Uncertainty and Cryptocurrency Returns: A Lesson from Turbulent Times

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Abstract

This paper explores the interplay between economic uncertainty and cryptocurrency behaviour. Using data spanning from April 2018 to December 2022, we examine the relationship between ten major cryptocurrencies and a repertoire of uncertainty measures covering geopolitical events, economic policy, and commodity, equity, and bond markets. Cryptocurrency returns exhibit dynamic and positive correlation with stock market and oil volatility, but no significant association with other uncertainty proxies. In terms of volatility spillovers, the transmission from uncertainty indices to cryptocurrency markets is weak, but intensifies during turbulent periods such as the Covid-19 outbreak or the Ukraine war. Overall, the pricing of cryptocurrencies remains largely disconnected from economic risks, which casts doubt on their alleged 'safe haven' properties.

Keywords: cryptocurrency, uncertainty indices, spillovers, networks, COVID-19, Ukrainian war;

1 Introduction

The question on the connectedness of cryptocurrency prices to macroeconomic risk has broad implications. One of the principal – yet uncertain – promises of crypto assets is their ability to hedge economic risks (Koutmos et al., 2021). Moreover, approaches of policymakers to contain or regulate crypto markets may be largely conditional on the extent to which risks are (or can be) isolated from the real economy (Aquilina et al., 2023). Risk inter-dependencies are also material to the permissibility of financial institutions' cryptocurrency exposures (Huang et al., 2022) and cryptocurrency ETF listings. Our aim with this paper is to inform these debates by addressing calls for a richer understanding of cryptocurrency volatilities, volatility spillovers, and their relationship to macroeconomic uncertainty (Urquhart and Lucey, 2022).

Prima facie, the existence of a meaningful connection between volatilities in crypto markets and the real economy is unclear. On one hand, trading in Bitcoin and other cryptocurrencies is argued to be speculative and detached from economic fundamentals (Yermack, 2015); differently to traditional investments, which are strongly fundamentals-driven. This view implies a lack of correlation between crypto prices and other asset classes, underpinning their usefulness for diversification and risk management. On the other hand, speculation in crypto plausibly links to developments in the wider economy which influence investor sentiment, risk appetite, availability and cost of risk capital, and general allure and prospect of wider crypto adoption. Economic turbulence could, for instance, lower cryptocurrency prices through increased discount rates and suppressed appetite for speculation (Anastasiou et al., 2021). Alternatively, the treatment of crypto as a 'safe haven' asset class could yield opposite impacts (Corbet et al., 2020a).

Consistent with the former view, some prior literature finds crypto serves as a good hedge against risk in traditional financial assets (Bouri et al., 2020b), and that Bitcoin may even outperform gold and commodities in terms of diversification potential (Bouri et al., 2020a). Yet, Uzonwanne (2021) observes significant return and volatility spillovers between stocks and Bitcoin, while Corbet et al. (2020b) observe some macroeconomic news impacts on Bitcoin prices. There is also some evidence of economic policy uncertainty predicting Bitcoin returns (Demir et al., 2018). To resolve the remaining ambiguities, we expand on the existing evidence base by examining dynamic correlations in returns and volatility spillovers among a broad range of economic uncertainty indices and cryptocurrencies. In doing so, we attempt to comprehensively map connections between risks in crypto assets and the wider economy.

We consider ten of the most capitalized coins that are relatively long-listed and widely examined in prior studies. Additionally, we include in our study a cryptocurrency index, CRIX, which allows us to account simultaneously for a wide portfolio of coins. From a variety of different risks that are considered in the literature, we identify several that are important in investment decisions. We take into account a large set of indices that cover diverse risk areas, among which are commonly used proxies, including the Economic Policy Uncertainty Index (EPU), the CBOE Volatility Index (VIX), Crude Oil Volatility Index (OVX), Gold Volatility Index (GVZ), and Geopolitical Risk (GPR). We enrich these with two other stock volatility indices, the Emerging Markets Volatility Index (VXEEM) and EFA Volatility Index (VXEFA), and the Treasury Bond Volatility Index (VXTLT) representing interest rate risk.

In terms of methodology, we use techniques that allow us to analyze dependencies in both returns and volatility. First, we apply dynamic conditional correlation models, which enable us to deeply analyze the time-varying dependency between various risks and coins. This step is important from the point of view of portfolio management and systemic risk assessment. Second, we conduct a volatility spillover analysis in order to identify the main receivers and senders between risk indices and coins. It enables us to indicate if any of the risk indices are leading coins and to what extent. Based on the volatility spillovers we apply network analysis, which helps identify key channels of transmission in a multidimensional system. It also allows us to visualize the dependency structure, as well as the roles of the various risk and coin indicators in the system.

By including different uncertainty indices and cryptocurrencies we were able to compare the significance and magnitudes of spillovers from risk indices to coins, the other way around, and from coins to coins. We found that the response of cryptocurrencies varies depending on the type of risk an index captures. The correlations between risk measures and coins are in most cases close to zero or negative, which implies cryptocurrencies are natural hedges for investors against risk in traditional assets. For stock market volatility indices and the oil market index, correlations with coins dropped after the Covid-19 pandemic. In contrast, in the case of economic policy and geopolitical risk indices, no such reactions are observed. We evidence that in terms of spillovers, risk indices are in the majority of cases the senders to coins, but the magnitude of the impact changes over time. The outbreak of the Covid-19 pandemic saw increased spillovers, especially from stock market volatility indices to coins. In the case of the Ukrainian war, the US volatility index (VIX) and the volatility index from developed countries became sources of volatility in coin markets. When the broad system is taken into account in a network setting, analyses show that among the risk indices considered in the study, the most influential is OVX followed by GVZ. Spillovers from one coin to another are usually two to three times stronger than from the risk indices to coins.

Our contribution to the existing literature is the following: we extend studies focusing disparately on dependencies between various uncertainty indices and cryptocurrencies (Al-Yahyaee et al., 2019; Singh et al., 2022; Wang et al., 2019) by examining together relations among a broad range of indices and coins, which includes a relatively novel cryptocurrency index, CRIX (Trimborn and Härdle, 2018). The literature considers various risks in relation to investment decisions in cryptocurrencies, and studies typically consider between one and three indices. In addition to the commonly used risk indices such as the VIX, OVX, GPR, GVZ or EPU (Al Mamun et al., 2020; Colon et al., 2021; Elsayed et al., 2022; Selmi et al., 2022), we additionally introduce the gold volatility index (GVZ), equity uncertainty indices that represent risk in emerging (VXEEM) and developed (VXEFA) equity markets, and the interest rate uncertainty index (VXTLT).

Moreover, we conduct not only a spillover analysis between a risk index and coins but also a joint analysis of the interactions among all indices and cryptocurrencies considered using the network analysis. It enables us to present a more general picture of the dependency (or its lack) between coins and risk indices and identify the key channels of transmission. Network analysis has been performed to map connections among different cryptocurrencies (Ji et al., 2019; Yi et al., 2018) and crypto assets (Qiao et al., 2023), and to include some nodes from outside the cryptosystem, such as technology stocks (Umar et al., 2021) or monetary policy (Elsayed and Sousa, 2022). To the best of our knowledge, our study is novel in its mapping of connectedness among a wide choice of uncertainty indices and coins.

We also make a contribution by covering an updated time period which includes significant periods of economic turbulence – different stages of the Covid-19 pandemic, as well as the outbreak of war in Ukraine. While prior evidence exists on initial impacts of the Covid outbreak on dynamic spillovers between risk indices and cryptocurrencies (Koutmos et al., 2021), studies incorporating later stages of the pandemic (Al-Shboul et al., 2022; Hasan et al., 2022a) and the Russian invasion of Ukraine (Będowska-Sójka et al., 2022) are limited in that they collectively speak to dynamic spillovers between only a few specific uncertainty indices and coins. In documenting volatility and return spillovers among a broad range of cryptocurrencies and risk factors, over multiple recent episodes of economic turbulence, we consider our paper to provide a more comprehensive and timely picture of these dynamics than is currently presented in the literature.

Our paper offers several implications for policymakers, corporates, and investors. In particular, our article sheds light on the limitations of cryptocurrencies' ability, as an asset class, to hedge against various sources of financial risk. The touted hedge potential of crypto is a key factor in policymakers' decisions to limit or regulate the exposure of retail investors, financial institutions and corporations to crypto assets. Our findings that (and how) the usually weak volatility transmissions accelerate materially during turbulent periods should therefore be informative to such policy decisions. In providing results on spillovers between multiple cryptocurrencies and uncertainty indices, our results lend to a nuanced understanding of the hedging properties of crypto, accounting for the relative strength of transmission across different coins and risk factors. In devising regulations and responding to future economic shocks, policymakers should benefit from this granular understanding of investors' vulnerabilities from exposure to cryptocurrency markets. In addition, our results should help investors and corporates to devise robust investment and diversification strategies which incorporate, or avoid, cryptocurrency assets, informed by a more developed understanding of temporal risk exposures of crypto investments.

2 Relevant Literature

Several strands in the literature dedicated to risk indices are developed. Firstly, there are studies examining the dependency on time and frequency within the wavelet approach. Al-Yahyaee et al. (2019) examine the dependency between risk measured by the Volatility Uncertainty Index (VIX) and Bitcoin (BTC) by simultaneously including the impact of the Crude Oil Volatility Index (OVX), the Economic Policy Uncertainty Index (EPU), and the Geopolitical Risk Index (GPR). They find that the relationship between VIX and BTC is time-varying both in high and low frequencies and that the remaining indices impact the BTC-VIX nexus. Only VIX has predictive power over BTC price changes. Also Singh et al. (2022) apply the wavelet approach to analyze the dependency between Bitcoin, GPR, and EPU on several markets. They confirm the strong dependence between EPU, GPR, and bitcoin returns as well as the short-term comovements between GPR and EPU. In the outbreak of the Ukrainian war which was a period of high geopolitical risk, Santorsola et al. (2022) and Będowska-Sójka et al. (2022) show that gold and BTC are resilient to the negative shocks caused by these events indicating that these asset classes exhibit hedging properties.

The second strand is dedicated to the contagion between cryptocurrencies and assets from various classes. Koutmos (2018) investigates spillovers among cryptocurrencies themselves. He finds that the volatility spillovers between 18 coins have risen over time and that spikes are related to major-specific, namely coin-related, events. Caporale et al. (2021) examine the spillovers within the cryptocurrency market during cyber-attacks. They find that the connectedness of coins and dynamic linkages between the cryptocurrencies under investigation are found in most cases when cyber-attacks occur. When contagion is examined between two asset classes, Uzonwanne (2021) finds evidence that volatility spillovers between stock markets and cryptocurrencies are either bi-directional or uni-directional. Huynh et al. (2020) investigate the spillover effects between coins, gold and silver. They find little or no dependence between gold and coins. Also, according to their results, size matters – with smaller coins more likely to cause wider shocks in the cryptocurrency market than larger ones. Abid et al. (2023) examine the spillovers between Bitcoin or traditional currencies and fixed-income or gold markets.

The third strand of the literature is related to the safe haven properties of cryptocurrencies and the transmission of shocks between them and risk indices. Colon et al. (2021) examine 25 cryptocurrencies, the geopolitical risk index and the economic policy uncertainty index. They find that cryptocurrencies possess a strong hedging ability against GPR, but can only be considered a weak hedge against EPU. Al Mamun et al. (2020) investigate dependency between GPR, EPU and several classes of assets including cryptocurrencies, represented by BTC. They take into account volatility, correlation and risk premia, and they find evidence that both GPR and EPU carry a risk premium in worsening market conditions. Bitcoin investors have an opportunity to hedge their portfolio with gold. Selmi et al. (2022) examine the safe haven properties of gold and bitcoin, which is the titular digital gold, when geopolitical risks are taken into account. They find that both assets are positively correlated to the geopolitical risk measure, which makes both of them comparably good hedges against the stock market. Aysan et al. (2019) examine the reaction of Bitcoin prices to changes in the GPR index. They find a significant negative effect on BTC returns and a significant positive effect on volatility. In a similar vein, Demir et al. (2018) conduct an analysis of the dependency between EPU and BTC. They find evidence supporting the predictive power of EPU over BTC. Hasan et al. (2022b) indicate that cryptocurrency uncertainty, EPU and crude oil volatility (OVX) can be weakly hedged by soybean markets. Moreover, cryptocurrency uncertainties and GPR could be also weakly hedged by GSCI commodity and crude oil.

