	12.15	8.21	17.78	11.88	6.55	7.68	10.29	5.88	3.64	0.43	3.8	5.35	5.95	82.22
LTC	0.14	0.1	0	0.02	0.07	0.03	0.08	0.03	10.3	10.42	12.27	15.84	7.47	8.35	11.33	7.35	2	0.8	3.02	4.92	5.43	84.16
XEM	0.01	0.03	0	0.01	0.07	0.03	0.01	0.01	6.64	7.38	8.2	9.76	28.2	9.07	8.24	7.64	0.72	0.44	1.13	6.38	6.01	71.8
XLM	0.01	0.06	0	0.01	0.1	0.07	0	0.02	8.01	7.91	10.32	9.88	8.5	22.09	7.19	12.86	1.49	0.45	1.73	3.76	5.55	77.91
XMR	0.38	0.17	0	0.03	0.13	0.04	0.29	0.3	10.15	11.36	11.6	12.16	7.1	7.17	17.99	5.49	1.74	0.31	2.78	5.41	5.41	82.01
XRP	0.01	0.09	0	0.03	0.05	0.05	0.06	0.02	6.57	6.47	8.09	9.44	7.52	13.45	6.13	29.03	0.79	0.49	1.26	3.27	7.19	70.97
DAI	0.04	0.38	0.05	0.63	1.03	0.11	0.43	0.45	7.1	2.95	8.89	5.15	1.86	2.56	3.96	1.52	45.19	0.01	9.99	2.97	4.74	54.81
TUSD	0.15	0.15	0.02	0.07	0.21	0.24	0.08	0.04	8.33	6.18	8.37	7.56	4.93	6.2	4.18	6.59	0.31	38.23	1.38	3.12	3.65	61.77
USDC	0.01	0.41	0.1	0.46	0.61	0.03	0.09	0.06	8.58	5.27	9.41	7.29	3.17	4.08	6.21	3.02	8.75	0.39	33.78	3.86	4.4	66.22
MANA	0.02	0.01	0.04	0.01	0.07	0.03	0.12	0.01	7.68	6.84	8.92	8.37	9.17	6.27	8.1	4.45	1.59	0.36	2.24	31.27	4.45	68.73
STACKS	0.02	0.39	0	0.01	0.08	0.02	0.02	0.01	7.98	5.92	8.71	7.87	6.28	6.62	7.23	7.53	2.66	0.24	2.66	4.34	31.38	68.62
TO	2.39	7.38	6.86	46.15	47.99	3.9	28.58	8.91	119.88	100.92	137.84	130.41	83.82	99.29	111.7	83.31	44.84	6.42	54.08	60.85	72.42	1257.94
Inc.Own	94.9	98.69	45.82	80.48	91.9	36.7	97.27	99.08	137.69	121.72	155.63	146.25	112.02	121.38	129.69	112.34	90.03	44.65	87.87	92.12	103.8	cTCI/TCI
NET	−5.1	−1.31	−54.18	−19.52	−8.1	−63.3	−2.73	−0.92	37.69	21.72	55.63	46.25	12.02	21.38	29.69	12.34	−9.97	−55.35	−12.13	−7.88	3.8	62.90/59.90
NPT	3	5	1	5	6	1	6	6	18	14	20	19	13	16	15	15	9	5	10	11	12	

Notes: Table 7 presents the Spillover Table for stock risk using the Net Elastic Estimator with ridge regression. The table provides insights into the interconnectedness and spillover effects among various financial and economic variables, cryptocurrencies, stablecoins, and non-fungible tokens. The variables included in the analysis are: 1. Measures of Financial Stability: Central Bank Digital Currency Index (CBDC), Global Systemic Risk (SRISK), Global TED Spread (TED), Global Financial Condition Index (FCI), and Volatility Index (VIX). 2. Measures of Economic Uncertainty: US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ER), Twitter-based Economic Uncertainty Index (TWEETS), and Geopolitical Risk Index (GPR). 3. Cryptocurrencies: Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), and Ripple (XRP). 4. Stablecoins: Dai (DAI), True USD (TUSD), and USD Coin (USDC). 5. Non-Fungible Tokens: Decentraland (MANA) and Stacks (STACKS). The table presents several measures of connectedness and spillover effects: The "FROM" column represents the total spillover received by each variable from all other variables in the network. The "TO" row represents the total spillover transmitted by each variable to all other variables in the network. The "Inc.Own" row represents the incremental own-variable spillover, which measures the spillover from a variable to itself. The "NET" row represents the net spillover effect, calculated as the difference between the "TO" and "FROM" values. Positive values indicate that the variable is a net transmitter of spillovers, while negative values indicate that the variable is a net receiver of spillovers. The "NPT" row represents the number of pairwise transmissions, which counts the number of significant pairwise spillovers between variables. The table also includes the Total Connectedness Index (TCI), which measures the overall connectedness or interdependence among the variables, and the Conditional Total Connectedness Index (cTCI), which measures the connectedness after controlling for other factors or variables. The ratio of cTCI to TCI (cTCI/TCI) is provided to assess the relative importance of direct connections between variables compared to the overall connectedness of the network. The Spillover Table helps to identify the key drivers of spillovers and the most interconnected variables within the network, providing valuable insights into the transmission of shocks and the overall stability of the financial system.

Table 8
Spillover Table, Stock Risk Using Net Elastic Estimator – Lasso Regression.

	CBDC	SRISK	TED	FCI	VIX	ER	TWEETS	GPR	BTC	DASH	ETH	LTC	XEM	XLM	XMR	XRP	DAI	TUSD	USDC	MANA	STACKS	FROM
CBDC	99.05	0.09	0.11	0.02	0.01	0.34	0.01	0.04	0	0.03	0.03	0	0	0.02	0.1	0	0.04	0.02	0	0.01	0.07	0.95
SRISK	0.08	96.04	0.36	0.02	0.11	0.05	1.08	0.01	0.01	0.25	0.19	0.15	0.05	0.37	0	0.28	0.21	0	0.23	0	0.5	3.96
TED	0.09	0.27	78.14	13.6	1.77	0.02	0.01	0	0.83	0.38	0.89	0.71	0.13	0.15	0.45	0.1	0.54	0.07	1.13	0.42	0.29	21.86
FCI	0.01	0	4.51	56.41	36.33	1.11	0.82	0.01	0.05	0.04	0.02	0.01	0.09	0.08	0.1	0.14	0.02	0.05	0.13	0.05	0.02	43.59
VIX	0	0.06	0.28	26.72	64.84	0.02	0.79	0	1.14	0.64	0.51	0.5	0.63	0.75	0.95	0.66	0.3	0.18	0.03	0.62	0.39	35.16
ER	0.33	0.04	0.07	2.05	0.02	94.61	0.02	0.44	0.32	0.2	0.06	0	0	0.06	0.18	0	0.14	1.21	0.15	0.03	0.05	5.39
TWEETS	0.01	0.52	0.01	14.16	11.18	0.24	66.73	0.9	0.74	0.83	0.4	0.61	0.4	0.39	1.61	0.35	0.19	0.1	0.03	0.3	0.3	33.27
GPR	0.05	0.01	0	0.02	0	0.68	1.19	96.63	0.05	0.03	0.06	0.05	0.14	0.12	0.14	0.02	0.47	0.03	0.07	0.1	0.1	3.37
BTC	0	0	0.03	0.03	0.26	0.07	0.01	0.01	20.25	7.31	14.44	12.06	5	6.72	10.16	4.75	3.65	0.65	4.32	4.79	5.51	79.75
DASH	0.01	0.06	0.02	0	0.24	0.05	0.04	0.01	8.59	24.56	9.31	12.55	5.63	7.69	12.42	5.69	1.37	0.53	2.14	4.69	4.39	75.44
ETH	0.01	0.04	0.04	0.03	0.16	0.01	0	0.01	13.31	7.52	19.83	13.01	5.41	6.79	10.15	5.19	3.71	0.52	3.95	4.9	5.42	80.17
LTC	0	0.03	0.03	0.01	0.15	0	0.01	0.01	10.91	9.74	12.47	18.94	6.5	7.19	11.38	6.1	2.62	0.77	3.06	4.81	5.28	81.06
XEM	0	0.02	0	0.01	0.29	0	0	0.03	7.07	6.79	8.08	10.13	29.62	9.12	8.14	6.83	0.87	0.47	1.15	6.04	5.35	70.38
XLM	0	0.1	0	0	0.29	0.02	0	0.02	8.15	7.92	8.65	9.57	7.78	25.28	7.61	11.33	1.43	0.58	1.63	4.03	5.59	74.72
XMR	0.02	0	0.02	0	0.32	0.04	0.06	0.04	10.45	10.84	10.96	12.68	5.89	6.46	21.44	4.85	2.08	0.31	2.84	5.02	5.67	78.56
XRP	0	0.09	0	0.02	0.3	0	0	0	6.65	6.8	7.69	9.43	6.77	13.16	6.65	29.36	0.86	0.55	1.2	3.63	6.83	70.64
DAI	0.02	0.1	0.16	0.02	0.19	0.07	0.01	0.12	8.08	2.58	8.67	6.38	1.35	2.6	4.48	1.35	46.45	0.01	10.65	2.34	4.38	53.55
TUSD	0.02	0	0.04	0.03	0.22	1.03	0.01	0.02	2.58	1.75	2.1	3.29	1.27	1.85	1.18	1.52	0.01	80.48	1.17	0.69	0.74	19.52
USDC	0	0.1	0.32	0.11	0.02	0.07	0.01	0.01	8.88	3.73	8.51	6.89	1.66	2.76	5.66	1.75	9.8	0.62	42.78	2.84	3.47	57.22
MANA	0.01	0	0.07	0	0.33	0.01	0	0.02	7.9	6.57	8.48	8.67	7.01	5.48	8.04	4.24	1.74	0.3	2.28	34.36	4.5	65.64
STACKS	0.02	0.16	0.02	0	0.19	0.02	0	0	8.21	5.55	8.48	8.61	5.61	6.87	8.22	7.22	2.93	0.28	2.52	4.07	31.04	68.96
TO	0.67	1.69	6.1	56.83	52.39	3.84	4.07	1.68	103.91	79.5	110	115.32	61.32	78.65	97.64	62.36	32.99	7.27	38.68	49.37	58.85	1023.15
Inc.Own	99.73	97.74	84.25	113.24	117.23	98.45	70.8	98.31	124.16	104.06	129.84	134.26	90.94	103.93	119.07	91.73	79.44	87.75	81.46	83.73	89.89	cTCI/TCI
NET	−0.27	−2.26	−15.75	13.24	17.23	−1.55	−29.2	−1.69	24.16	4.06	29.84	34.26	−9.06	3.93	19.07	−8.27	−20.56	−12.25	−18.54	−16.27	−10.11	51.16/48.72
NPT	1	2	5	7	8	4	3	0	18	16	18	20	13	15	17	14	9	7	10	11	12	