3 Data

The data sample starts 1$^{\text{st}}$ April 2018 and ends 31$^{\text{st}}$ December 2022; thus covering several episodes of economic turbulence relating to the Covid-19 pandemic, with a consecutive drop in economic activity, the outbreak of the war in Ukraine, a stark rise in oil prices, and high inflation. The following series are included in the study. Among the global risk factors we consider are the U.S. Economic Policy Uncertainty Index (EPU), the Geopolitical Risk Index (GPR), the CBOE Volatility Index (VIX), and the Crude Oil Volatility Index (OVX). Further, we consider three additional uncertainty indices listed on the Chicago Board Options Exchange (CBOE): Gold Volatility Index (GVZ), Emerging Markets ETF Volatility Index (VXEEM) and the EFA ETF Volatility Index (VXEFA). As all prices are quoted in US Dollars, we also include the nominal broad US Dollar Index (USDX) (Al-Yahyaee et al., 2019; Hasan et al., 2022b). The data sources and frequencies are presented in Table 1. As in Demir et al. (2018) and Qian et al. (2023), among others, EPU represents economic policy uncertainty. Furthermore, GPR reflects geopolitical risk, GVZ captures uncertainty related to the crucial metals market, and OVX represents oil market risk. The last three indices, VIX, VXEEM and VXEFA represent the uncertainty of stock markets: VIX tracks U.S. investors' 'fear'; VXEEM for the emerging markets; and VXEFA for developed markets.

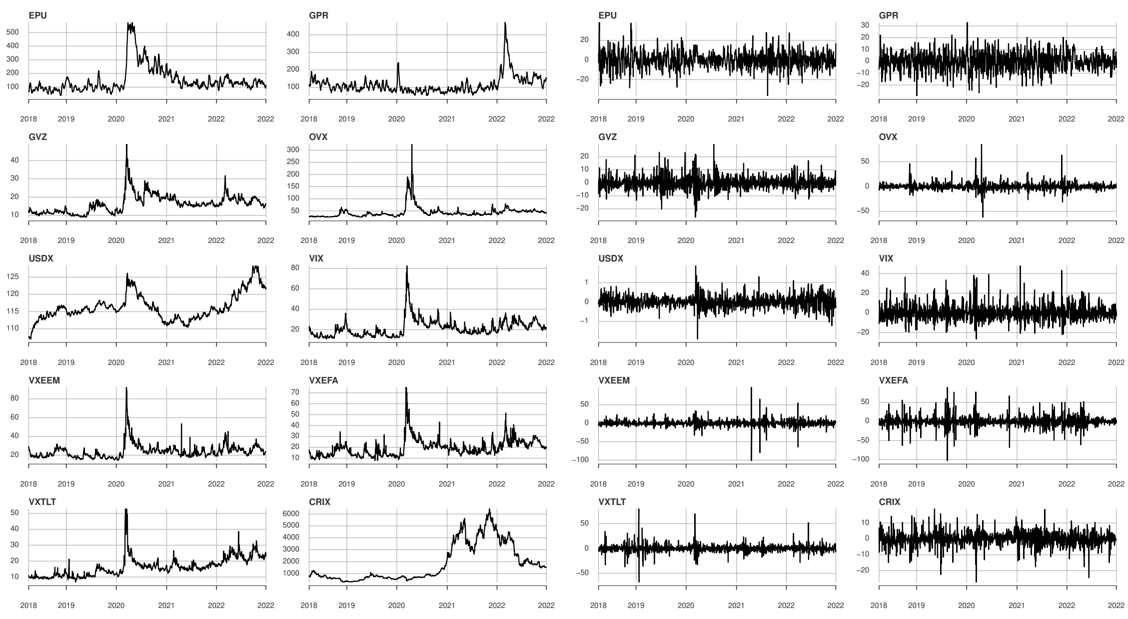
From the broad class of cryptocurrency assets, we select ten coins with a large capitalization, which have been listed since at least 1$^{\text{st}}$ April 2018. Due to their characteristics, stablecoins are excluded from the sample. The considered coins are (in alphabetical order of tickers): Cardano (ADA), BNB, Bitcoin (BTC), Dogecoin (DOGE), Ethereum (ETH), Lithium (LTH), TRON (TRX), Stellar (XLM), Mondero (XMR) and XRP. These coins represent different proofing mechanisms (proof-of-work vs. proof-of-stake), are traded on different exchanges and are used for different purposes. Apart from well-known cryptocurrencies, such as BTC, ETH or LTC, there are other highly capitalized coins that perform different functions. BNB is a native token of the Binance exchange; Cardano and Tron serve as a decentralized ecosystem for digital content; Dogecoin arose as a meme-based cryptocurrency; Stellar aims to facilitate the transfer of digital assets between different financial systems; Monero's focus is on the privacy and confidentiality of transactions; while XRP (Ripple) aims to provide fast and efficient transactions. These various features may affect the relationship between a given cryptocurrency and risk indices. In the subsequent analysis, each coin is considered separately, which allows us to compare results across the group. Broad movements in the cryptocurrency market are also examined, by way of the cryptocurrency index, Royalton Crypto Index (CRIX), which is calculated on a daily basis. Most risk indices (e.g., EPU, VIX, OVX) do not include data for Saturdays and Sundays. Therefore, in order to align all series, we remove these days from the cryptocurrency data. A list of the series included in the study is presented in Table 1.

Figure 1 and 2 show the financial time series of indices and cryptocurrencies, respectively, as well as their returns, over the sample period. The last index among the indices is the cryptocurrency index, CRIX. In the case of indices, the dynamics are similar apart from GPR and the CRIX index – all other indices exhibit notable increases during the Covid-19 pandemic outbreak. In the case of GPR, the main rise is observed in February 2022, which reflects the outbreak of war in Ukraine, while CRIX rises to higher values starting from 2021, and after reaching maximum in

Table 1: The Financial Series Included in the Study

Ticker	Time series name	Frequency	Source
EPU	Economic Policy Uncertainty Index for US	daily 7-days	fred.stlouisfed.org
GPR	Geopolitical Risk Index	daily 7-days	matteoiacoviello.com
GVZ	CBOE Gold Volatility Index	daily 5-days	cboe.com
OVX	CBOE Crude Oil Volatility Index	daily 5-days	cboe.com
USDX	Nominal Broad U.S. Dollar Index	daily 5-days	fred.stlouisfed.org
VIX	CBOE Volatility Index	daily 5-days	cboe.com
VXEEM	CBOE Emerging Markets ETF Volatility Index	daily 5-days	cboe.com
VXEFA	EFA ETF Volatility Index	daily 5-days	cboe.com
VXTLT	CBOE 20+Year Treasury Bond ETF	daily 5-days	cboe.com
CRIX	Royalton CRIX Crypto Index	daily 5-days	royalton-crix.com
ADA	Cardano USD	daily 7-days	finance.yahoo.com
BNB	BNB USD	daily 7-days	finance.yahoo.com
BTC	Bitcoin USD	daily 7-days	finance.yahoo.com
DOGE	Dogecoin USD	daily 7-days	finance.yahoo.com
ETH	Ethereum USD	daily 7-days	finance.yahoo.com
LTH	Litecoin USD	daily 7-days	finance.yahoo.com
TRX	TRON USD	daily 7-days	finance.yahoo.com
XLM	Stellar USD	daily 7-days	finance.yahoo.com
XMR	Monero USD	daily 7-days	finance.yahoo.com
XRP	XRP-USD	daily 7-days	finance.yahoo.com

November 2021, reverts to previous levels. Quite a similar pattern as for CRIX is observed for single cryptocurrencies, but some start to decrease earlier in 2021.

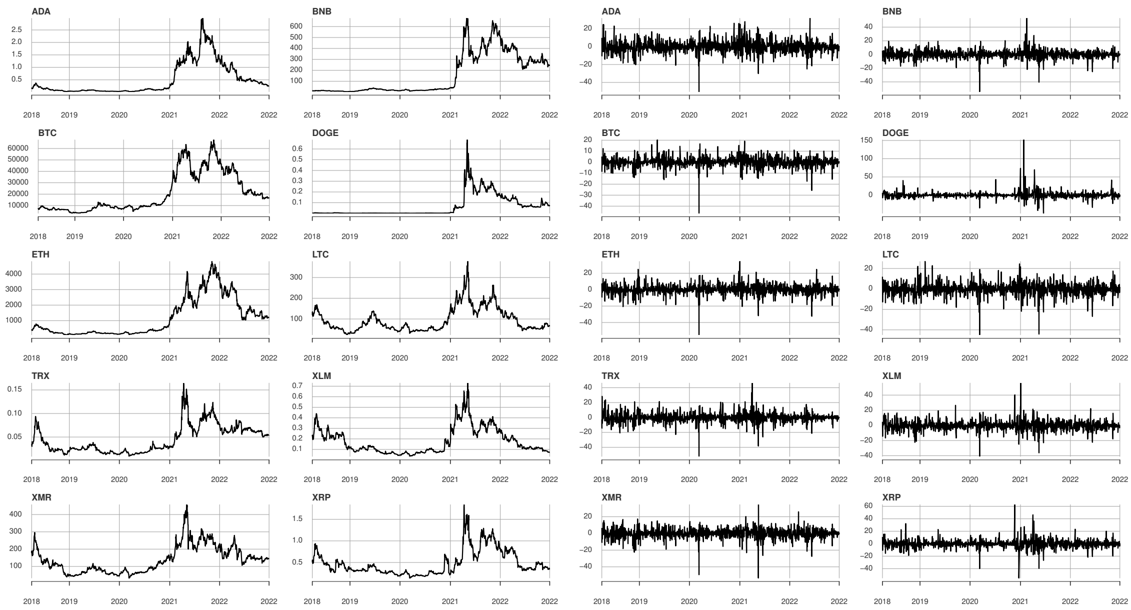


a) Indices levels

b) Indices returns

Figure 1: Time-Series of Uncertainty Indices

The two columns on the left represent prices of indices (the levels), and the two on the right are for returns. Ten indices are presented in the following order from top to bottom: EPU, GVZ, USDX, VXEEM, VXTLT, GPR, OVX, VIX, VXEFA, and CRIX.



a) Prices b) Returns

Figure 2: Time-Series of Cryptocurrency Prices and Returns

The two columns on the left represent the prices of coins (the levels), and the two on the right are for returns. Ten cryptocurrencies are presented in the following order from top to bottom: ADA, BTC, ETH, TRX, XMR, BNB, DOGE, LTC, XLM, and XRP.

Figure 3 presents correlations between all return series considered in the study. The highest positive correlations are observed within the group of coins and within stock volatility indices (VIX, VXEEM, VXEFA). Other indices are weakly positively correlated between themselves with the exception of GPR and EPU, for which correlations are close to zero. The correlation between risk indices and coins is in most cases negative but weak.

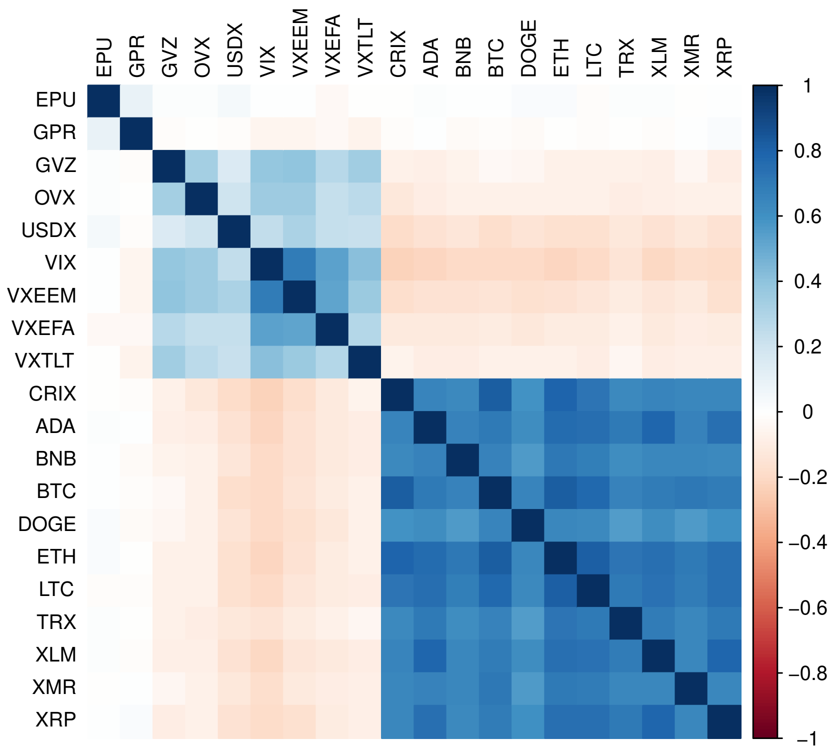


Figure 3: Spearman Correlation for Rates of Return

Table 2 presents descriptive statistics of the daily returns. In the case of risk indices, means are not statistically significantly different from zero. The highest standard deviation is observed for VXEFA and the lowest for USDX. For some series the skewness is positive (OXV and VIX), or negative (VXEEM) while for the remaining the distribution is symmetric. The highest excess kurtosis is for VXEEM and OVX signifying the fat tails and the presence of extreme observations. In the case of cryptocurrencies, means are also not significant – the lowest standard deviation is for BTC, while the highest is the one for DOGE. The latter is significantly right-skewed, while the distribution of the remaining coins is symmetric. The highest excess kurtosis is observed for DOGE, which might be explained by its memetic nature.