Notes: Table 8 presents the Spillover Table for stock risk using the Net Elastic Estimator with lasso regression. The table provides insights into the interconnectedness and spillover effects among various financial and economic variables, cryptocurrencies, stablecoins, and non-fungible tokens. The variables included in the analysis are: 1. Measures of Financial Stability: Central Bank Digital Currency Index (CBDC), Global Systemic Risk (SRISK), Global TED Spread (TED), Global Financial Condition Index (FCI), and Volatility Index (VIX). 2. Measures of Economic Uncertainty: US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ER), Twitter-based Economic Uncertainty Index (TWEETS), and Geopolitical Risk Index (GPR). 3. Cryptocurrencies: Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), and Ripple (XRP). 4. Stablecoins: Dai (DAI), True USD (TUSD), and USD Coin (USDC). 5. Non-Fungible Tokens: Decentraland (MANA) and Stacks (STACKS). The table presents several measures of connectedness and spillover effects: The "FROM" column represents the total spillover received by each variable from all other variables in the network. The "TO" row represents the total spillover transmitted by each variable to all other variables in the network. The "Inc.Own" row represents the incremental own-variable spillover, which measures the spillover from a variable to itself. The "NET" row represents the net spillover effect, calculated as the difference between the "TO" and "FROM" values. Positive values indicate that the variable is a net transmitter of spillovers, while negative values indicate that the variable is a net receiver of spillovers. The "NPT" row represents the number of pairwise transmissions, which counts the number of significant pairwise spillovers between variables. The table also includes the Total Connectedness Index (TCI), which measures the overall connectedness or interdependence among the variables, and the Conditional Total Connectedness Index (cTCI), which measures the connectedness after controlling for other factors or variables. The ratio of cTCI to TCI (cTCI/TCI) is provided to assess the relative importance of direct connections between variables compared to the overall connectedness of the network. The Spillover Table helps to identify the key drivers of spillovers and the most interconnected variables within the network, providing valuable insights into the transmission of shocks and the overall stability of the financial system.

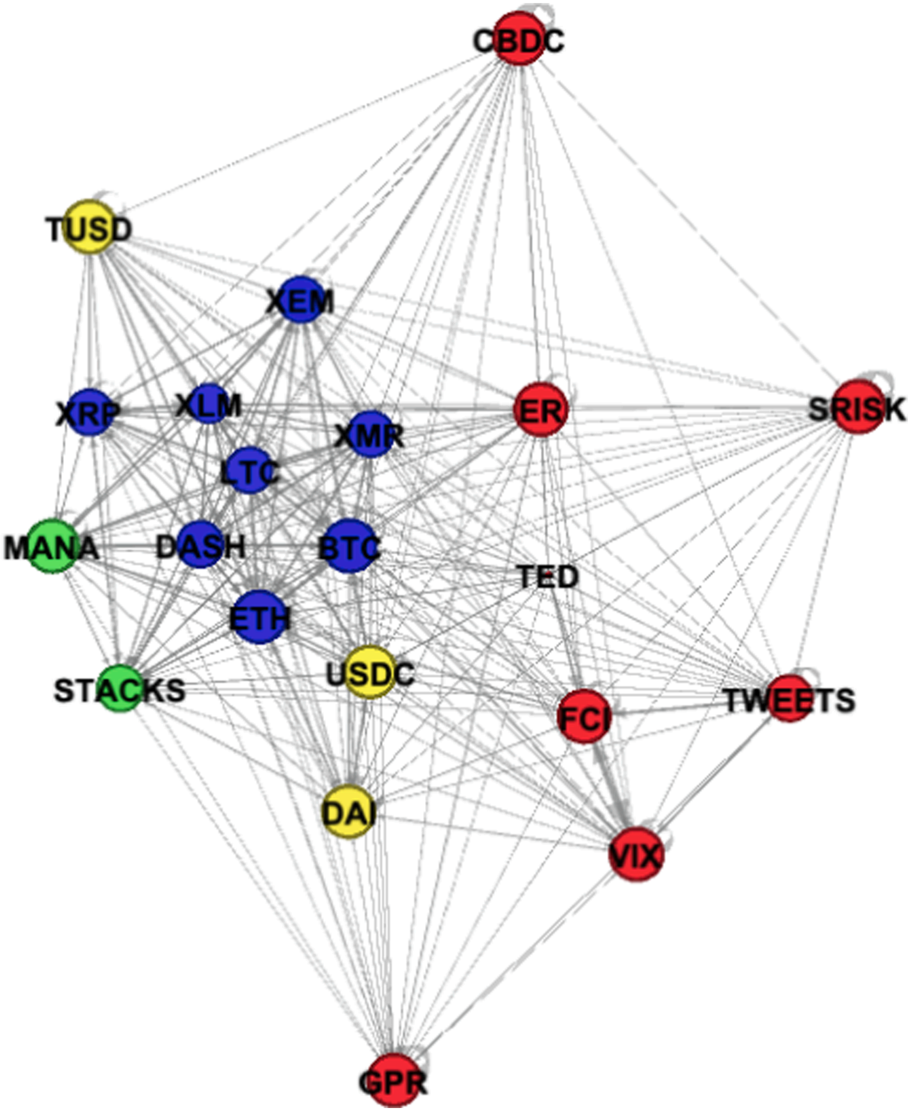

Fig. 9. Network Representation of Estimated Connectedness (Risk, Ridge Regularisation). **Notes:** This figure presents a network representation of the estimated connectedness among various assets based on their risk using ridge regularisation. The interpretation of the nodes, edges, and colours is similar to Fig. 7. The network has a density where nodes have between 35 and 42 connections. The closeness centrality is 1.00 for all nodes except one, suggesting high information flow efficiency. The harmonic centrality is also 1.00 for all nodes except one. The coefficient of assortativity is −0.1213712, indicating a slight tendency for nodes with dissimilar degrees to connect.

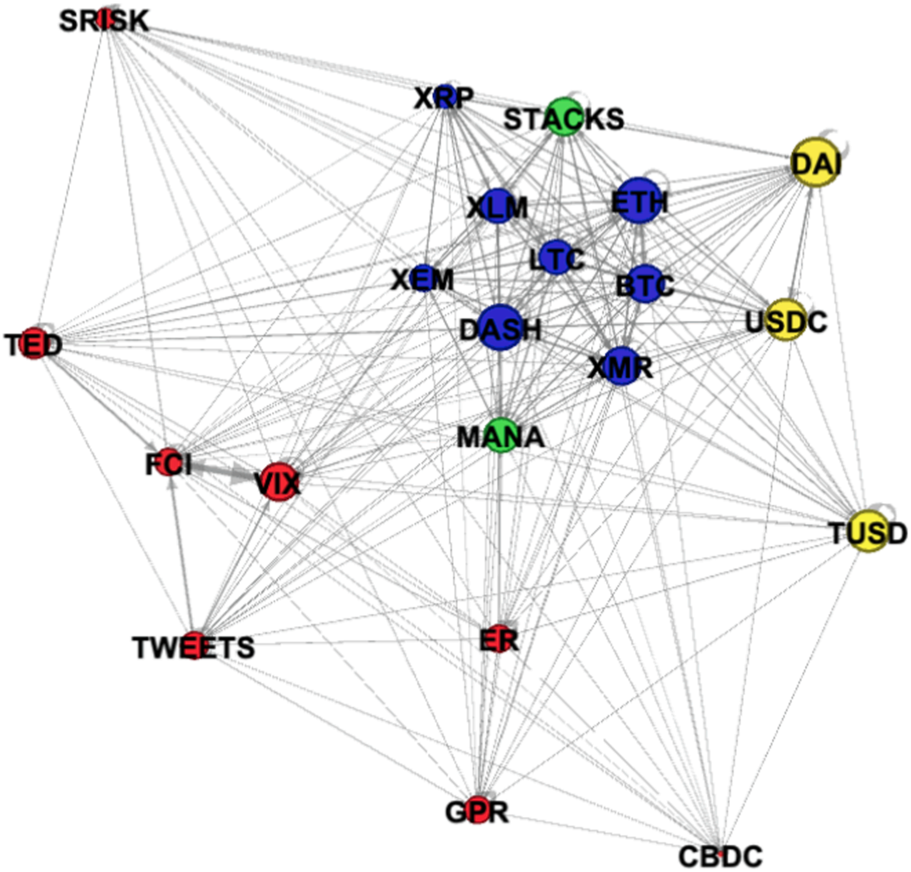

Fig. 10. Network Representation of Estimated Connectedness (Risk, Lasso Regularisation). **Notes:** This figure displays a network representation of the estimated connectedness among various assets based on their risk using lasso regularisation. The interpretation of the nodes, edges, and colours is similar to Figure 7. The network has a density where nodes have between 30 and 42 connections. The closeness centrality is 1.00 for some nodes and between 0.80 and 0.95 for others, indicating varying levels of information flow efficiency. The harmonic centrality is 1.00 for some nodes and between 0.875 and 0.975 for others. The coefficient of assortativity is −0.0600541, suggesting a slight tendency for nodes with dissimilar degrees to connect.

curation.

Declaration of competing interest

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.

Data availability

Data will be made available on request.

Appendix A1. Spillover table, stock returns using ridge regression

	CBDC	SRISK	TED	FCI	VIX	ER	TWEETS	GPR	BTC	DASH	ETH	LTC	XEM	XLM	XMR	XRP	DAI	TUSD	USDC	MANA	STACKS	FROM
CBDC	96.09	0.79	0.06	0.08	0.06	0.19	0.17	0.82	0.11	0.17	0.26	0.18	0.25	0.06	0.36	0.04	0.01	0.12	0.09	0.02	0.06	6.92
SRISK	0.1	93.08	0.91	0.13	0.43	0.09	2.52	0.27	0.12	0.29	0.11	0.14	0.04	0.14	0.09	0.16	0.12	0.13	0.25	0.06	0.82	49.4
TED	0.09	2.07	50.6	17.88	14.13	0.54	2.59	0.08	1.76	0.57	1.87	1.28	1.04	1	0.98	0.65	0.32	0.11	0.48	1.17	0.8	69.51
FCI	0.15	0.02	3.87	30.49	27.3	0.55	9.82	0.23	3.96	1.59	4.22	3.08	1.98	2.31	2.48	1.52	0.93	0.12	0.53	2.48	2.39	60.32
VIX	0.25	0.09	0.5	16.34	39.68	0.09	5.58	0.27	5.05	2.82	5.35	4.52	2.53	2.82	4	1.98	1.24	0.13	0.65	3.24	2.87	44.17
ER	1.07	1.46	0.64	4.11	2.17	55.83	3.8	8.06	3.61	1.28	3.7	2.17	1.98	2.23	1.9	1.25	0.24	0.08	0.27	2.16	1.98	32.99
TWEETS	0.05	1.25	0.83	9.78	8.96	0.57	67.01	1.87	1.32	0.73	1.42	1.07	0.53	0.73	0.84	0.56	0.25	0.07	0.11	0.84	1.2	9.51
GPR	0.27	0.03	0.03	0.78	0.31	1.28	1.79	90.49	0.43	0.27	0.72	0.64	0.37	0.44	0.32	0.47	0.37	0.01	0.12	0.59	0.27	81.7
BTC	0.03	0.01	0	0.73	2.42	0.13	0.02	0.04	18.3	8.34	12.99	12.14	6.63	8.36	9.66	6.88	1.07	0.11	0.79	5.79	5.55	79.42
DASH	0.02	0	0.05	0.31	1.54	0.05	0.02	0.04	9.38	20.58	10.06	12.01	7.1	8.79	10.44	7.57	0.68	0.19	0.43	5.7	5.06	82.33
ETH	0.05	0.01	0	0.71	2.34	0.13	0.01	0.1	12.54	8.64	17.67	12.24	6.94	8.88	8.99	7.37	0.87	0.07	0.78	5.83	5.82	82.29
LTC	0.02	0.01	0	0.51	2.08	0.05	0.02	0.08	11.75	10.34	12.28	17.71	6.81	8.95	9.14	8.07	0.76	0.07	0.53	5.64	5.18	76.21
XEM	0.07	0	0	0.45	1.5	0.11	0	0.03	8.61	8.21	9.35	9.14	23.79	10.08	7.5	8.38	0.4	0.25	0.49	6.04	5.59	79.96
XLM	0.03	0.03	0	0.52	1.4	0.1	0	0.05	9.15	8.56	10.07	10.12	8.49	20.04	7.47	11.42	0.64	0.08	0.52	5.62	5.68	79.19
XMR	0.04	0	0.02	0.49	2.33	0.08	0.02	0.04	10.98	10.56	10.58	10.74	6.56	7.75	20.81	6.42	0.68	0.12	0.61	5.76	5.4	77.64
XRP	0.02	0.04	0	0.32	1.14	0.03	0.01	0.08	8.41	8.23	9.33	10.18	7.88	12.74	6.89	22.36	0.49	0.35	0.47	5.36	5.65	31.71
DAI	0	0.09	0.03	1.39	2.88	0.01	0.01	0.22	3.98	2.24	3.35	2.93	1.15	2.19	2.22	1.51	68.29	0.01	4.1	1.37	2.04	11.55
TUSD	0.1	0.09	0	0.04	0.17	0	0.06	0	0.7	0.98	0.52	0.52	1.1	0.5	0.64	1.55	0.03	88.45	3.07	1.32	0.15	38.01
USDC	0.05	0.08	0.02	0.34	2	0.08	0	0.05	4.2	2.5	4.25	3.26	2.26	2.78	3.11	2.3	4.2	2.18	61.99	2.28	2.07	72.94
MANA	0	0	0	0.59	2.26	0.09	0.03	0.07	8.57	7.5	8.93	8.62	6.87	7.59	7.49	6.48	0.54	0.36	0.63	27.06	6.31	72.25
STACKS	0.03	0.26	0.02	0.85	1.97	0.06	0.04	0.05	8.42	6.82	9.15	8.11	6.52	7.86	7.21	7.02	0.83	0.03	0.54	6.47	27.75	1141.93
TO	2.44	6.32	6.99	56.34	77.4	4.22	26.51	12.43	113.05	90.63	118.51	113.09	77.04	96.19	91.73	81.62	14.66	4.6	15.47	67.75	64.92	cTCI/TCI
Inc.Own	98.53	99.41	57.59	86.82	117.08	60.05	93.53	102.92	131.36	111.21	136.18	130.81	100.83	116.23	112.54	103.98	82.95	93.06	77.46	94.8	92.67	57.10/54.38
NET	−1.47	−0.59	−42.41	−13.18	17.08	−39.95	−6.47	2.92	31.36	11.21	36.18	30.81	0.83	16.23	12.54	3.98	−17.05	−6.94	−22.54	−5.2	−7.33	
NPT	4	3	1	5	9	0	5	5	18	16	20	19	13	17	15	14	8	7	8	12	11	

Notes: Table Appendix A1 presents the Spillover Table for stock returns using ridge regression. The table provides insights into the interconnectedness and spillover effects among various financial and economic variables, cryptocurrencies, stablecoins, and non-fungible tokens. The variables included in the analysis are: 1. Measures of Financial Stability: Central Bank Digital Currency Index (CBDC), Global Systemic Risk (SRISK), Global TED Spread (TED), Global Financial Condition Index (FCI), and Volatility Index (VIX). 2. Measures of Economic Uncertainty: US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ER), Twitter-based Economic Uncertainty Index (TWEETS), and Geopolitical Risk Index (GPR). 3. Cryptocurrencies: Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), and Ripple (XRP). 4. Stablecoins: Dai (DAI), True USD (TUSD), and USD Coin (USDC). 5. Non-Fungible Tokens: Decentraland (MANA) and Stacks (STACKS). The table presents several measures of connectedness and spillover effects: The "FROM" column represents the total spillover received by each variable from all other variables in the network. The "TO" row represents the total spillover transmitted by each variable to all other variables in the network. The "Inc.Own" row represents the incremental own-variable spillover, which measures the spillover from a variable to itself. The "NET" row represents the net spillover effect, calculated as the difference between the "TO" and "FROM" values. Positive values indicate that the variable is a net transmitter of spillovers, while negative values indicate that the variable is a net receiver of spillovers. The "NPT" row represents the number of pairwise transmissions, which counts the number of significant pairwise spillovers between variables. The table also includes the Total Connectedness Index (TCI), which measures the overall connectedness or interdependence among the variables, and the Conditional Total Connectedness Index (cTCI), which measures the connectedness after controlling for other factors or variables. The ratio of cTCI to TCI (cTCI/TCI) is provided to assess the relative importance of direct connections between variables compared to the overall connectedness of the network. The Spillover Table helps to identify the key drivers of spillovers and the most interconnected variables within the network, providing valuable insights into the transmission of shocks and the overall stability of the financial system.