Table 2: Descriptive Statistics of Percentage Logarithmic Rates of Return

Ticker	Minimum	Maximum	Mean	Stdev	Skewness	Excess Kurtosis
EPU	-36.7016	38.3335	0.0504	8.0569	0.1281	1.6265
GPR	-29.1843	32.9558	0.0208	7.4298	-0.0586	0.7980
GVZ	-26.5662	29.7680	0.0199	5.1677	0.6504	3.6461
OVX	-62.2251	85.7700	0.0344	7.5487	2.1023	27.0363
USDX	-1.9088	1.8744	0.0102	0.3189	0.2138	2.9769
VIX	-26.6228	48.0214	-0.0073	8.1169	1.1258	3.8927
VXEEM	-101.3565	97.6168	-0.0167	9.3645	-0.2451	31.0537
VXEFA	-102.7436	89.6763	0.0120	14.2564	0.1890	8.4592
VXTLT	-68.0776	79.9710	0.0613	8.0908	0.9973	20.6187
CRIX	-27.2552	18.9390	0.0592	4.6073	-0.5127	3.5746
ADA	-50.3638	31.6747	0.0383	6.8302	-0.0294	4.5595
BNB	-54.3084	52.9218	0.2523	6.2561	-0.2488	12.0704
BTC	-46.4730	20.3046	0.0724	4.5150	-1.1002	11.9547
DOGE	-49.6124	151.6328	0.2716	9.0832	5.0152	74.8491
ETH	-55.0732	34.3523	0.0962	6.0697	-0.7691	8.8880
LTC	-44.9062	26.8725	-0.0478	6.0580	-0.7512	6.6102
TRX	-52.3147	46.2230	0.0356	6.5145	-0.1256	8.3534
XLM	-40.9951	55.9184	-0.0964	6.5140	0.5658	9.7507
XMR	-53.4196	34.4954	-0.0166	6.1190	-1.1749	10.3244
XRP	-55.0503	62.6741	-0.0316	6.7398	0.4701	15.4100

4 Methodology

In this section, we present the methods used in the study: the conditional correlation models, time-varying vector autoregressive models and the spillover analysis based on generalised forecast error variance.

4.1 Dynamic Conditional Correlation Models

The dynamic linkages between indices and coins are examined within the dynamic conditional correlation approach (DCC-GARCH) of Engle (2002), which is defined by the following equations:

$$
\begin{aligned}
\mathbf{r}_t =& \mu_\mathbf{t} + \varepsilon_t, \qquad \mu_\mathbf{t} = E(\mathbf{r}_t|\Omega_{t-1}), \qquad \varepsilon_t = \sqrt{\mathbf{H}_t}\mathbf{z}_t \\
\mathbf{H}_t =& \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t \\
\mathbf{R}_t =& \mathbf{Q}_t^{*-1/2}\mathbf{Q}_t\mathbf{Q}_t^{*-1/2} \\
\mathbf{Q_t} =& (1-\alpha-\beta)\overline{\mathbf{Q}} + \alpha(\varepsilon_{t-i}\varepsilon_{t-i}^{'}) + \beta\mathbf{Q}_{t-j}
\end{aligned}
\tag{1}
$$

where:

$\mathbf{D}_t$ – a diagonal matrix of time-varying standard deviations from univariate GARCH models,

$\mathbf{z}_t$ – a vector of the standardized residuals ε_t,

$\mathbf{R}_t$ – a time-varying conditional correlation matrix of the $\mathbf{z}_t$,

$\overline{\mathbf{Q}}$ – an unconditional correlation matrix of the $\mathbf{z}_t$,

$\mathbf{Q}_t^*$ – a diagonal matrix composed of the square roots of the diagonal elements of $\mathbf{Q}_t$.

The model is estimated using the Quasi Maximum Likelihood (QML) in two stages. In the first step, we estimate univariate GARCH models for each asset series (Engle, 2002; Engle and Sheppard, 2001; Tse and Tsui, 2002). From the broad family of GARCH models, we selected an appropriate specification for each series using the Akaike (AIC) and Bayesian (BIC) information criteria. The specifications of the models chosen are presented in the Appendix. In the second step, we apply the standardized residuals from the first step and estimate the parameters of the dynamic conditional correlation models.

The multivariate Student's t-distribution is applied as the null hypothesis of the multivariate normal distribution is rejected. The estimated DCC-GARCH models satisfy the restrictions imposed on conditional variance and conditional correlation in the case of the pairs of returns.

4.2 Spillover Analysis

When calculating the connectedness between risk indices and coins we follow the approach presented in Diebold and Yilmaz (2012) and Demirer et al. (2018). The volatility spillovers are based on conditional variances from univariate GARCH models. Here we apply the method presented in Diebold and Yilmaz (2012) and the extension of this approach proposed by Antonakakis et al. (2020).

Diebold and Yilmaz (2012) consider a covariance stationary K-variable VAR(p) model:

$$\mathbf{y}_t = \mathbf{c} + \mathbf{\Phi}_1 \mathbf{y}_{t-1} + \mathbf{\Phi}_2 y_{t-2} + ... + \mathbf{\Phi}_p y_{t-p} + \varepsilon_t \qquad \varepsilon \sim (\mathbf{0}, \mathbf{\Sigma}), \tag{2}$$

where $\mathbf{y}_t$ is the vector of endogenous variables, $\mathbf{\Phi}_i$ is an $K \times K$ dimensional matrix of parameters, ε_t is an $K \times 1$ dimensional error vector, and $\mathbf{\Sigma}$ represents the variance-covariance matrix. Each variable is expressed as a linear function of its own past values and the past values of all other variables within the K-variable system. The error terms can be interpreted as surprise movements or shocks in the variables after taking into account previous values.

The time-varying parameter vector autoregression (TVP-VAR) model approach extends the traditional VAR model by allowing the parameters, such as coefficients and covariance matrices, to vary over time. Thus, it captures time-varying dynamics and structural changes in the relationships among variables. As indicated by Korobilis and Yilmaz (2018), the TVP-VAR-based connectedness index captures changes in the series more accurately and is more sensitive to innovation than traditional VAR. In the case of TVP-VAR, it does not show excessive persistence and the linkage rate decreases gradually as the impact of a volatility shock in one series fades into another. For VAR it remains high as long as the moment-of-crisis data are kept within the rolling sample window.

The TVP-VAR(p) model can be represented as follows (Antonakakis et al., 2020):

$$\mathbf{y}_t = \mathbf{\Phi}_{1t} \mathbf{y}_{t-1} + \mathbf{\Phi}_{2t} y_{t-2} + ... + \mathbf{\Phi}_{pt} y_{t-p} + \mathbf{u}_t \qquad \mathbf{u}_t | \mathbf{\Omega}_{t-1} \sim N(\mathbf{0}, \mathbf{\Sigma}_t) \tag{3}$$

$$vec(\mathbf{\Phi}_t) = vec(\mathbf{\Phi}_{t-1}) + \xi_t \qquad \xi_t | \mathbf{\Omega}_{t-1} \sim N(\mathbf{0}, \mathbf{\Xi}_t) \tag{4}$$

where $\mathbf{\Omega}_{t-1}$ contains all the information available until $t-1$, $\mathbf{y}_t$ represents $N \times 1$ dimensional vector of the observed variables, $\mathbf{\Phi}_{1t}$ is an $N \times N$ dimensional matrix of parameters, $\mathbf{\Phi}_t = [\mathbf{\Phi}_{1t}, \mathbf{\Phi}_{2t}, \ldots, \mathbf{\Phi}_{pt}]$ is an $N \times Np$ dimensional matrix, $\mathbf{u}_t$ is an $N \times 1$ vector, ξ_t is an $N^2 p \times 1$ vector, $vec(\mathbf{\Phi}_t)$ is the vectorisation of $\mathbf{\Phi}_t$ which is an $N^2 p \times 1$ dimensional vector, $\mathbf{\Sigma}_t$ and $\mathbf{\Xi}_t$ are $N \times N$ and $N^2 p \times N^2 p$ variance-covariance matrices, respectively.

The transformation of the TVP-VAR to its vector moving average (VMA) representation based on the Wold representation theorem is as follows (see Antonakakis et al., 2020): $\mathbf{y}_i = \sum_{i=0}^{\infty} \mathbf{A}_{it} u_{t-i}$, where $\mathbf{A}_{it}$ is an $N \times N$ dimensional matrix. This transformation allows estimating the Diebold and Yilmaz (2014) connectedness approach based on generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD). The GIRF provides the analysis of the magnitude, direction, and persistence of the responses of each variable to a shock in another variable. The GFEVD provides information on the relative importance of different shocks in explaining the forecast error variance of each variable.

The H-step-ahead generalized forecast error variance decomposition (GFEVD) is obtained as:

$$\Theta^{g}_{ij,t}(H) = \frac{\sigma^{-1}_{jj,t} \sum_{h=0}^{H-1} (\mathbf{e}_i' \mathbf{A}_{h,t} \boldsymbol{\Sigma}_t \mathbf{e}_j)^2}{\sum_{h=0}^{H-1} (\mathbf{e}_i' \mathbf{A}_{h,t} \boldsymbol{\Sigma}_t \mathbf{A}_{h,t}' \mathbf{e}_i)} \tag{5}$$

where $\sigma_{jj,t}$ is the jth diagonal element of the $\boldsymbol{\Sigma}_t$ variance matrix, $\mathbf{A}_{h,t}$ is an $N \times N$ dimensional matrix, $\mathbf{e}_j$ is an $N \times 1$ selection vector with unity in the jth position, and zero otherwise. The value $\Theta^{g}_{ij,t}(H)$ is the contribution of variable j into the forecast error variance of variable i at forecast horizon H. Each element of the generalized variance decomposition matrix is normalized according to the following formula:

$$\tilde{\Theta}^{g}_{ij,t}(H) = \frac{\Theta^{g}_{ij,t}(H)}{\sum_{j=1}^{K} \Theta^{g}_{ij,t}(H)} \tag{6}$$

with $\sum_{j=1}^{N} \tilde{\Theta}^{g}_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\Theta}^{g}_{ij,t}(H) = N$.

These normalized values are further used in the construction of the spillover indices, for which formulas are presented in Table 3.

Table 3: Formulas for the Calculation of Spillover Indices

TVP-VAR: Spillover Indices		
Total:	$S^{g}_{t}(H) = \frac{\sum_{i,j=1, i\neq j}^{K} \tilde{\Theta}^{g}_{ij,t}(H)}{\sum_{i,j=1}^{K} \tilde{\Theta}^{g}_{ij,t}(H)}$	spillovers of volatility shocks across asset classes
From:	$S^{g}_{i\cdot,t}(H) = \frac{\sum_{j=1, j\neq i}^{K} \tilde{\Theta}^{g}_{ij,t}(H)}{\sum_{i,j=1}^{K} \tilde{\Theta}^{g}_{ij,t}(H)}$	directional volatility: spillovers received by market i from all other markets
To:	$S^{g}_{\cdot i,t}(H) = \frac{\sum_{j=1, j\neq i}^{K} \tilde{\Theta}^{g}_{ij,t}(H)}{\sum_{i,j=1}^{K} \tilde{\Theta}^{g}_{ij,t}(H)}$	directional volatility: spillovers transmitted by market i to all other markets
Net:	$S^{g}_{i,t}(H) = S^{g}_{\cdot i,t}(H) - S^{g}_{i\cdot,t}(H)$	a difference between *To* and *From*

Usually, when the above-mentioned indicators are calculated, two approaches are considered, static and dynamic. Static connectedness assumes that the relationships among variables are constant, while dynamic connectedness assumes changing patterns of interconnectedness among variables over time. As we observe structural breaks in our sample period applying a dynamic model is more appropriate (Bouri et al., 2019).

In the dynamic connectedness, we apply two approaches: first, using the VAR model with a rolling window and second, by using TVP-VAR models[1]. As shown Antonakakis et al. (2020), the TVP-VAR models outperform the rolling-window VAR model in four ways: (i) they allow for capturing possible changes in the parameters more accurately; (ii) they are not as outlier-sensitive; (iii) there is no need to arbitrarily set the rolling-window size; and (iv) there is no loss any valuable observations. The estimations are done in R package 'ConnectednessApproach' of Gabauer (2022).