Appendix A2. Spillover table, stock returns using lasso regression

	CBDC	SRISK	TED	FCI	VIX	ER	TWEETS	GPR	BTC	DASH	ETH	LTC	XEM	XLM	XMR	XRP	DAI	TUSD	USDC	MANA	STACKS	FROM
CBDC	97.6	0.09	0.11	0.02	0.01	0.34	0	0.06	0.16	0.12	0.25	0.12	0.3	0.13	0.18	0.08	0.02	0.24	0.08	0.02	0.08	2.4
SRISK	0.08	96.11	0.37	0.01	0.08	0.05	1.31	0.04	0.04	0	0.04	0.02	0.02	0.14	0.03	0.16	0.2	0.1	0.09	0	1.11	3.89
TED	0.09	0.28	79.39	15.13	3.26	0.04	0.03	0	0.25	0.07	0.24	0.17	0.14	0.18	0.13	0.09	0.07	0	0.06	0.27	0.1	20.61
FCI	0.01	0	3.11	39.38	24.91	0.75	0.71	0	4.36	1.65	4.14	3.28	2.25	2.54	3.22	1.64	1.97	0.02	0.87	2.75	2.44	60.62
VIX	0	0.03	0.13	16.12	38.35	0.01	0.78	0	6.07	3.33	5.88	5.15	2.61	3.28	4.52	2.42	2.76	0.06	1.52	3.83	3.13	61.65
ER	0.34	0.05	0.09	2.33	0.06	90.3	0	0.75	0.74	0.63	1.18	0.75	0.62	0.76	0.46	0.42	0.02	0.07	0.06	0.13	0.24	9.7
TWEETS	0	0.73	0.37	7.81	5.57	0.1	78.24	0.84	0.87	0.41	0.78	0.79	0.3	0.38	0.74	0.35	0.28	0.04	0.11	0.63	0.66	21.76
GPR	0.05	0.05	0	0.01	0	0.82	1.04	95.23	0.21	0.15	0.49	0.39	0.11	0.2	0.16	0.29	0.16	0	0.16	0.3	0.18	4.77
BTC	0.03	0.01	0	1.36	2.86	0.06	0.03	0.04	18.09	8.24	12.84	12	6.55	8.26	9.55	6.8	1.05	0.14	0.87	5.73	5.49	81.91
DASH	0.03	0	0.04	0.47	1.78	0.07	0.03	0.03	9.33	20.47	10.01	11.95	7.06	8.74	10.39	7.53	0.67	0.22	0.46	5.67	5.03	79.53
ETH	0.04	0.01	0	1.24	2.68	0.11	0.03	0.09	12.42	8.55	17.49	12.12	6.87	8.79	8.9	7.3	0.86	0.1	0.84	5.77	5.77	82.51
LTC	0.02	0	0	0.93	2.36	0.06	0.04	0.07	11.65	10.25	12.17	17.57	6.75	8.87	9.06	8	0.75	0.1	0.59	5.59	5.13	82.43
XEM	0.07	0	0	0.99	1.61	0.09	0	0.03	8.55	8.15	9.28	9.08	23.62	10.01	7.45	8.32	0.4	0.28	0.51	6	5.55	76.38
XLM	0.03	0.03	0	0.9	1.7	0.09	0	0.04	9.08	8.49	9.99	10.05	8.43	19.89	7.41	11.33	0.64	0.11	0.58	5.58	5.63	80.11
XMR	0.04	0.01	0.01	1.14	2.43	0.04	0.05	0.03	10.88	10.47	10.49	10.64	6.51	7.69	20.62	6.36	0.67	0.14	0.72	5.71	5.36	79.38
XRP	0.02	0.04	0	0.61	1.4	0.04	0.02	0.07	8.36	8.18	9.27	10.12	7.83	12.66	6.85	22.22	0.49	0.39	0.5	5.32	5.62	77.78
DAI	0.01	0.14	0.03	2.25	4.76	0.03	0.01	0.11	3.84	2.17	3.24	2.82	1.11	2.11	2.14	1.46	65.91	0	4.57	1.32	1.97	34.09
TUSD	0.21	0.09	0.01	0.02	0.15	0.09	0.05	0	0.7	0.94	0.5	0.48	1.06	0.48	0.6	1.57	0	88.18	3.45	1.3	0.12	11.82
USDC	0.06	0.07	0.13	0.9	2.7	0.02	0	0.11	3.26	1.52	3.27	2.27	1.48	1.97	2.38	1.52	4.7	2.66	67.86	1.74	1.39	32.14
MANA	0	0	0	1.28	2.67	0.01	0.05	0.08	8.47	7.41	8.82	8.52	6.79	7.5	7.4	6.41	0.53	0.39	0.69	26.74	6.24	73.26
STACKS	0.02	0.31	0.01	1.21	2.24	0.02	0.07	0.05	8.36	6.77	9.08	8.05	6.47	7.81	7.16	6.97	0.82	0.04	0.57	6.42	27.55	72.45
TO	1.16	1.91	4.43	54.73	63.24	2.83	4.26	2.46	107.6	87.51	111.97	108.77	73.27	92.5	88.74	79.01	17.09	5.1	17.28	64.09	61.22	1049.19
Inc.Own	98.76	98.02	83.82	94.11	101.59	93.13	82.5	97.7	125.69	107.99	129.47	126.34	96.89	112.38	109.37	101.23	82.99	93.29	85.14	90.83	88.77	cTCI/TCI
NET	−1.24	−1.98	−16.18	−5.89	1.59	−6.87	−17.5	−2.3	25.69	7.99	29.47	26.34	−3.11	12.38	9.37	1.23	−17.01	−6.71	−14.86	−9.17	−11.23	52.46/49.96
NPT	0	2	7	8	9	6	4	2	18	16	20	19	13	17	15	14	7	4	6	12	11	

Notes: Table Appendix A2 presents the Spillover Table for stock returns using lasso regression. The table provides insights into the interconnectedness and spillover effects among various financial and economic variables, cryptocurrencies, stablecoins, and non-fungible tokens. The variables included in the analysis are: 1. Measures of Financial Stability: Central Bank Digital Currency Index (CBDC), Global Systemic Risk (SRISK), Global TED Spread (TED), Global Financial Condition Index (FCI), and Volatility Index (VIX). 2. Measures of Economic Uncertainty: US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ER), Twitter-based Economic Uncertainty Index (TWEETS), and Geopolitical Risk Index (GPR). 3. Cryptocurrencies: Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), and Ripple (XRP). 4. Stablecoins: Dai (DAI), True USD (TUSD), and USD Coin (USDC). 5. Non-Fungible Tokens: Decentraland (MANA) and Stacks (STACKS). The table presents several measures of connectedness and spillover effects: The "FROM" column represents the total spillover received by each variable from all other variables in the network. The "TO" row represents the total spillover transmitted by each variable to all other variables in the network. The "Inc.Own" row represents the incremental own-variable spillover, which measures the spillover from a variable to itself. The "NET" row represents the net spillover effect, calculated as the difference between the "TO" and "FROM" values. Positive values indicate that the variable is a net transmitter of spillovers, while negative values indicate that the variable is a net receiver of spillovers. The "NPT" row represents the number of pairwise transmissions, which counts the number of significant pairwise spillovers between variables. The table also includes the Total Connectedness Index (TCI), which measures the overall connectedness or interdependence among the variables, and the Conditional Total Connectedness Index (cTCI), which measures the connectedness after controlling for other factors or variables. The ratio of cTCI to TCI (cTCI/TCI) is provided to assess the relative importance of direct connections between variables compared to the overall connectedness of the network. The Spillover Table helps to identify the key drivers of spillovers and the most interconnected variables within the network, providing valuable insights into the transmission of shocks and the overall stability of the financial system.

Appendix A3. Spillover table, stock risk using ridge regression

	CBDC	SRISK	TED	FCI	VIX	ER	TWEETS	GPR	BTC	DASH	ETH	LTC	XEM	XLM	XMR	XRP	DAI	TUSD	USDC	MANA	STACKS	FROM
CBDC	92.12	0.85	0.1	0.06	0.02	0.08	0.28	0.88	0.56	1.1	0.46	0.6	0.2	0.37	1.16	0.33	0.13	0.3	0.1	0.11	0.18	7.88
SRISK	0.09	91.43	0.83	0.18	0.57	0.08	2.59	0.23	0.06	0.5	0.13	0.25	0.22	0.43	0.08	0.37	0.55	0.09	0.72	0.02	0.56	8.57
TED	0.03	1.51	38.96	11.95	7.26	0.55	1.29	0.3	5.52	3.45	5.66	4.81	0.97	1.29	4.7	0.7	2.48	0.24	4.98	1.75	1.6	61.04
FCI	0.21	0.05	4.17	34.5	26.61	0.87	11.25	0.16	3.14	0.65	3.9	1.88	0.25	0.29	1.48	0.1	4.08	0.03	4.84	0.7	0.86	65.5
VIX	0.26	0.16	0.44	18.78	44.55	0.04	6.58	0.12	3.78	1.16	4.69	2.92	1	1.08	2.58	0.35	4.18	0.3	4.2	1.39	1.44	55.45
ER	0.39	1.05	0.48	2.78	1.44	33.42	2.19	4.48	3.64	5.42	3.76	6.49	5.21	7.33	5.45	5.85	2.68	0.34	1.61	2.69	3.32	66.58
TWEETS	0.14	1.55	0.58	10.34	8.66	0.43	68.66	1.84	0.6	1.28	0.14	0.64	0.37	0.22	1.69	0.61	1.24	0.07	0.31	0.39	0.23	31.34
GPR	0.27	0.03	0.02	0.51	0.34	1.12	1.82	90.15	0.38	0.11	0.47	0.43	0.55	0.51	0.19	0.38	1.06	0.09	0.49	0.42	0.67	9.85
BTC	0.03	0.03	0.01	0.12	0.37	0.02	0.09	0.06	18.01	8.41	13.99	11.19	5.74	7.2	10.18	5.44	3.4	0.51	4.31	5.06	5.82	81.99
DASH	0.13	0.41	0	0.04	0.07	0.04	0.18	0.11	9.07	20.94	10.07	11.34	6.67	8.42	11.5	6.62	1.65	0.63	2.44	4.77	4.88	79.06
ETH	0.03	0.03	0.01	0.07	0.22	0.01	0.01	0.03	12.32	8.25	17.89	11.76	6.51	7.52	10.34	5.84	3.69	0.44	3.78	5.3	5.94	82.11
LTC	0.13	0.1	0	0.02	0.07	0.03	0.08	0.03	10.47	10.47	12.33	15.78	7.44	8.18	11.38	7.31	2.03	0.83	2.99	4.89	5.42	84.22
XEM	0.01	0.03	0	0.01	0.08	0.03	0.01	0.01	6.78	7.42	8.26	9.66	28.23	8.87	8.29	7.61	0.75	0.46	1.14	6.34	6.02	71.77
XLM	0.01	0.06	0	0.01	0.1	0.07	0	0.01	8.19	8	10.37	9.79	8.42	21.89	7.31	12.66	1.53	0.47	1.76	3.79	5.56	78.11
XMR	0.37	0.17	0	0.03	0.13	0.04	0.29	0.3	10.3	11.43	11.66	12.04	7.07	7.01	18.11	5.46	1.77	0.33	2.75	5.36	5.39	81.89
XRP	0.01	0.09	0	0.02	0.06	0.05	0.06	0.01	6.7	6.53	8.15	9.37	7.5	13.16	6.2	29.04	0.81	0.51	1.26	3.27	7.19	70.96
DAI	0.04	0.39	0.06	0.65	1.06	0.11	0.43	0.46	7.2	2.94	8.92	5.04	1.84	2.49	3.96	1.5	45.19	0.01	10.03	2.94	4.75	54.81
TUSD	0.13	0.15	0.02	0.07	0.21	0.23	0.07	0.03	8.5	6.13	8.42	7.38	4.9	6.04	4.11	6.56	0.3	38.68	1.34	3.1	3.64	61.32
USDC	0.01	0.41	0.1	0.47	0.62	0.03	0.09	0.06	8.69	5.28	9.43	7.18	3.16	4	6.22	3.01	8.8	0.4	33.81	3.82	4.41	66.19
MANA	0.02	0.01	0.04	0.01	0.07	0.03	0.12	0.01	7.81	6.88	8.97	8.25	9.07	6.14	8.14	4.44	1.63	0.37	2.23	31.29	4.47	68.71
STACKS	0.02	0.38	0	0.01	0.08	0.02	0.02	0.01	8.09	5.94	8.75	7.77	6.26	6.46	7.26	7.49	2.72	0.24	2.64	4.29	31.54	68.46
TO	2.34	7.46	6.85	46.14	48.06	3.9	27.45	9.16	121.78	101.35	138.51	128.78	83.33	97	112.22	82.65	45.48	6.67	53.91	60.42	72.37	1255.82
Inc.Own	94.46	98.89	45.82	80.64	92.61	37.32	96.11	99.31	139.79	122.3	156.39	144.56	111.56	118.89	130.33	111.69	90.67	45.35	87.72	91.71	103.91	cTCI/TCI
NET	−5.54	−1.11	−54.18	−19.36	−7.39	−62.68	−3.89	−0.69	39.79	22.3	56.39	44.56	11.56	18.89	30.33	11.69	−9.33	−54.65	−12.28	−8.29	3.91	62.79/59.80
NPT	3	5	1	5	6	1	5	7	18	13	20	19	13	16	15	15	9	6	10	11	12	

Notes: Table Appendix A3 presents the Spillover Table for stock risk using ridge regression. The table provides insights into the interconnectedness and spillover effects among various financial and economic variables, cryptocurrencies, stablecoins, and non-fungible tokens. The variables included in the analysis are: 1. Measures of Financial Stability: Central Bank Digital Currency Index (CBDC), Global Systemic Risk (SRISK), Global TED Spread (TED), Global Financial Condition Index (FCI), and Volatility Index (VIX). 2. Measures of Economic Uncertainty: US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ER), Twitter-based Economic Uncertainty Index (TWEETS), and Geopolitical Risk Index (GPR). 3. Cryptocurrencies: Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), and Ripple (XRP). 4. Stablecoins: Dai (DAI), True USD (TUSD), and USD Coin (USDC). 5. Non-Fungible Tokens: Decentraland (MANA) and Stacks (STACKS). The table presents several measures of connectedness and spillover effects: The "FROM" column represents the total spillover received by each variable from all other variables in the network. The "TO" row represents the total spillover transmitted by each variable to all other variables in the network. The "Inc.Own" row represents the incremental own-variable spillover, which measures the spillover from a variable to itself. The "NET" row represents the net spillover effect, calculated as the difference between the "TO" and "FROM" values. Positive values indicate that the variable is a net transmitter of spillovers, while negative values indicate that the variable is a net receiver of spillovers. The "NPT" row represents the number of pairwise transmissions, which counts the number of significant pairwise spillovers between variables. The table also includes the Total Connectedness Index (TCI), which measures the overall connectedness or interdependence among the variables, and the Conditional Total Connectedness Index (cTCI), which measures the connectedness after controlling for other factors or variables. The ratio of cTCI to TCI (cTCI/TCI) is provided to assess the relative importance of direct connections between variables compared to the overall connectedness of the network. The Spillover Table helps to identify the key drivers of spillovers and the most interconnected variables within the network, providing valuable insights into the transmission of shocks and the overall stability of the financial system.

Appendix A4. Spillover table, stock risk using lasso regression

	CBDC	SRISK	TED	FCI	VIX	ER	TWEETS	GPR	BTC	DASH	ETH	LTC	XEM	XLM	XMR	XRP	DAI	TUSD	USDC	MANA	STACKS	FROM
CBDC	99.08	0.09	0.11	0.02	0.01	0.34	0.01	0.04	0	0.03	0.03	0	0	0.02	0.1	0	0.04	0.02	0	0.01	0.07	0.92
SRISK	0.08	95.87	0.36	0.02	0.1	0.04	1.23	0.01	0.01	0.24	0.18	0.15	0.05	0.37	0	0.3	0.21	0	0.23	0	0.52	4.13
TED	0.09	0.27	78.22	13.72	1.63	0.02	0.01	0	0.88	0.35	0.88	0.73	0.12	0.15	0.44	0.09	0.59	0.08	1.05	0.42	0.27	21.78
FCI	0.01	0	4.6	56.86	35.89	1.05	0.8	0.01	0.05	0.05	0.02	0.01	0.09	0.09	0.11	0.14	0.02	0.05	0.07	0.05	0.02	43.14
VIX	0.01	0.04	0.24	26.85	64.47	0.01	0.8	0	1.13	0.67	0.56	0.5	0.66	0.78	1	0.67	0.28	0.2	0.1	0.62	0.43	35.53
ER	0.33	0.04	0.08	2.08	0.01	94.48	0.02	0.39	0.36	0.22	0.07	0	0	0.08	0.19	0.01	0.15	1.24	0.16	0.03	0.07	5.52
TWEETS	0.01	0.56	0.06	12.7	9.56	0.18	71.22	0.94	0.42	0.7	0.24	0.45	0.31	0.32	1.39	0.26	0.2	0.08	0.02	0.21	0.18	28.78
GPR	0.1	0.01	0	0.02	0.01	0.64	1.19	96.2	0.08	0.04	0.09	0.08	0.15	0.15	0.15	0.04	0.58	0.04	0.09	0.12	0.2	3.8
BTC	0	0	0.03	0.02	0.3	0.07	0	0.01	20.3	7.26	14.39	12.05	4.95	6.72	10.14	4.71	3.71	0.67	4.39	4.78	5.5	79.7
DASH	0.01	0.06	0.02	0	0.26	0.06	0.04	0.01	8.57	24.6	9.31	12.58	5.59	7.7	12.44	5.67	1.37	0.52	2.11	4.7	4.39	75.4
ETH	0.01	0.04	0.04	0.03	0.18	0.01	0	0.01	13.34	7.5	19.83	13.04	5.36	6.79	10.14	5.18	3.74	0.51	3.95	4.89	5.4	80.17
LTC	0	0.03	0.04	0.01	0.16	0	0.01	0.01	10.92	9.72	12.5	18.98	6.48	7.2	11.29	6.08	2.62	0.79	3.11	4.81	5.27	81.02
XEM	0	0.02	0	0.01	0.31	0	0	0.02	7.05	6.77	8.06	10.17	29.81	9.12	8.18	6.84	0.85	0.43	1.11	5.95	5.3	70.19
XLM	0	0.1	0	0	0.31	0.02	0	0.01	8.17	7.92	8.66	9.59	7.74	25.3	7.62	11.26	1.43	0.57	1.64	4.03	5.61	74.7
XMR	0.02	0	0.02	0	0.34	0.04	0.06	0.04	10.44	10.83	10.96	12.69	5.88	6.45	21.42	4.85	2.08	0.31	2.86	5.02	5.68	78.58
XRP	0	0.09	0	0.02	0.31	0	0	0	6.63	6.79	7.7	9.43	6.76	13.1	6.67	29.45	0.86	0.51	1.17	3.64	6.85	70.55
DAI	0.02	0.1	0.18	0	0.21	0.07	0.02	0.1	8.23	2.58	8.72	6.36	1.31	2.61	4.48	1.35	46.27	0.01	10.76	2.32	4.3	53.73
TUSD	0.01	0	0.04	0.02	0.25	1.06	0.01	0.02	2.64	1.72	2.09	3.34	1.17	1.82	1.18	1.4	0.01	80.66	1.2	0.68	0.67	19.34
USDC	0	0.1	0.3	0.12	0.08	0.07	0	0	9.05	3.65	8.49	6.98	1.59	2.76	5.69	1.7	9.92	0.63	42.66	2.87	3.34	57.34
MANA	0.01	0	0.07	0	0.34	0.01	0	0.02	7.89	6.57	8.49	8.7	6.86	5.48	8.05	4.25	1.73	0.29	2.31	34.4	4.53	65.6
STACKS	0.02	0.17	0.02	0	0.22	0.02	0	0	8.23	5.55	8.48	8.61	5.53	6.9	8.25	7.23	2.89	0.26	2.43	4.1	31.09	68.91
TO	0.72	1.73	6.21	55.64	50.48	3.74	4.22	1.64	104.07	79.17	109.92	115.45	60.62	78.61	97.5	62.04	33.28	7.21	38.75	49.23	58.61	1018.82
Inc.Own	99.8	97.6	84.43	112.5	114.95	98.22	75.44	97.84	124.36	103.77	129.74	134.43	90.43	103.91	118.93	91.49	79.56	87.87	81.41	83.63	89.71	cTCI/TCI
NET	−0.2	−2.4	−15.57	12.5	14.95	−1.78	−24.56	−2.16	24.36	3.77	29.74	34.43	−9.57	3.91	18.93	−8.51	−20.44	−12.13	−18.59	−16.37	−10.29	50.94/48.52
NPT	1	2	5	8	8	4	3	0	18	16	18	20	13	15	17	14	9	7	9	11	12	

Notes: Table Appendix A4 presents the Spillover Table for stock risk using lasso regression. The table provides insights into the interconnectedness and spillover effects among various financial and economic variables, cryptocurrencies, stablecoins, and non-fungible tokens. The variables included in the analysis are: 1. Measures of Financial Stability: Central Bank Digital Currency Index (CBDC), Global Systemic Risk (SRISK), Global TED Spread (TED), Global Financial Condition Index (FCI), and Volatility Index (VIX). 2. Measures of Economic Uncertainty: US dollar exchange rate in terms of market exchange rates of specified quantities of the SDR (ER), Twitter-based Economic Uncertainty Index (TWEETS), and Geopolitical Risk Index (GPR). 3. Cryptocurrencies: Bitcoin (BTC), Dash (DASH), Ethereum (ETH), Litecoin (LTC), NEM (XEM), Stellar (XLM), Monero (XMR), and Ripple (XRP). 4. Stablecoins: Dai (DAI), True USD (TUSD), and USD Coin (USDC). 5. Non-Fungible Tokens: Decentraland (MANA) and Stacks (STACKS). The table presents several measures of connectedness and spillover effects: The "FROM" column represents the total spillover received by each variable from all other variables in the network. The "TO" row represents the total spillover transmitted by each variable to all other variables in the network. The "Inc.Own" row represents the incremental own-variable spillover, which measures the spillover from a variable to itself. The "NET" row represents the net spillover effect, calculated as the difference between the "TO" and "FROM" values. Positive values indicate that the variable is a net transmitter of spillovers, while negative values indicate that the variable is a net receiver of spillovers. The "NPT" row represents the number of pairwise transmissions, which counts the number of significant pairwise spillovers between variables. The table also includes the Total Connectedness Index (TCI), which measures the overall connectedness or interdependence among the variables, and the Conditional Total Connectedness Index (cTCI), which measures the connectedness after controlling for other factors or variables. The ratio of cTCI to TCI (cTCI/TCI) is provided to assess the relative importance of direct connections between variables compared to the overall connectedness of the network. The Spillover Table helps to identify the key drivers of spillovers and the most interconnected variables within the network, providing valuable insights into the transmission of shocks and the overall stability of the financial system.