4.3 The Network Approach

We use a network approach based on the connectedness measured for volatility of cryptocurrencies' returns and risk indices. Any study of financial networks usually allows one to analyze the structure

[1]In both cases, a sample size of 200 was used.

and connections within the examined structure and to identify key players. In the network, nodes are represented by the risk indices and examined coins. Values representing "TO" and "FROM" obtained within the spillover analysis are used as the weights (edges) in the networks. The convention for building the network is the following: networks are presented graphically using (1) node names, which are tickers of the risk indices or coins, (2) edge colours, where darker colours and wider edges indicate higher dependency. We also calculate three centrality measures commonly used in network analysis such as a betweenness, closeness and eigenvector centrality (Giudici et al., 2020; Karim et al., 2022; Onnela et al., 2004):

- **betweenness** centrality is the fraction of shortest paths s_{hj} between node h and node j that pass through node i to all possible paths from h to j :

$$b_i = \sum_{h,j=1}^{N} s_{hj}(i)/s_{hj} \tag{7}$$

- **closeness** centrality is the inverse of the average length of the shortest paths between node i and any other node j:

$$c_i = \frac{N-1}{\sum_{i \neq j} d_{ij}} \tag{8}$$

- **eigenvector** centrality which is the measure of prestige and accounts for the importance of a node's neighbours:

$$e_i = 1/\lambda \sum_j \mathbf{A}_{ij} ej \tag{9}$$

  where λ is the largest eigenvalue of the adjacency matrix $\mathbf{A}$ and e is the corresponding eigenvector $\lambda a = ae$.

These measures are calculated for a network consisting of all risk indices and coins allowing us to indicate the main leaders in the network.

5 Empirical Findings

In the first step, we estimate dynamic conditional correlation models and investigate how strongly risk indices are correlated with individual cryptocurrencies and whether these correlations change over time. The dynamic conditional correlation models allow us to examine the dependency between returns and the dynamics of the conditional covariances. Within that analysis we answer the question if the conditional correlations are dynamic or stable and what are the correlation coefficient levels. The volatility estimates from GARCH models are used in the next step for the spillover analysis, where time-varying parameter vector autoregression (TVP-VAR) models for volatility estimates of one risk index and 10 coins are estimated. The spillover index analysis provides a different picture of the financial market as here we focus on the ability to transmit volatility from one market to another. It enables us to assess the connectedness between different risk measures and cryptocurrencies. In the last part, we utilize values from spillover analysis to build a network of dependencies between risk indices and all coins. It enables us to visualize transmission channels between all considered series and indicate the most important nodes in the system.

5.1 The Conditional Correlations

We start with the estimation of conditional correlations within the Dynamic Conditional Correlation models. These models are obtained for each risk index and 10 coins separately. Figure 4 presents the conditional correlations of coins and the VIX index. In most cases, apart from DOGE and XLM, we observed a drop in the correlation at the beginning of the pandemic. The overall risk on the U.S. stock market measured by VIX is for most of the time weakly negatively correlated with cryptocurrency returns. Table 9 in the Appendix shows the minimum, mean, maximum and range of values of the correlations. In the case of VIX, mean correlations are negative for all coins.

The conditional correlations for the remaining series are presented in the Appendix (Figure 10 and Table 9). Analyzing the correlation charts (Figure 10), we conclude that in most cases, dynamic correlations are either constant (as for all pairs with GPR and six coins with EPU where the correlation coefficient is a straight line) or only slightly changing. However, a few pairs can be identified for which the range of variation in dynamic correlations exceeds 0.8 (Table 9). These are GVZ with DOGE (1.19), XMR (0.874); VXEFA with TRX (0.963), XMR (0.894); VXTLT with DOGE (1.319), ETH (1.165), XRP (1.154). Furthermore, in the case of the OVX, USDX, VXTLT and equity risk indices, VXEEM and VXEFA, the correlations with cryptocurrencies are negative on average. For these indices, excluding VXTLT, we observed a decrease in correlation during the Covid-19 pandemic period (similar to the one earlier described for VIX). In the case of VXTLT (Figure 10, Panel h), we observe notable declines in all correlations around 12$^{\text{th}}$ August 2022, coinciding with news of peak inflation in the US, which caused a sharp drop in the bond market.

In summary, simultaneous correlations show either very weak correlations, both positive and negative or no correlations in the returns of the series studied. Cryptocurrency returns mostly appear not to depend on changes in risk perceptions in the markets. The results support the idea that cryptocurrencies serve as a natural hedge for investors who seek diversification. Similar results were obtained by Koutmos et al. (2021) for 11 major cryptocurrencies. They found that coins performed as better hedges against equity market risk indices and commodity risk indices. However, they neither cover interest rate risks nor the geopolitical risk index. Our results concerning the latter index are contrary to those of Colon et al. (2021), who find evidence that the cryptocurrency market can serve as a strong hedge against geopolitical risk. We find that geopolitical risk can serve only as a weak hedge. With respect to the economic uncertainty, the results of Colon et al. (2021) are similar to ours.

5.2 Volatility Spillovers

In Table 4 we present the averaged dynamic volatility spillovers between the GPR index and 10 cryptocurrencies. The row 'TO' and the column 'FROM' show sums of all values in each column or row, respectively, omitting the value on the diagonal. On average the spillover from GPR to various coins is rather minor, with the highest values 'FROM' and 'TO' DOGE. Also, the sum of 'FROM' values is much higher than the total 'TO' value (20.5 versus 4.12), showing that on average the risk index receives more volatility than it sends. The spillovers between coins are much stronger than between the risk index and cryptocurrencies.

The spillovers for remaining indices are presented in Table 10. The overall spillovers from indices to coins are similar, but patterns of sending and receiving are different. Among those that receive more than they send are EPU, GVZ, USDX, VIX, VXEEM, and VXEFA. On the contrary, among those that send to cryptocurrencies more than received is only the OVX index for which 'FROM' is equal to 12.79, while 'TO' accounts for 26.94. The last among those presented in Table 10 shows the averaged values of spillovers between the cryptocurrency index CRIX and other risk indices (Table 10i)). Here the highest spillovers are observed 'TO' the VIX index and 'FROM' VXEFA. The values confirm the earlier finding that cryptocurrencies are less contagious to other indices than these indices are contagious to themselves. When it comes to receiving, CRIX receives even less than it sends.

So far we have presented the averaged spillovers. In the next step, we conduct the dynamic spillover analysis between the same variables in order to show changes (or lack of them) over time. Figure 5 presents spillovers in a moving window. Blue lines represent spillovers 'FROM', while

Table 4: TVP-VAR: Averaged Dynamic Connectedness between GPR and 10 Cryptocurrencies

	GPR	ADA	BNB	BTC	DOGE	ETH	LTC	TRX	XLM	XMR	XRP	FROM
GPR	79.50	1.93	1.30	1.63	4.43	2.65	2.12	0.88	1.14	3.25	1.18	20.50
ADA	0.58	22.55	8.13	8.95	5.72	10.50	9.60	7.50	10.44	8.60	7.43	77.45
BNB	0.35	7.88	31.32	8.24	4.39	9.49	9.40	7.66	6.55	8.97	5.75	68.68
BTC	0.28	8.64	8.27	24.81	5.51	10.84	11.21	6.04	7.45	12.15	4.79	75.19
DOGE	1.22	5.67	4.91	4.90	49.25	6.25	5.81	4.45	6.28	5.86	5.40	50.75
ETH	0.17	9.71	9.31	10.87	4.94	20.54	12.24	7.70	7.10	10.56	6.86	79.46
LTC	0.18	8.58	9.37	11.31	4.89	12.18	20.99	8.02	7.31	10.38	6.79	79.01
TRX	0.21	8.51	8.06	7.50	4.36	8.58	9.34	26.80	7.66	9.19	9.77	73.20
XLM	0.25	11.98	6.90	7.36	6.35	8.75	7.71	7.61	23.75	7.54	11.80	76.25
XMR	0.49	7.87	9.72	11.66	6.10	9.24	10.22	7.31	7.37	24.47	5.56	75.53
XRP	0.39	8.79	6.02	5.74	4.69	8.39	7.44	8.90	11.41	7.10	31.13	68.87
TO	4.12	79.56	71.99	78.15	51.39	86.87	85.09	66.06	72.72	83.60	65.34	TCI
NET	-16.37	2.10	3.31	2.96	0.64	7.40	6.09	-7.14	-3.53	8.07	-3.53	67.72

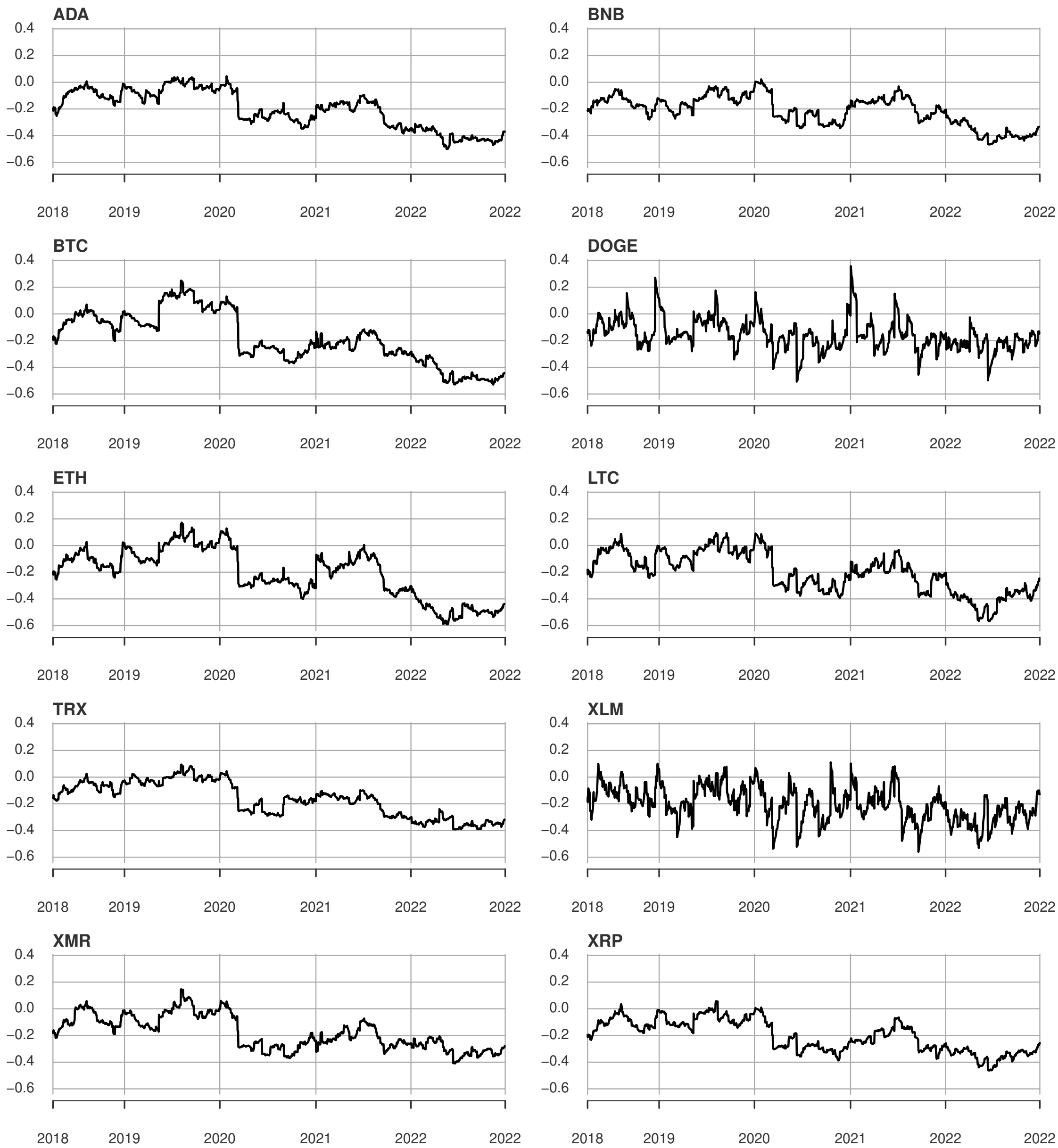
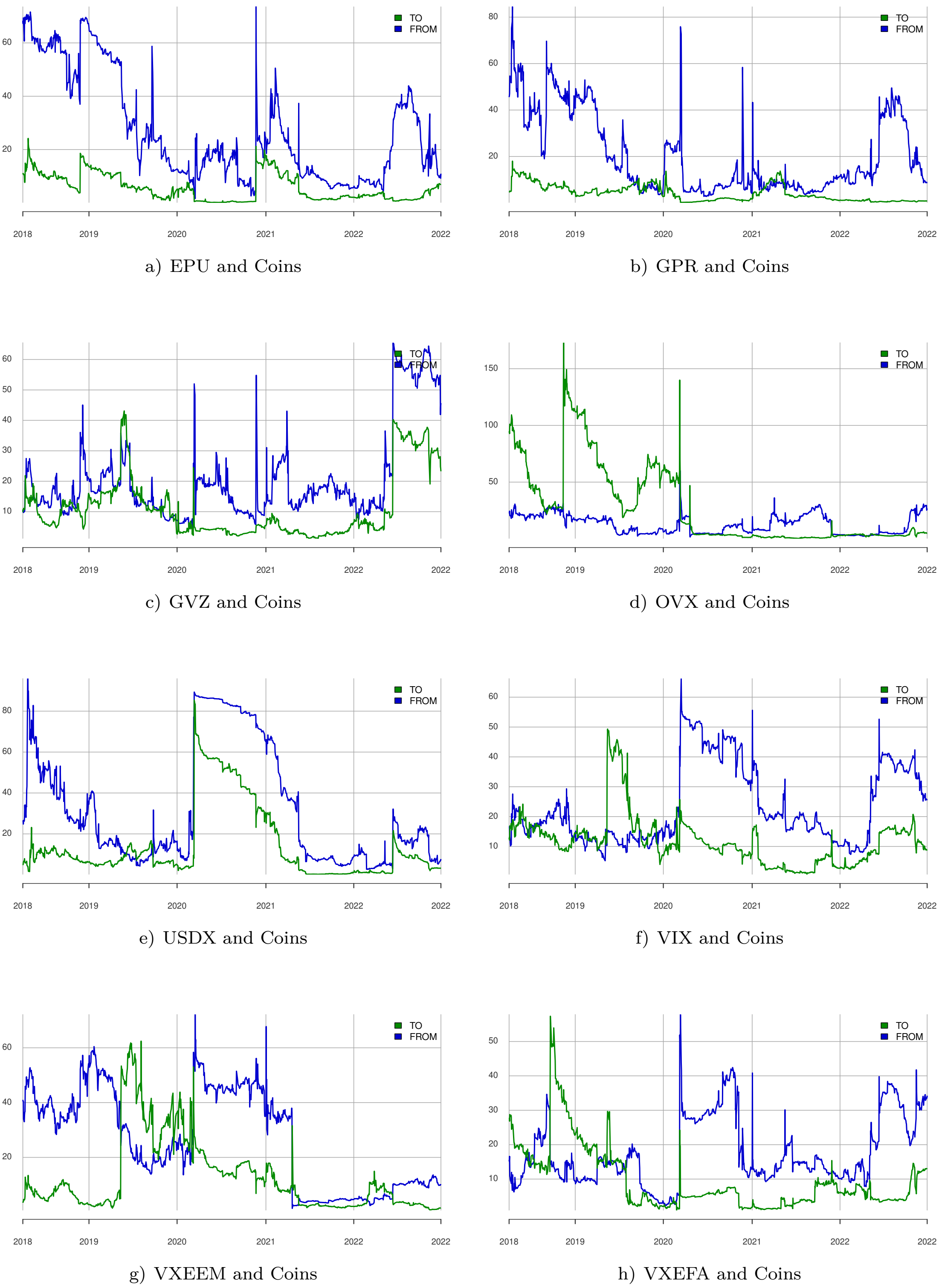