Appendix A5. Network structure: Elastic net model with ridge regression (Returns)

Series	In-Degree	Out-Degree	Degree	Weighted In-Degree	Weighted Out-Degree	Weighted Degree	Eccentricity	Closeness Centrality	Harmonic	Modularity Class	Clustering Coefficient
CBDC	19	21	40	98.44	99.99	198.43	1.00	1.00	1.00	0	0.96
SRISK	19	21	40	99.32	100.00	199.32	1.00	1.00	1.00	0	0.96
TED	13	21	34	58.71	100.02	158.73	1.00	1.00	1.00	0	0.96
FCI	21	21	42	87.34	100.04	187.38	1.00	1.00	1.00	0	0.96
VIX	21	21	42	115.28	100.00	215.28	1.00	1.00	1.00	0	0.96
ER	20	21	41	59.62	99.99	159.61	1.00	1.00	1.00	0	0.96
TWEETS	18	21	39	95.39	100.00	195.39	1.00	1.00	1.00	0	0.96
GPR	20	21	41	102.74	100.03	202.77	1.00	1.00	1.00	0	0.96
BTC	21	20	41	131.20	100.00	231.20	2.00	0.95	0.98	1	0.96
DASH	21	20	41	111.16	99.99	211.15	2.00	0.95	0.98	1	0.96
ETH	21	20	41	136.08	100.02	236.10	2.00	0.95	0.98	1	0.96
LTC	21	20	41	130.62	99.98	230.60	2.00	0.95	0.98	1	0.96
XEM	21	19	40	100.68	100.00	200.68	2.00	0.91	0.95	1	0.96
XLM	21	19	40	116.15	99.98	216.13	2.00	0.91	0.95	1	0.96
XMR	21	21	42	112.48	100.03	212.51	1.00	1.00	1.00	1	0.96
XRP	21	20	41	103.91	100.00	203.91	2.00	0.95	0.98	1	0.96
DAI	21	19	40	82.94	100.01	182.95	2.00	0.91	0.95	2	0.96
TUSD	20	18	38	93.59	99.99	193.58	2.00	0.87	0.93	2	0.96
USDC	21	20	41	77.15	100.01	177.16	2.00	0.95	0.98	2	0.96
MANA	21	18	39	94.53	99.99	194.52	2.00	0.87	0.93	1	0.96
STACKS	21	21	42	92.75	100.01	192.76	1.00	1.00	1.00	1	0.96

Notes: Appendix A5 presents the network structure of the Elastic Net Model with ridge regression for stock returns. The table provides various network measures for each variable in the analysis, offering insights into their interconnectedness and centrality within the network. The variables included in the analysis are the same as in Table 5, covering measures of financial stability, economic uncertainty, cryptocurrencies, stablecoins, and non-fungible tokens. The network measures provided in the table are: 1. In-Degree: The number of incoming connections or links to a variable from other variables in the network. 2. Out-Degree: The number of outgoing connections or links from a variable to other variables in the network. 3. Degree: The total number of connections or links (both incoming and outgoing) for a variable. 4. Weighted In-Degree: The sum of the weights of incoming connections to a variable, considering the strength or importance of the links. 5. Weighted Out-Degree: The sum of the weights of outgoing connections from a variable, considering the strength or importance of the links. 6. Weighted Degree: The sum of the weighted in-degree and weighted out-degree, providing an overall measure of a variable's importance in the network. 7. Eccentricity: The maximum distance from a variable to any other variable in the network, measuring how far a variable is from the furthest node. 8. Closeness Centrality: A measure of how close a variable is to all other variables in the network, calculated as the reciprocal of the average shortest path distance. 9. Harmonic Centrality: A variant of closeness centrality that considers the harmonic mean of the shortest path distances, giving more weight to shorter distances. 10. Modularity Class: A measure of the community or cluster to which a variable belongs, based on the density of connections within and between communities. 11. Clustering Coefficient: A measure of the tendency of a variable's neighbours to cluster together, indicating the presence of local clusters or communities. These network measures help to identify the most central and influential variables within the network, as well as the overall structure and organisation of the network. Variables with high centrality scores (e.g., high degree, closeness, or harmonic centrality) are likely to be important in the transmission of shocks and information within the network. The modularity class and clustering coefficient provide insights into the presence of communities or clusters of closely connected variables.

Appendix A6. Network structure: Elastic net model with lasso regression (Returns)

Series	In-Degree	Out-Degree	Degree	Weighted In-Degree	Weighted Out-Degree	Weighted Degree	Eccentricity	Closeness Centrality	Harmonic	Modularity Class	Clustering Coefficient
CBDC	18	20	38	98.76	100.01	198.77	2.00	0.95	0.98	0	0.93
SRISK	16	19	35	98.02	100.00	198.02	2.00	0.91	0.95	0	0.93
TED	13	19	32	85.39	100.00	185.39	2.00	0.91	0.95	0	0.93
FCI	20	20	40	95.23	100.00	195.23	2.00	0.95	0.98	0	0.93
VIX	20	19	39	101.79	99.99	201.78	2.00	0.91	0.95	0	0.93
ER	21	20	41	89.83	100.01	189.84	2.00	0.95	0.98	0	0.93
TWEETS	19	19	38	97.54	99.99	197.53	2.00	0.91	0.95	0	0.95
GPR	21	20	41	126.20	100.00	226.20	2.00	0.95	0.98	1	0.93
BTC	20	20	40	108.33	99.99	208.32	2.00	0.95	0.98	1	0.94
DASH	21	20	41	130.12	100.00	230.12	2.00	0.95	0.98	1	0.93
ETH	21	19	40	126.90	99.98	226.88	2.00	0.91	0.95	1	0.93
LTC	21	18	39	97.18	99.98	197.16	2.00	0.87	0.93	1	0.93
XEM	21	20	41	112.75	100.01	212.76	2.00	0.95	0.98	1	0.93
XLM	21	21	42	109.78	100.02	209.80	1.00	1.00	1.00	1	0.93
XMR	21	20	41	101.46	100.00	201.46	2.00	0.95	0.98	1	0.93
XRP	19	20	39	83.13	100.00	183.13	2.00	0.95	0.98	0	0.93
DAI	19	19	38	93.62	99.99	193.61	2.00	0.91	0.95	0	0.93
TUSD	21	20	41	85.29	100.00	185.29	2.00	0.95	0.98	0	0.93
USDC	20	18	38	90.96	100.01	190.97	2.00	0.87	0.93	1	0.94
MANA	21	21	42	89.00	100.00	189.00	1.00	1.00	1.00	1	0.93
STACKS	18	20	38	78.69	99.99	178.68	2.00	0.95	0.98	0	0.93

Notes: Appendix A6 presents the network structure of the Elastic Net Model with lasso regression for stock returns. The table provides various network measures for each variable in the analysis, offering insights into their interconnectedness and centrality within the network. The variables included in the analysis are the same as in Table 5, covering measures of financial stability, economic uncertainty, cryptocurrencies, stablecoins, and non-fungible tokens. The network measures provided in the table are: 1. In-Degree: The number of incoming connections or links to a variable from other variables in the network. 2. Out-Degree: The number of outgoing connections or links from a variable to other variables in the network. 3. Degree: The total number of connections or links (both incoming and outgoing) for a variable. 4. Weighted In-Degree: The sum of the weights of incoming connections to a variable, considering the strength or importance of the links. 5. Weighted Out-Degree: The sum of the weights of outgoing connections from a variable, considering the strength or importance of the links. 6. Weighted Degree: The sum of the weighted in-degree and weighted out-degree, providing an overall measure of a variable's importance in the network. 7. Eccentricity: The maximum distance from a variable to any other variable in the network, measuring how far a variable is from the furthest node. 8. Closeness Centrality: A measure of how close a variable is to all other variables in the network, calculated as the reciprocal of the average shortest path distance. 9. Harmonic Centrality: A variant of closeness centrality that considers the harmonic mean of the shortest path distances, giving more weight to shorter distances. 10. Modularity Class: A measure of the community or cluster to which a variable belongs, based on the density of connections within and between communities. 11. Clustering Coefficient: A measure of the tendency of a variable's neighbours to cluster together, indicating the presence of local clusters or communities. These network measures help to identify the most central and influential variables within the network, as well as the overall structure and organisation of the network. Variables with high centrality scores (e.g., high degree, closeness, or harmonic centrality) are likely to be important in the transmission of shocks and information within the network. The modularity class and clustering coefficient provide insights into the presence of communities or clusters of closely connected variables.

Appendix A7. Network structure: Elastic net model with ridge regression (Risk)

Series	In-Degree	Out-Degree	Degree	Weighted In-Degree	Weighted Out-Degree	Weighted Degree	Eccentricity	Closeness Centrality	Harmonic	Modularity Class
CBDC	21	21	42	94.89	100.00	194.89	1.00	1.00	1.00	0
SRISK	21	21	42	98.70	100.01	198.71	1.00	1.00	1.00	0
TED	14	21	35	45.80	99.99	145.79	1.00	1.00	1.00	1
FCI	21	21	42	80.47	100.00	180.47	1.00	1.00	1.00	0
VIX	21	21	42	91.90	99.98	191.88	1.00	1.00	1.00	0

(continued on next page)

(*continued*)

Series	In-Degree	Out-Degree	Degree	Weighted In-Degree	Weighted Out-Degree	Weighted Degree	Eccentricity	Closeness Centrality	Harmonic	Modularity Class
ER	21	21	42	36.68	99.99	136.67	1.00	1.00	1.00	0
TWEETS	20	21	41	97.25	100.01	197.26	1.00	1.00	1.00	0
GPR	21	21	42	99.09	99.99	199.08	1.00	1.00	1.00	0
BTC	21	21	42	137.71	100.02	237.73	1.00	1.00	1.00	1
DASH	21	20	41	121.71	99.99	221.70	2.00	0.95	0.98	1
ETH	21	21	42	155.64	99.99	255.63	1.00	1.00	1.00	1
LTC	21	20	41	146.24	99.97	246.21	2.00	0.95	0.98	1
XEM	21	20	41	112.01	99.98	211.99	2.00	0.95	0.98	1
XLM	21	19	40	121.36	100.01	221.37	2.00	0.91	0.95	1
XMR	21	20	41	129.68	100.01	229.69	2.00	0.95	0.98	1
XRP	21	20	41	112.32	100.01	212.33	2.00	0.95	0.98	1
DAI	21	21	42	90.03	100.01	190.04	1.00	1.00	1.00	1
TUSD	21	21	42	44.66	99.99	144.65	1.00	1.00	1.00	1
USDC	21	21	42	87.86	99.98	187.84	1.00	1.00	1.00	1
MANA	21	21	42	92.11	100.02	192.13	1.00	1.00	1.00	1
STACKS	21	20	41	103.81	99.97	203.78	2.00	0.95	0.98	1

Notes: Appendix A7 presents the network structure of the Elastic Net Model with ridge regression for stock risk. The table provides various network measures for each variable in the analysis, offering insights into their interconnectedness and centrality within the network. The variables included in the analysis are the same as in Table 5, covering measures of financial stability, economic uncertainty, cryptocurrencies, stablecoins, and non-fungible tokens. The network measures provided in the table are: 1. In-Degree: The number of incoming connections or links to a variable from other variables in the network. 2. Out-Degree: The number of outgoing connections or links from a variable to other variables in the network. 3. Degree: The total number of connections or links (both incoming and outgoing) for a variable. 4. Weighted In-Degree: The sum of the weights of incoming connections to a variable, considering the strength or importance of the links. 5. Weighted Out-Degree: The sum of the weights of outgoing connections from a variable, considering the strength or importance of the links. 6. Weighted Degree: The sum of the weighted in-degree and weighted out-degree, providing an overall measure of a variable's importance in the network. 7. Eccentricity: The maximum distance from a variable to any other variable in the network, measuring how far a variable is from the furthest node. 8. Closeness Centrality: A measure of how close a variable is to all other variables in the network, calculated as the reciprocal of the average shortest path distance. 9. Harmonic Centrality: A variant of closeness centrality that considers the harmonic mean of the shortest path distances, giving more weight to shorter distances. 10. Modularity Class: A measure of the community or cluster to which a variable belongs, based on the density of connections within and between communities. 11. Clustering Coefficient: A measure of the tendency of a variable's neighbours to cluster together, indicating the presence of local clusters or communities. These network measures help to identify the most central and influential variables within the network, as well as the overall structure and organisation of the network. Variables with high centrality scores (e.g., high degree, closeness, or harmonic centrality) are likely to be important in the transmission of shocks and information within the network. The modularity class and clustering coefficient provide insights into the presence of communities or clusters of closely connected variables.

Appendix A8. Network structure: Elastic net model with lasso regression (Risk)

Series	In-Degree	Out-Degree	Degree	Weighted In-Degree	Weighted Out-Degree	Weighted Degree	Eccentricity	Closeness Centrality	Harmonic	Modularity Class
CBDC	14	16	30	99.73	99.99	199.72	2	0.8	0.875	0
SRISK	16	18	34	97.73	99.99	197.72	2	0.869565217	0.925	0
TED	17	20	37	84.23	99.99	184.22	2	0.952380952	0.975	0
FCI	16	20	36	113.26	100.00	213.26	2	0.952380952	0.975	0
VIX	20	19	39	117.22	100.01	217.23	2	0.909090909	0.95	0
ER	18	18	36	98.46	99.98	198.44	2	0.869565217	0.925	0
TWEETS	15	21	36	70.80	100.00	170.80	1	1	1	0
GPR	17	19	36	98.33	99.96	198.29	2	0.909090909	0.95	0
BTC	21	20	41	104.06	99.99	204.05	2	0.952380952	0.975	1
DASH	21	20	41	129.83	100.01	229.84	2	0.952380952	0.975	1
ETH	21	17	38	103.91	99.98	203.89	2	0.833333333	0.9	1
LTC	20	19	39	119.06	99.99	219.05	2	0.909090909	0.95	1
XEM	21	21	42	79.43	100.01	179.44	1	1	1	1
XLM	20	20	40	87.73	100.00	187.73	2	0.952380952	0.975	1
XMR	20	18	38	83.74	100.01	183.75	2	0.869565217	0.925	1
XRP	21	18	39	89.89	100.02	189.91	2	0.869565217	0.925	1
DAI	20	19	39	124.17	100.02	224.19	2	0.909090909	0.95	1
TUSD	19	19	38	134.24	100.01	234.25	2	0.909090909	0.95	1
USDC	19	17	36	90.94	100.01	190.95	2	0.833333333	0.9	1
MANA	19	16	35	91.73	99.99	191.72	2	0.8	0.875	1
STACKS	20	20	40	81.46	99.99	181.45	2	0.952380952	0.975	1

Notes: Appendix A8 presents the network structure of the Elastic Net Model with lasso regression for stock risk. The table provides various network measures for each variable in the analysis, offering insights into their interconnectedness and centrality within the network. The variables included in the analysis are the same as in Table 5, covering measures of financial stability, economic uncertainty, cryptocurrencies, stablecoins, and non-fungible tokens. The network measures provided in the table are: 1. In-Degree: The number of incoming connections or links to a variable from other variables in the network. 2. Out-Degree: The number of outgoing connections or links from a variable to other variables in the network. 3. Degree: The total number of connections or links (both incoming and outgoing) for a variable. 4. Weighted In-Degree: The sum of the weights of incoming connections to a variable, considering the strength or importance of the links. 5. Weighted Out-Degree: The sum of the weights of outgoing connections from a variable, considering the strength or importance of the links. 6. Weighted Degree: The sum of the weighted in-degree and weighted out-degree, providing an overall measure of a variable's importance in the network. 7. Eccentricity: The maximum distance from a variable to any other variable in the network, measuring how far a variable is from the furthest node. 8. Closeness Centrality: A measure of how close a variable is to all other variables in the network, calculated as the reciprocal of the average shortest path distance. 9. Harmonic Centrality: A variant of closeness centrality that considers the harmonic mean of the shortest path distances, giving more weight to shorter distances. 10. Modularity Class: A measure of the community or cluster to which a variable belongs, based on the density of connections within and between communities. 11. Clustering Coefficient: A measure of the tendency of a variable's neighbours to cluster together, indicating the presence of local clusters or communities. These network measures help to identify the most central and influential variables within the network, as well as the overall structure and organisation of the network. Variables with high centrality scores (e.g., high degree, closeness, or harmonic centrality) are likely to be important in the transmission of shocks and information within the network. The modularity class and clustering coefficient provide insights into the presence of communities or clusters of closely connected variables.

Appendix A9. Global SRISK construction

To measure systemic risk, we employ the SRISK metric developed by Brownlees and Engle (2016). SRISK quantifies the expected capital shortfall of a firm conditional on a severe market downturn, providing a forward-looking assessment of the firm's vulnerability to systemic events. The computation of SRISK involves several steps:

Step 1: Estimate the dynamic marginal expected shortfall (MES) for each firm. The MES measures the firm's expected equity loss when the market experiences a significant decline. It is computed as follows:

$$MES_{it} = E[r_{it}|r_{mt} < c]$$

where r_{it} is the daily stock return of firm i at time t, r_{mt} is the daily market return at time t, and c is a predetermined threshold for a substantial market decline (e.g., -2% or lower).

Step 2: Estimate the long-run marginal expected shortfall (LRMES) by extrapolating the MES to a longer and more extreme market downturn. The LRMES is calculated as:

$$LMES_{it} = 1 - \exp(\ln(1-d) \times beta_{it}$$

where d is the market decline threshold (e.g., -40 %) and $beta_{it}$ is the firm's time-varying beta (sensitivity to market returns) estimated using a dynamic conditional beta model.

Step 3: Calculate the SRISK for each firm by combining the LRMES, the firm's market capitalisation (MC), and its book value of debt (D). The SRISK is computed as:

$$SRISK_{it} = max[0, (kD_{it}) - (1-k)(1-LRMES_{it})(MC_{it})]$$

where k is a regulatory capital ratio (typically set at 8 % for banks).

In our study, we obtain the firm-level SRISK data directly from the V-Lab (Volatility Laboratory) of the NYU Stern Volatility and Risk Institute. The V-Lab team computes the SRISK for a large number of firms across various countries using the methodology described above. Instead of estimating the MES and LRMES ourselves, we rely on the expertise and established procedures of the V-Lab team to provide accurate and reliable SRISK estimates.

The SRISK data used in our paper is based on raw data of daily SRISK for 1982 banks across 90 countries, as shown in Table A10 below. We chose to use daily data instead of monthly data to capture more granular variations in SRISK over time. To obtain the country-level or regional aggregate SRISK on a given date, we sum the positive part (i.e., max(0,x)) for all firms in that country/region on that date. This approach also applies to global SRISK, where we take the sum of the positive part of all firms. If a firm has negative SRISK on a given date, that value is not included in the aggregate SRISK for that date. Positive SRISK corresponds to an expected capital shortfall, while negative SRISK corresponds to an expected capital surplus.

By utilising the firm-level SRISK data from the V-Lab and aggregating it at the country and global levels, we can assess the overall level of systemic risk in the financial system and examine its relationship with other variables of interest, such as central bank digital currencies (CBDCs) and digital assets.