Figure 4: DCC Conditional Correlation between VIX and Coins

green – spillovers 'TO'. The patterns of spillovers are similar for stock risk indices, with an increase of 'FROM' spillovers at the beginning of the Covid-19 pandemic.



a) EPU and Coins

b) GPR and Coins

c) GVZ and Coins

d) OVX and Coins

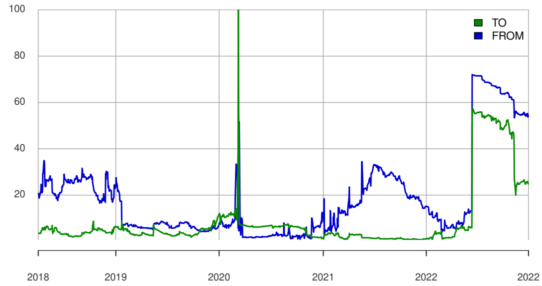
e) USDX and Coins

f) VIX and Coins

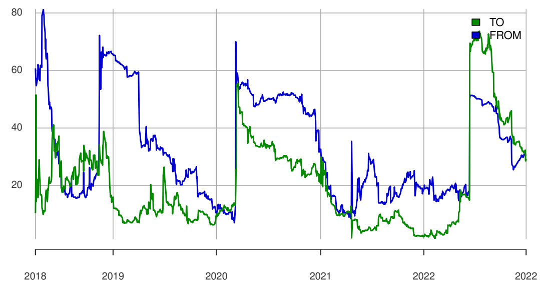
g) VXEEM and Coins

h) VXEFA and Coins

Figure 5: Total Directional Connectedness (TVP-VAR) between Indices and Cryptocurrencies
Note: The blue line represents the spillover FROM an index to coins and the green line represents the spillover from coins TO index.



i) VXTLT and Coins

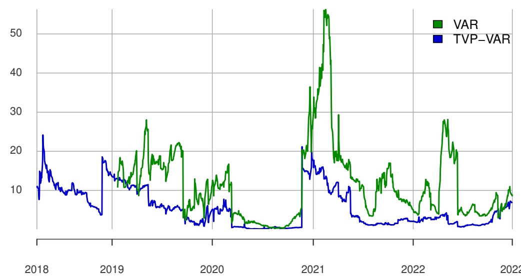


j) CRIX and various risk indices

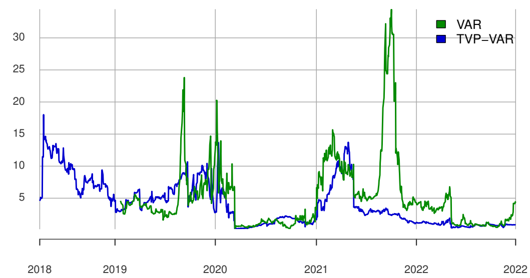
Figure 5: Total Directional Connectedness (TVP-VAR) between Indices and Cryptocurrencies (*continued*)

Next, we also present the spillovers between the group of risk factors. Figures 6–8 show the spillovers between all risk indices and cryptocurrency CRIX index in the moving window 'TO', 'FROM' and 'NET', respectively. We present here two approaches, one based on the forecast error from the VAR model, and the other based on the forecast error from a time-varying VAR model (TVP-VAR). These two approaches give quite similar results, although the latter produces less volatile spillovers.

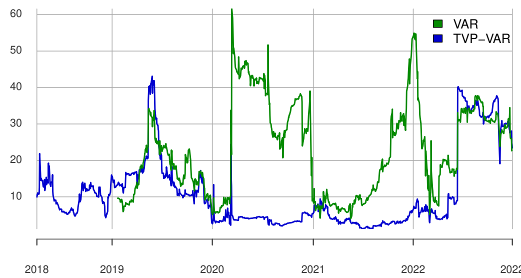
In all cases over time, the spillovers change very dynamically. The highest rise in 'TO', 'FROM' and 'NET' spillovers is observed in March 2020, making the outbreak of pandemic the most crucial risk factor within the sample period. In the case of VXTLT the highest increase in 'FROM' is observed in May 2022, which may be due to an accelerated increase in US interest rates.



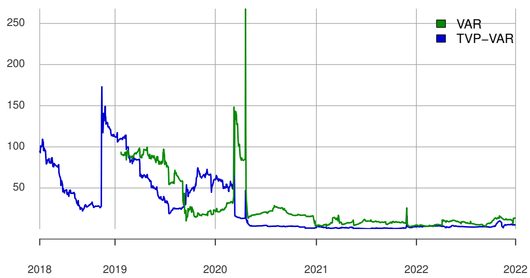
a) EPU and Coins



b) GPR and Coins



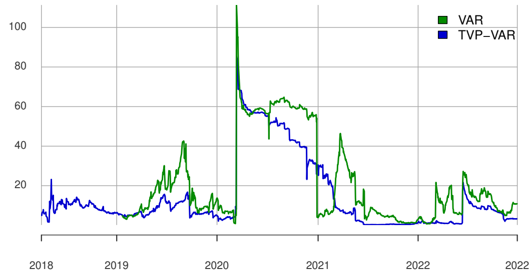
c) GVZ and Coins



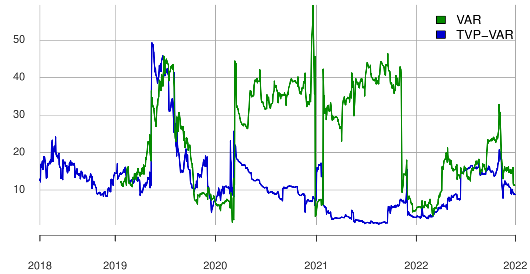
d) OVX and Coins

Figure 6: Total Directional Connectedness TO Others

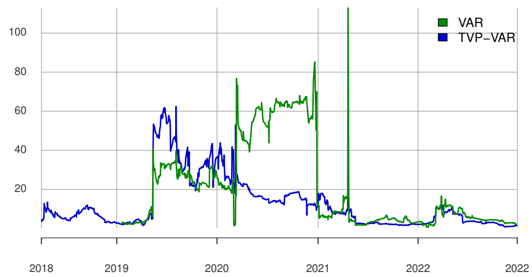
Note: The blue line represents the spillover TO obtained from the TVP-VAR model and the green line represents the spillover TO obtained from the VAR model.



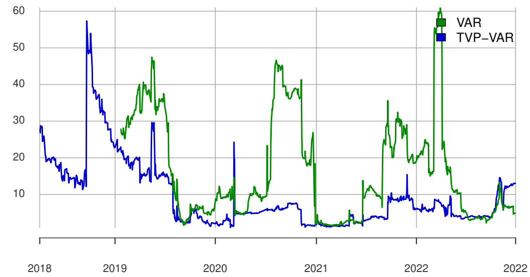
e) USDX and Coins



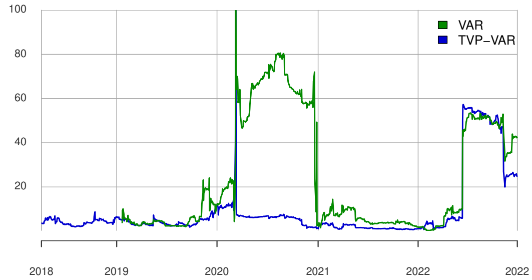
f) VIX and Coins



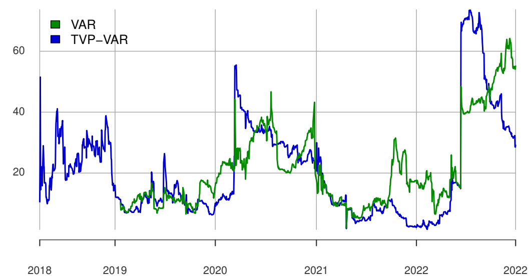
g) VXEEM and Coins



h) VXEFA and Coins

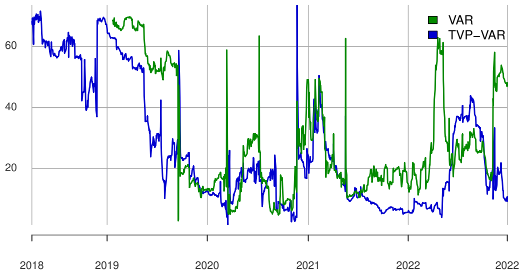


i) VXTLT and Coins

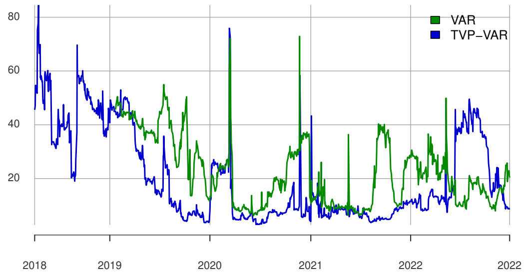


j) CRIX and various risk indices

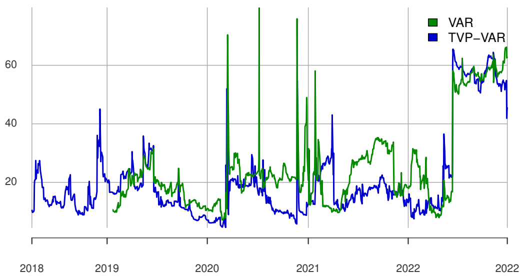
Figure 6: Total Directional Connectedness TO Others (*continued*)