Appendix A10. Number of firms in the SRISK computation across countries

Country	*Freq.*	*Percent*
Argentina	5	0.25
Australia	22	1.11
Austria	12	0.61
Bahrain	3	0.15
Bangladesh	4	0.20
Barbados	1	0.05
Belgium	11	0.55
Bermuda	28	1.41
Brazil	23	1.16
Canada	45	2.27
Cayman Islands	3	0.15
Chile	9	0.45
China	102	5.15
Colombia	6	0.30
Croatia	2	0.10
Curacao	1	0.05
Cyprus	5	0.25
Czech Republic	2	0.10
Denmark	9	0.45
Egypt	4	0.20
Estonia	2	0.10
Finland	8	0.40
France	38	1.92
Georgia	1	0.05
Germany	30	1.51
Greece	11	0.55
Guernsey	2	0.10
Hong Kong	28	1.41
Hungary	2	0.10
Iceland	5	0.25
India	56	2.83
Indonesia	21	1.06
Ireland	7	0.35
Israel	14	0.71
Italy	36	1.82
Jamaica	1	0.05
Japan	79	3.99
Jersey	1	0.05
Jordan	9	0.45
Kazakhstan	5	0.25
Kenya	2	0.10
Korea	32	1.61
Kuwait	10	0.50
Lebanon	2	0.10
Liechtenstein	2	0.10
Lithuania	1	0.05
Luxembourg	6	0.30
Malaysia	17	0.86
Malta	2	0.10
Mauritius	1	0.05
Mexico	10	0.50
Morocco	7	0.35
Netherlands	12	0.61
New Zealand	1	0.05
Nigeria	4	0.20
North Macedonia	1	0.05
Norway	17	0.86
Oman	6	0.30
Pakistan	7	0.35
Panama	1	0.05
Peru	6	0.30
Philippines	13	0.66
Poland	15	0.76
Portugal	4	0.20
Qatar	9	0.45
Romania	2	0.10
Russian Federation	10	0.50
Saudi Arabia	18	0.91

(*continued on next page*)

(*continued*)

Country	*Freq.*	*Percent*
Singapore	15	0.76
Slovak Republic	1	0.05
Slovenia	4	0.20
South Africa	17	0.86
Spain	21	1.06
Sri Lanka	6	0.30
Sweden	17	0.86
Switzerland	33	1.66
Taiwan	31	1.56
Tanzania	1	0.05
Thailand	18	0.91
Togo	1	0.05
Trinidad and Tobago	1	0.05
Tunisia	2	0.10
Turkey	25	1.26
Ukraine	2	0.10
United Arab Emirates	14	0.71
United Kingdom	58	2.93
United States	821	41.42
Uruguay	1	0.05
Vietnam	21	1.06
Zimbabwe	1	0.05
Total	1982	100.00

References

Agur, I., Ari, A., Dell'Ariccia, G., 2022. Designing central bank digital currencies. J. Monet. Econ. 125, 62–79.

Aharon, D.Y., Demir, E., Lau, C.K., Zaremba, A., 2022. Twitter-based uncertainty and cryptocurrency returns. Res. Int. Bus. Financ. 59, 101546.

Al Mamun, M., Uddin, G.S., Suleman, M.T., Kang, S.H., 2020. Geopolitical risk, uncertainty and bitcoin investment. Phys. A: Stat. Mech. Appl. 540, 123107.

Andolfatto, D., 2020. Assessing the impact of central bank digital currency on private banks. Econ. J. 131 (634), 525–540.

Ayadi, A., Ghabri, Y., Guesmi, K., 2023. Directional predictability from central bank digital currency to cryptocurrencies and stablecoins. Res. Int. Bus. Financ. 65, 101909.

Aysan, A.F., Demir, E., Gozgor, G., Lau, C.K.M., 2019. Effects of the geopolitical risks on bitcoin returns and volatility. Res. Int. Bus. Financ. 47, 511–518.

Baker, S.R., Bloom, N., Davis, S.J., Renault, T., 2021. Twitter-derived measures of economic uncertainty. Mimeo.

Bas, T., Malki, I., Sivaprasad, S., 2024. Do returns and volatility spillovers exist across tech stocks, cryptocurrencies and NFTs? Heliyon 10 (2), e24615.

Blockchain News (2020). Alibaba Founder and China's Richest Man Jack Ma: Digital Currency Could Redefine Money. https://blockchain.news/news/alibaba-founder-china-richest-man-jack-ma-digital-currency-redefine-money (Accessed: 04/12/2022).

Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77 (3), 623–685.

Bouri, E., Gupta, R., Tiwari, A.K., Roubaud, D., 2017. Does bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Financ. Res. Lett. 23, 87–95.

Brunnermeier, M.K., Landau, J.P., 2022. The digital euro: policy implications and perspectives. European Parliament.

Caldara, D., Iacoviello, M., 2022. Measuring geopolitical risk. Am. Econ. Rev. 112 (4), 1194–1225.

Carapella, F. and Flemming, J. (2020). *Central Bank Digital Currency: A Literature Review, FEDS Notes*. Washington: Board of Governors of the Federal Reserve System.

Castrén, O., Kavonius, I.K., Rancan, M., 2022. Digital currencies in financial networks. J. Financ. Stab. 60, 101000.

Chen, H., Siklos, P.L., 2022. Central bank digital currency: A review and some macro-financial implications. J. Financ. Stab. 60, 100985.

Demir, E., Gozgor, G., Lau, C.K.M., Vigne, S.A., 2018. Does economic policy uncertainty predict the bitcoin returns? An empirical investigation. Financ. Res. Lett. 26, 145–149.

Dickey, D.A., Fuller, W.A., 1981. Likelihood ratio statistics for autoregressive time series with a unit root. Econ.: J. Econ. Soc. 49 (4), 1057–1072.

Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119 (534), 158–171.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.

Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. J. Econ. 182 (1), 119–134.

Dunbar, K., 2023. CBDC uncertainty: Financial market implications. Int. Rev. Financ. Anal. 87, 102607.

Elsayed, A.H., Helmi, M.H., 2021. Volatility transmission and spillover dynamics across financial markets: The role of geopolitical risk. Ann. Oper. Res. 305 (1–2), 1–22.

Elsayed, A.H., Nasir, M.A., 2022. Central bank digital currencies: An agenda for future research. Res. Int. Bus. Financ. 62, 101736.

Elsayed, A.H., Gozgor, G., Lau, C.K.M., 2022. Risk transmissions between bitcoin and traditional financial assets during the COVID-19 era: The role of global uncertainties. Int. Rev. Financ. Anal. 81, 102069.

Fang, L., Bouri, E., Gupta, R., Roubaud, D., 2019. Does global economic uncertainty matter for the volatility and hedging effectiveness of bitcoin? Int. Rev. Financ. Anal. 61, 29–36.

Financial Times (2022a). *Report suggests bright future for central bank digital currencies*. https://www.ft.com/content/05753dfd-c5ed-44bb-be77-c54bd5e4f066 (Accessed: 04/12/2022).

Financial Times (2022b). *Blockchain may have a green future regardless of crypto.* Available at https://www.ft.com/content/6d049669-1fac-40d8-bd24-955de5d29730 (Accessed: 04/12/2022).

Grobys, K., Junttila, J., Kolari, J.W., Sapkota, N., 2021. On the stability of stablecoins. J. Empir. Financ. 64, 207–223.

Hatemi-J, A. (2003). A new method to choose optimal lag order in stable and unstable VAR models. *Applied Economics Letters*, 10(3), pp.135-137.

Hatemi-J, A. (2008). Forecasting properties of a new method to determine optimal lag order in stable and unstable VAR models. *Applied Economics Letters*, 15(4), pp.239-243.

Helmi, M.H., Catik, A.N., Akdeniz, C., 2023. The impact of central bank digital currency news on the stock and cryptocurrency markets: Evidence from the TVP-VAR model. Res. Int. Bus. Financ. 65, 101968.

Hoang, Y.H., Ngo, V.M., Vu, N.B., 2023. Central bank digital currency: A systematic literature review using text mining approach. Res. Int. Bus. Financ., 101889

Jacomy, M., Heymann, S., Venturini, T., Bastian, M., 2014. ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the gephi software. PLoS One 9 (6), e98679.
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.
Karau, S., 2023. Central bank digital currency competition and the impossible trinity. Financ. Res. Lett. 54, 103723.
Kim, Y.S., Kwon, O., 2022. Central bank digital currency, credit supply, and financial stability. J. Money Credit Bank. 55 (1), 297–321.
Koutmos, D., 2018. Return and volatility spillovers among cryptocurrencies. Econ. Lett. 173, 122–127.
Kumhof, M., Noone, C., 2021. Central bank digital currencies — Design principles for financial stability. Econ. Anal. Policy 71, 553–572.
Kwiatkowski, D., Phillips, P.C., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? J. Econ. 54 (1–3), 159–178.
Minesso, M.F., Mehl, A., Stracca, L., 2022. Central bank digital currency in an open economy. J. Monet. Econ. 127, 54–68.
Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econ. Lett. 58 (1), 17–29.
Phillips, P.C., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75 (2), 335–346.
Toda, H.Y., Yamamoto, T., 1995. Statistical inference in vector autoregressions with possibly integrated processes. J. Econ. 66 (1–2), 225–250.
Wang, P., Li, X., Shen, D., Zhang, W., 2020. How does economic policy uncertainty affect the bitcoin market? Res. Int. Bus. Financ. 53, 101234.
Wang, Y., Lucey, B.M., Vigne, S.A., Yarovaya, L., 2022. The effects of central bank digital currencies news on financial Markets. Technol. Forecast. Soc. Chang. 180, 121715.
Wang, Y., Wei, Y., Lucey, B., Su, Y., 2023. Return spillover analysis across central bank digital currency attention and cryptocurrency markets. Res. Int. Bus. Financ. 64, 101896.
Wu, W., Tiwari, A.K., Gozgor, G., Leping, H., 2021. Does economic policy uncertainty affect cryptocurrency markets? Evidence from twitter-based uncertainty measures. Res. Int. Bus. Financ. 58, 101478.
Yarovaya, L., Brzeszczyński, J., Goodell, J.W., Lucey, B., Lau, C.K.M., 2022. Rethinking financial contagion: Information transmission mechanism during the COVID-19 pandemic. J. Int. Finan. Markets. Inst. Money 79, 101589.
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.
Yousaf, I., Goodell, J.W., 2023. Linkages between CBDC and cryptocurrency uncertainties, and digital payment stocks. Financ. Res. Lett. 54, 103765.