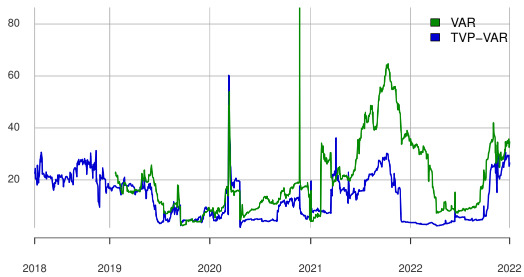
a) EPU and Coins



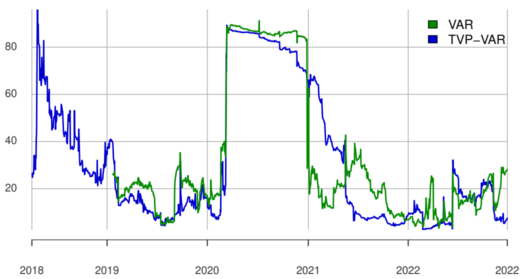
b) GPR and Coins



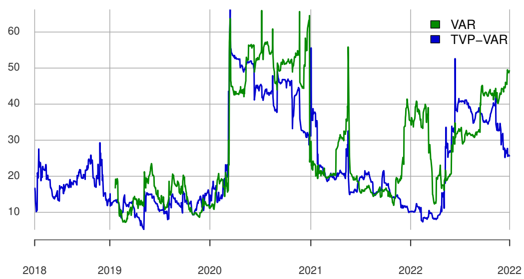
c) GVZ and Coins



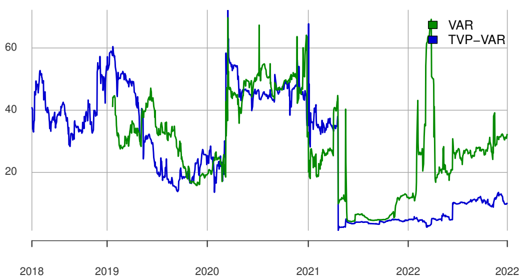
d) OVX and Coins



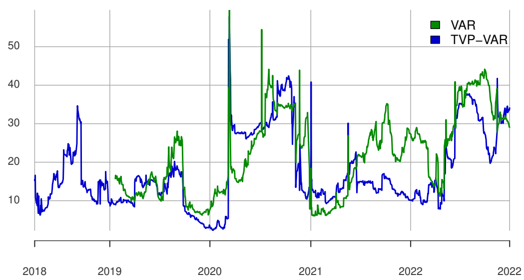
e) USDX and Coins



f) VIX and Coins



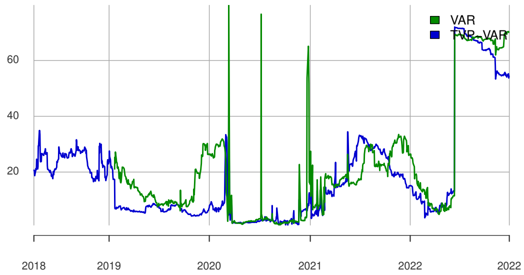
g) VXEEM and Coins



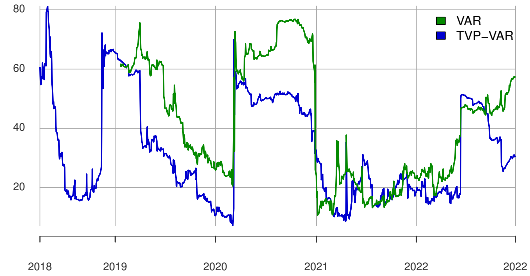
h) VXEFA and Coins

Figure 7: Total Directional Connectedness FROM Others

Note: The blue line represents the spillover FROM obtained from the TVP-VAR model and the green line represents the spillover FROM obtained from the VAR model.

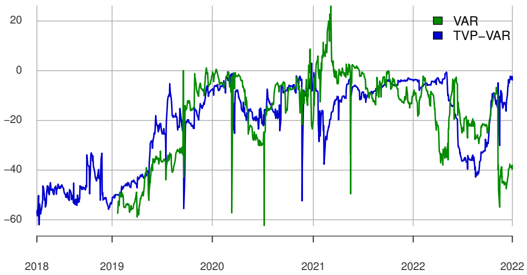


i) VXTLT and Coins

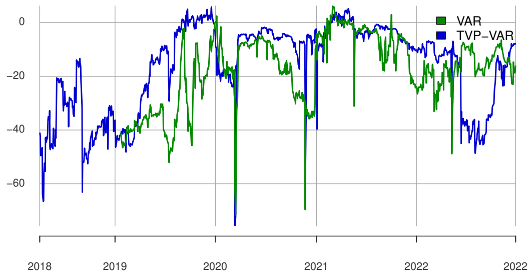


j) CRIX and various risk indices

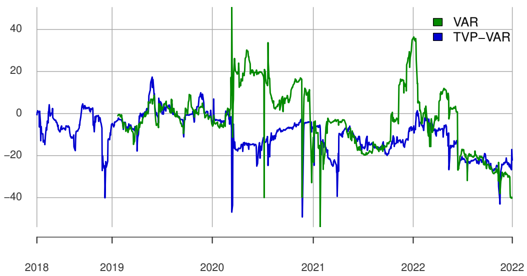
Figure 7: Total Directional Connectedness FROM Others (*continued*)



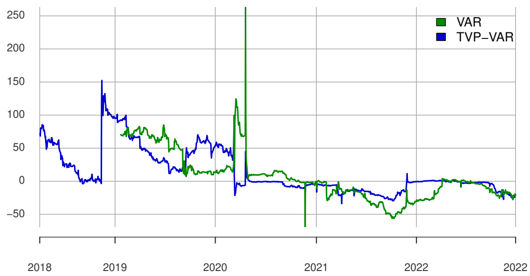
a) EPU and Coins



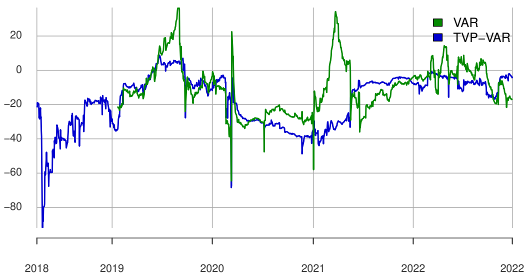
b) GPR and Coins



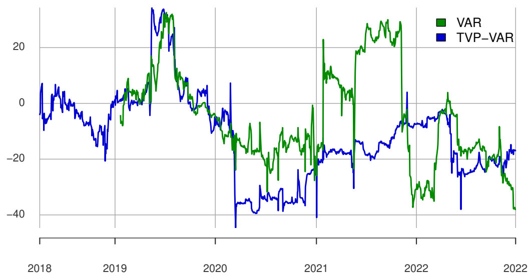
c) GVZ and Coins



d) OVX and Coins

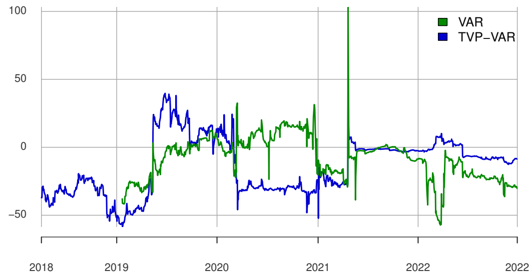


e) USDX and Coins

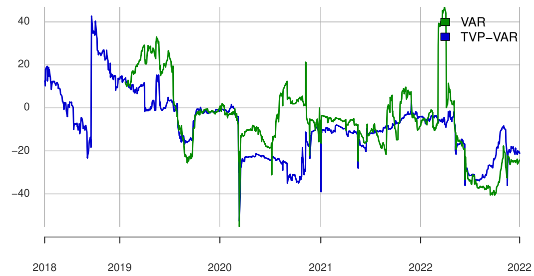


f) VIX and Coins

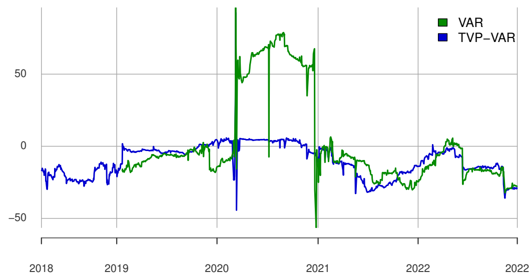
Figure 8: NET Total Directional Connectedness
Note: The blue line represents the spillover NET obtained from the TVP-VAR model and the green line represents the spillover NET obtained from the VAR model.



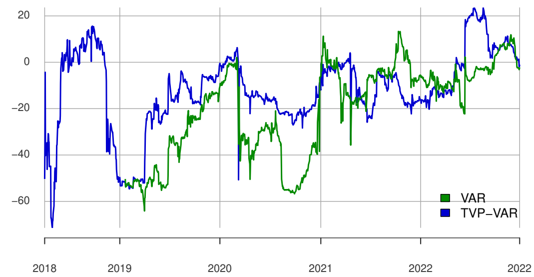
g) VXEEM and Coins



h) VXEFA and Coins



i) VXTLT and Coins



j) CRIX and various risk indices

Figure 8: NET Total Directional Connectedness (*continued*)

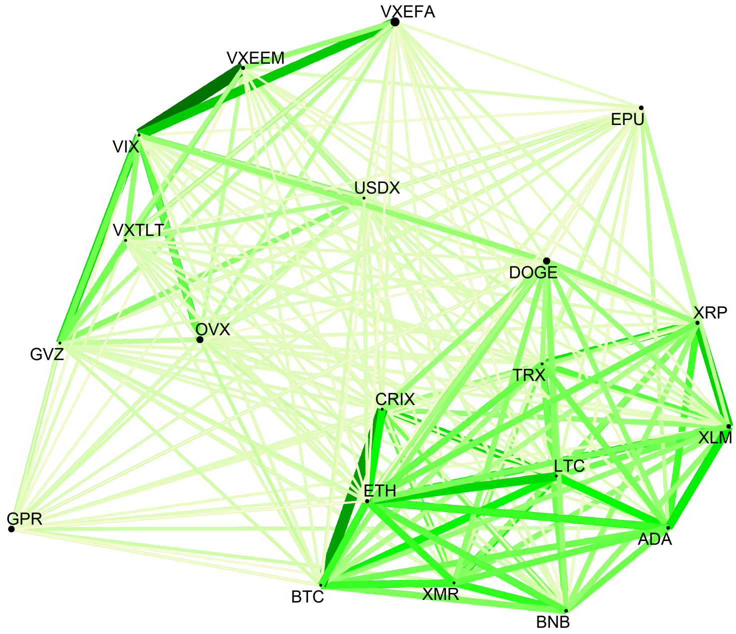
5.3 Networks Based on the Average Spillovers

In this step, we build spillover networks in which nodes represent indices and cryptocurrencies, while edges represent 'FROM' and 'TO' values obtained as the averages of values from spillover analysis (Elsayed et al., 2023). We continue considering two approaches; in the first one, we apply values from spillover analysis based on VAR models, while in the second we utilize values from spillover analysis with TVP-VAR models. Such an approach allows us to verify if differences between the methods of estimation would have an impact on the network structure. TVP-VAR is said to be more sensitive to innovation and more accurately captures changes in the series. It is also a better candidate for measuring the systemic risk than the connectedness index based on the rolling window VAR (Korobilis and Yilmaz, 2018).

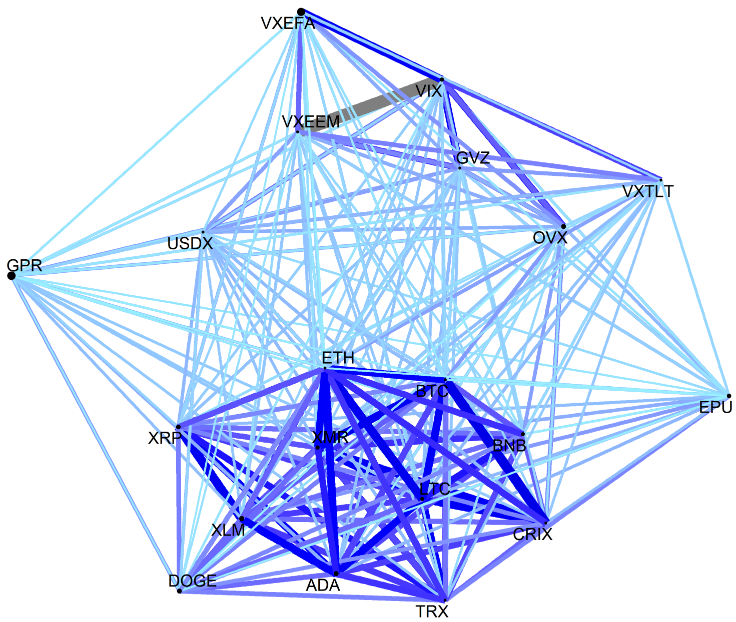
In our networks, the size of a node depends on the betweenness centrality of an index or a coin, which is interpreted as a measure of the importance of a node based on its position in the paths between other nodes. The colour of the edge depends on the strength of spillover – the more intense the colour is, the higher the transmission of shocks. The network with green colour corresponds to the VAR model, while the blue one – to TVP-VAR. Both networks are presented in Figure 9. The position of nodes is random and indicated by a Fruchterman-Reingold force-directed layout algorithm.

Both graphs show that the cryptocurrencies are mainly transmitters among themselves (they cluster in the bottom parts of the networks), and risk indices also transmit to other indices to some extent. In the latter case, the most pronounced dependency is between indices related to the volatility of the stock markets, that is VIX, VXEEM, and VXEFA. There is much less transmission between the two groups of indices and cryptocurrencies. Such findings are similar to Karimi et al. (2023) who found that cryptocurrencies experience spillovers between each other, while their spillovers on oil or gold are less pronounced and of minor significance. Here we show that the same phenomenon is observed when other risk indices are considered. These results are similar regardless of which approach, VAR or TVP-VAR was used when calculating the connectedness index.

We also calculate centrality measures for both networks and present them in Table 5. It allows us to assess what is the impact of particular nodes, either coins or indices in the system. There are some differences in the results for both approaches. This seems to confirm the need for different



a) Spillovers Based on the VAR Model



b) Spillovers Based on the TVP-VAR Model

Figure 9: Network Based on FROM Spillovers for Risk Indices and Cryptocurrencies

Nodes in the networks represent risk indices and coins. The size of the node is proportional to the betweenness measure for each node. The colour and the width of the edges represent the value of a spillover FROM - the wider and more intense in colour an edge is, the stronger the impact of a given node on the other one. For the layout of the graph, we use the Fruchterman-Reingold force-directed algorithm.

models. Eigenvector centrality measures the influence of a node on a network – the higher the value, the more influential a node is. In the first approach with the VAR model, the highest value is observed for VIX, while in the second one, the most influential node is OVX. In the case of betweenness, the highest value is observed for GPR (VAR) and VXEFA (TVP-VAR). Nodes with higher betweenness centrality send more volatility within the system than those with low betweenness. Concerning closeness, there are no substantial differences in values obtained within the networks. Nodes with high closeness centrality, such as LTC and GPR (in spillovers from the VAR model) or GPR (from TVP-VAR) act as crucial nodes, which are responsible for volatility transfer across the network. In sum, among indices, GPR, OVX, VIX and VXEFA appear to be the most crucial from the point of view of the transmission of shocks within the system. However, their impact is differently assessed when one utilizes various centrality measures.

Table 5: Centrality Measures for Networks Based on the Volatility Spillovers

	VAR			TVP-VAR		
	eigenvector	betweenness	closeness	eigenvector	betweenness	closeness
ADA	0.86	8.00	0.05	0.90	1.00	0.08
BNB	0.83	2.00	0.05	0.86	1.00	0.07
BTC	0.90	0.00	0.05	0.92	0.00	0.08
DOGE	0.68	9.00	0.05	0.82	38.00	0.08
ETH	0.94	0.00	0.06	0.94	3.00	0.09
LTC	0.93	2.00	**0.07**	0.99	0.00	0.09
TRX	0.83	0.00	0.05	0.85	0.00	0.08
XLM	0.80	10.00	0.06	0.82	5.50	0.09
XMR	0.85	3.00	0.05	0.97	0.00	0.07
XRP	0.80	6.00	0.06	0.82	3.50	0.08
CRIX	0.86	0.00	0.06	0.80	0.00	0.08
EPU	0.38	4.00	0.05	0.27	6.00	0.09
GPR	0.32	**67.50**	**0.07**	0.19	26.50	**0.12**
GVZ	0.92	0.00	0.03	0.47	0.00	0.06
OVX	0.88	9.00	0.03	**1.00**	36.00	0.06
USDX	0.64	0.00	0.03	0.44	0.00	0.04
VIX	**1.00**	3.00	0.04	0.77	0.00	0.06
VXEEM	0.84	0.00	0.04	0.68	2.00	0.06
VXEFA	0.54	57.00	0.05	0.51	**81.00**	0.09
VXTLT	0.76	0.00	0.03	0.44	0.00	0.05

Note: Centrality measures are calculated for two networks, on the left panel there is one based on the spillovers with VAR, on the right panel there are centrality measures for the network based on the TVP-VAR. The maximum values for each column are in bold.

6 Conclusion

The study examines the instantaneous dependency between various uncertainty proxies and major cryptocurrencies as well as the spillover effects, which account for the lagged responses. Within the first group, we consider several risk indices such as the economic policy uncertainty index, the volatility index, the crude oil volatility index, the gold volatility index, the geopolitical risk index, three stock market risk indices, and the bond market risk index. Among cryptocurrencies, we take into account the ten most capitalized coins. The data sample encompasses several upturns and downturns in the coin market. We find that for pairs of stock market uncertainty indices, oil and gold market uncertainty indices, the dynamic correlations with coins returns close to zero or negative. In the remaining cases, the correlations between uncertainty indices and cryptocurrencies are higher. This indicates that cryptocurrencies might be considered as hedges for uncertainties coming from equity, oil and commodity markets, but less from geopolitical risk or overall economic uncertainty.

In the case of volatility spillovers between uncertainty indices and cryptocurrencies, the results are unambiguous. On average the transmission of shocks from risk indices to coins is rather weak and irregular. In most cases, spillovers are observed within the risk indices themselves and within cryptocurrencies, but not between the former and the latter. When we focus on the rolling window the picture changes. We find that the strongest overall spillovers between a particular risk index and the remaining indices are observed at the beginning of the Covid-19 pandemic. Uncertainty indices based on stock market implied volatility behave similarly, transmitting spillovers to coins during the pandemic period, while OVX transmits volatility, over 2021, to coins. Shocks in volatility of indices are transmitted to coins and vice versa, but they have a limited short-term impact on the volatility of coins.

The conducted network analysis enables us to obtain more general results on the relationships and volatility transmissions between all series used in the study, explaining what patterns of linkages account for the transmission of volatility. The strength of connections and spread of volatility is much higher for cryptocurrencies themselves than between any risk indices, whose influence is more diffuse. Based on centrality measures, we find that the geopolitical risk index is at the center of volatility transmissions between indices and cryptocurrencies. The results are important from the point of view of risk management, portfolio diversification and systemic risk assessment. We show that although spillovers on average appear to have no impact, in short and turbulent periods the transmission of shocks through various channels accelerates, exerting a strong influence on asset prices and risk.

The findings offer several implications for policymakers and investors. In particular, in evidencing the nature and relative strength of dynamic spillovers between uncertainty indices and cryptocurrencies, we highlight important nuance in the hedge-potential of crypto assets. This should have implications for the diversification strategies of investors, as well as debates around the regulation of crypto. Policymakers and investors should be aware that while crypto investments appear to serve as a good hedging instrument during normal economic conditions, their hedging ability in relation to certain risk factors is distorted (weakened) in periods of economic turbulence, as evidenced during the Covid-19 pandemic and the Russian invasion of Ukraine. As such, we conclude that the ability of the asset class to serve as a 'safe-haven' may be limited.

Our study is subject to some limitations. First, while our analysis has richness in terms of exploring dynamic spillovers in both returns and volatility, it is possible that higher moments of the returns distribution are also relevant, particularly in the context of spillovers from extreme shocks. While outside the scope of the present study, we consider that future research on the topic could advance understanding in this regard through examining the tail spillover relationship[2]. Moreover, while we provide evidence on temporal spillovers from uncertainty indices to cryptocurrencies, the economic mechanisms explaining such transmission remain ambiguous. It is unclear, for example, if transmission is driven by the attachment of crypto assets to economic fundamentals, speculative capital flows, or investor psychology. We consider that further research on the topic will be enlightening.

References

Abid, I., Bouri, E., Galariotis, E., Guesmi, K., and Mzoughi, H. (2023). Bitcoin vs. fiat currencies: Insights from extreme dependence and risk spillover analysis with financial markets. *International Review of Financial Analysis*, page 102806.

Al Mamun, M., Uddin, G. S., Suleman, M. T., and Kang, S. H. (2020). Geopolitical risk, uncertainty and bitcoin investment. *Physica A: Statistical Mechanics and its Applications*, 540:123107.

Al-Shboul, M., Assaf, A., and Mokni, K. (2022). When bitcoin lost its position: Cryptocurrency uncertainty and the dynamic spillover among cryptocurrencies before and during the covid-19 pandemic. *International Review of Financial Analysis*, 83:102309.

Al-Yahyaee, K. H., Rehman, M. U., Mensi, W., and Al-Jarrah, I. M. W. (2019). Can uncertainty indices predict bitcoin prices? a revisited analysis using partial and multivariate wavelet approaches. *The North American Journal of Economics and Finance*, 49:47–56.

Anastasiou, D., Ballis, A., and Drakos, K. (2021). Cryptocurrencies' price crash risk and crisis sentiment. *Finance Research Letters*, 42:101928.

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

[2]We thank the anonymous referee for this interesting suggestion.

Aquilina, M., Frost, J., and Schrimpf, A. (2023). Addressing the risks in crypto: laying out the options. https://www.bis.org/publ/bisbull66.pdf. online: accessed 19-July-2023.

Aysan, A. F., Demir, E., Gozgor, G., and Lau, C. K. M. (2019). Effects of the geopolitical risks on bitcoin returns and volatility. *Research in International Business and Finance*, 47:511–518.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics*, 31:307–327.

Bouri, E., Gupta, R., and Roubaud, D. (2019). Herding behaviour in cryptocurrencies. *Finance Research Letters*, 29:216–221.

Bouri, E., Lucey, B., and Roubaud, D. (2020a). Cryptocurrencies and the downside risk in equity investments. *Finance Research Letters*, 33:101211.

Bouri, E., Shahzad, S. J. H., Roubaud, D., Kristoufek, L., and Lucey, B. (2020b). Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. *Quarterly Review of Economics and Finance*, 77:156–164.

Brockwell, P. J. and Davis, R. A. (1991). *Time Series: Theory and Methods*. Springer, New York.

Będowska-Sójka, B., Demir, E., and Zaremba, A. (2022). Hedging geopolitical risks with different asset classes: A focus on the russian invasion of ukraine. *Finance Research Letters*, 50:103192.

Caporale, G. M., Kang, W.-Y., Spagnolo, F., and Spagnolo, N. (2021). Cyber-attacks, spillovers and contagion in the cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money*, 74:101298.

Colon, F., Kim, C., Kim, H., and Kim, W. (2021). The effect of political and economic uncertainty on the cryptocurrency market. *Finance Research Letters*, 39:101621.

Corbet, S., Hou, Y. G., Hu, Y., Larkin, C., and Oxley, L. (2020a). Any port in a storm: Cryptocurrency safe-havens during the covid-19 pandemic. *Economics Letters*, 194:109377.

Corbet, S., Larkin, C., Lucey, B. M., Meegan, A., and Yarovaya, L. (2020b). The impact of macroeconomic news on bitcoin returns. *The European Journal of Finance*, 26(14):1396–1416.

Demir, E., Gozgor, G., Lau, C. K. M., and Vigne, S. A. (2018). Does economic policy uncertainty predict the bitcoin returns? an empirical investigation. *Finance Research Letters*, 26:145–149.

Demirer, M., Diebold, F. X., Liu, L., and Yilmaz, K. (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics*, 33(1):1–15.

Diebold, F. X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1):57–66.

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

Elsayed, A. H., Gozgor, G., and Yarovaya, L. (2022). Volatility and return connectedness of cryptocurrency, gold, and uncertainty: Evidence from the cryptocurrency uncertainty indices. *Finance Research Letters*, 47:102732.

Elsayed, A. H., Naifar, N., Uddin, G. S., and Wang, G.-J. (2023). Multilayer information spillover networks between oil shocks and banking sectors: Evidence from oil-rich countries. *International Review of Financial Analysis*, 87:102602.

Elsayed, A. H. and Sousa, R. M. (2022). International monetary policy and cryptocurrency markets: dynamic and spillover effects. *The European Journal of Finance*, pages 1–21.

Engle, R. (2002). Dynamic Conditional Correlation – a Simple Class of Multivariate Garch Models. *Journal of Business and Economic Statistics*, 20(3):339–350.

Engle, R. F. and Sheppard, K. (2001). Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH. *NBER Working Paper No. 8554*.

Gabauer, D. (2022). Package ‘connectednessapproach’. Last accessed 2023-03-10.

Giudici, P., Sarlin, P., and Spelta, A. (2020). The interconnected nature of financial systems: Direct and common exposures. *Journal of Banking and Finance*, 112:105149.

Glosten, L., Jagannathan, R., and Runkle, D. (1993). On the Relation Between Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance*, 48(5):1779–1801.

Hasan, M. B., Hassan, M. K., Karim, Z. A., and Rashid, M. M. (2022a). Exploring the hedge and safe haven properties of cryptocurrency in policy uncertainty. *Finance Research Letters*, 46:102272.

Hasan, M. B., Hossain, M. N., Junttila, J., Uddin, G. S., and Rabbani, M. R. (2022b). Do commodity assets hedge uncertainties? what we learn from the recent turbulence period? *Annals of Operations Research*.

Huang, X., Lin, J., and Wang, P. (2022). Are institutional investors marching into the crypto market? *Economics Letters*, 220:110856.

Huynh, T. L. D., Nasir, M. A., Vo, X. V., and Nguyen, T. T. (2020). “small things matter most”: The spillover effects in the cryptocurrency market and gold as a silver bullet. *The North American Journal of Economics and Finance*, 54:101277.

Ji, Q., Bouri, E., Lau, C. K. M., and Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis*, 63:257–272.

Karim, S., Naeem, M. A., Hu, M., Zhang, D., and Taghizadeh–Hesary, F. (2022). Determining dependence, centrality, and dynamic networks between green bonds and financial markets. *Journal of Environmental Management*, 318:115618.

Karimi, P., Mirzaee Ghazani, M., and Ebrahimi, S. B. (2023). Analyzing spillover effects of selected cryptocurrencies on gold and brent crude oil under covid-19 pandemic: Evidence from gjr-garch and evt copula methods. *Resources Policy*, 85:103887.

Korobilis, D. and Yilmaz, K. (2018). Measuring Dynamic Connectedness with Large Bayesian VAR Models. Essex Finance Centre Working Papers 20937, University of Essex, Essex Business School.

Koutmos, D. (2018). Return and volatility spillovers among cryptocurrencies. *Economics Letters*, 173:122–127.

Koutmos, D., King, T., and Zopounidis, C. (2021). Hedging uncertainty with cryptocurrencies: Is bitcoin your best bet? *Journal of Financial Research*, 44(4):815–837.

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59(2):347.

Onnela, J.-P., Kaski, K., and Kertész, J. (2004). Clustering and information in correlation based financial networks. *The European Physical Journal B*, 38:353–362.

Qian, L., Jiang, Y., and Long, H. (2023). What drives the dependence between the Chinese and global stock markets? *Modern Finance*, 1(1):12–16.

Qiao, X., Zhu, H., Tang, Y., and Peng, C. (2023). Time-frequency extreme risk spillover network of cryptocurrency coins, defi tokens and nfts. *Finance Research Letters*, 51:103489.

Santorsola, M., Caferra, R., and Morone, A. (2022). The financial repercussions of military escalation. *Physica A: Statistical Mechanics and its Applications*, 603:127791.

Selmi, R., Bouoiyour, J., and Wohar, M. E. (2022). “Digital Gold” and geopolitics. *Research in International Business and Finance*, 59:101512.

Singh, S., Bansal, P., and Bhardwaj, N. (2022). Correlation between geopolitical risk, economic policy uncertainty, and bitcoin using partial and multiple wavelet coherence in p5 + 1 nations. *Research in International Business and Finance*, 63:101756.

Trimborn, S. and Härdle, W. K. (2018). Crix an index for cryptocurrencies. *Journal of Empirical Finance*, 49:107–122.

Tse, Y. K. and Tsui, A. K. (2002). A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. *Journal of Business and Economic Statistics*, 20(3):351–362.

Umar, Z., Trabelsi, N., and Alqahtani, F. (2021). Connectedness between cryptocurrency and technology sectors: International evidence. *International Review of Economics & Finance*, 71:910–922.

Urquhart, A. and Lucey, B. (2022). Crypto and digital currencies — nine research priorities. *Nature*, 604:36–39.

Uzonwanne, G. (2021). Volatility and return spillovers between stock markets and cryptocurrencies. *The Quarterly Review of Economics and Finance*, 82:30–36.

Wang, G.-J., Xie, C., Wen, D., and Zhao, L. (2019). When bitcoin meets economic policy uncertainty (epu): Measuring risk spillover effect from epu to bitcoin. *Finance Research Letters*, 31.

Yermack, D. (2015). Is Bitcoin a Real Currency? An Economic Appraisal. In Lee Kuo Chuen, D., editor, *Handbook of Digital Currency*, pages 31–43. Academic Press, San Diego.

Yi, S., Xu, Z., and Wang, G.-J. (2018). Volatility connectedness in the cryptocurrency market: Is bitcoin a dominant cryptocurrency? *International Review of Financial Analysis*, 60:98–114.

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A Appendix

For the univariate time series, an ARMA model was used to describe the conditional mean in the following form (Brockwell and Davis, 1991):

$$r_t = \phi_1 r_{t-1} + \ldots + \phi_2 r_{t-2} + \varepsilon_t - \theta_1 \varepsilon_{t-1} + \ldots + \theta_2 \varepsilon_{t-2}, \tag{10}$$

where $\varepsilon_t \sim i.i.d.(0, h_t)$, $r_t = 100 \ln \frac{P_t}{P_{t-1}}$, P_t – a closing price/value at time t, h_t – the conditional variance modeled as a GARCH family process.

Finally, from the GARCH family of models, the following models were used:

- The standard GARCH(q,p) model (Bollerslev, 1986):
$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}. \tag{11}$$
- The integrated GARCH (IGARCH) model ($\alpha + \beta \approx 1$).
- The Exponential GARCH (EGARCH) model (Nelson, 1991):
$$\ln h_t = \omega + \alpha z_{t-1} + \gamma \left(|z_{t-1}| - E|z_{t-1}|\right) + \beta \ln h_{t-1} \tag{12}$$
where α – the sign effect, γ – the size effect. $E|z_{t-1}|$ is the expected value of the absolute standardized innovation z_t.
- The Glosten–Jagannathan–Runkle GARCH (GJR-GARCH) model (Glosten et al., 1993)
$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma I_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1}. \tag{13}$$
where γ – the 'leverage' term. The indicator function I takes on value of 1 for $\varepsilon \leq 0$ and zero otherwise.

Table 6: Unit Root Tests for Percentage Logarithmic Returns

Ticker	ADF	p-value	PP	p-value	KPSS	p-value
EPU	-12.2733	0.0100	-927.4217	0.0100	0.0311	0.1000
GPR	-12.4227	0.0100	-969.3493	0.0100	0.0146	0.1000
GVZ	-11.2659	0.0100	-1249.5757	0.0100	0.0288	0.1000
OVX	-11.1510	0.0100	-1131.3693	0.0100	0.0286	0.1000
USDX	-10.4919	0.0100	-1114.6882	0.0100	0.1087	0.1000
VIX	-11.0629	0.0100	-1229.6328	0.0100	0.0236	0.1000
VXEEM	-11.7646	0.0100	-1446.5742	0.0100	0.0199	0.1000
VXEFA	-11.8706	0.0100	-1461.0270	0.0100	0.0146	0.1000
VXTLT	-11.2620	0.0100	-1155.3992	0.0100	0.0133	0.1000
CRIX	-9.1993	0.0100	-1246.1888	0.0100	0.1958	0.1000
ADA	-8.7911	0.0100	-1354.0949	0.0100	0.2704	0.1000
BNB	-9.1277	0.0100	-1301.3053	0.0100	0.1526	0.1000
BTC	-9.2200	0.0100	-1273.2089	0.0100	0.2086	0.1000
DOGE	-9.7765	0.0100	-1057.3005	0.0100	0.1560	0.1000
ETH	-9.1820	0.0100	-1341.5682	0.0100	0.2024	0.1000
LTC	-9.4658	0.0100	-1294.5349	0.0100	0.0930	0.1000
TRX	-9.6525	0.0100	-1268.0736	0.0100	0.0820	0.1000
XLM	-10.0892	0.0100	-1169.0409	0.0100	0.1175	0.1000
XMR	-9.9846	0.0100	-1293.8212	0.0100	0.1148	0.1000
XRP	-9.9248	0.0100	-1171.0708	0.0100	0.0554	0.1000

Table 7: Tests of Percentage Logarithmic Rates of Return

Ticker	Ljung-Box (4)	p-value	Jarque-Bera	p-value	Engle (4)	p-value
EPU	120.0411	0.0000	134.2207	0.0000	27.4378	0.0000
GPR	85.3529	0.0000	32.4100	0.0000	8.5134	0.0745
GVZ	11.4404	0.0220	739.2240	0.0000	179.8402	0.0000
OVX	12.3145	0.0152	36852.3370	0.0000	41.7979	0.0000
USDX	10.6213	0.0312	446.5613	0.0000	105.9256	0.0000
VIX	17.4031	0.0016	996.8743	0.0000	57.9193	0.0000
VXEEM	125.0841	0.0000	47481.0023	0.0000	379.1452	0.0000
VXEFA	180.1472	0.0000	3532.5490	0.0000	274.8512	0.0000
VXTLT	46.5190	0.0000	21126.1026	0.0000	119.4703	0.0000
CRIX	6.0388	0.1963	682.2659	0.0000	40.2748	0.0000
ADA	14.5196	0.0058	1025.4495	0.0000	33.9193	0.0000
BNB	9.4411	0.0510	7187.7251	0.0000	53.9611	0.0000
BTC	4.2795	0.3695	7276.6638	0.0000	11.6394	0.0202
DOGE	15.7452	0.0034	280670.1833	0.0000	7.4980	0.1118
ETH	12.0021	0.0173	4008.1286	0.0000	20.9589	0.0003
LTC	7.2202	0.1247	2264.4721	0.0000	17.3120	0.0017
TRX	5.4291	0.2460	3441.0442	0.0000	38.9535	0.0000
XLM	7.5001	0.1117	4746.4147	0.0000	39.0698	0.0000
XMR	10.2817	0.0359	5521.9907	0.0000	44.6751	0.0000
XRP	2.6536	0.6174	11736.7524	0.0000	11.4543	0.0219

Note: Ljung-Box (4) – Ljung-Box test for autocorrelation with lag 4; Jarque-Bera – Jarque-Bera test for normality; Engle (4) – Lagrange multiplier test for conditional heteroscedasticity of Engle ARCH with lag 4.

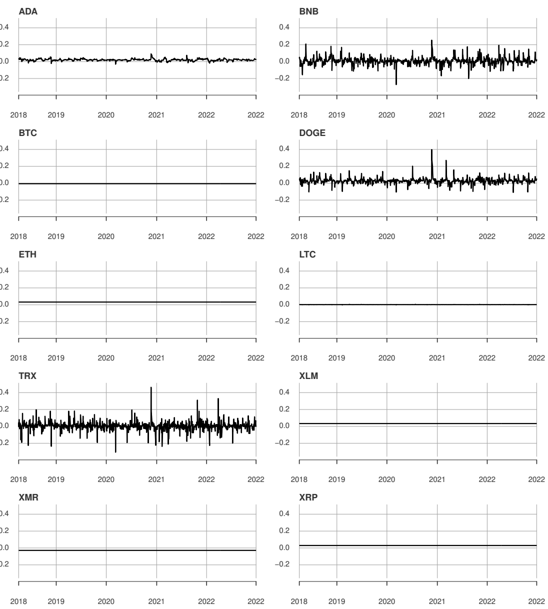
Table 8: The Specifications of ARMA-GARCH Models

	ADA	BNB	BTC	DOGE	ETH	LTC	TRX
Model	GARCH	IGARCH	EGARCH	IGARCH	GARCH	IGARCH	IGARCH
Distribution	ged	std	std	std	ged	std	std
ϕ_1				-1.298***			
ϕ_2				-0.987***			
θ_1				1.300***			
θ_2				0.996***			
ω	5.007**	2.825**	0.082***	5.925***	4.203**	4.204	2.330**
α	0.151***	0.230***	0.014	0.444***	0.106***	0.198**	0.263***
β	0.745***	0.770	0.974***	0.556	0.777***	0.802	0.737
γ			0.254***				
shape	1.088***	3.362***	2.738***	2.865***	0.969***	2.768***	3.256***
Akaike	6.463	6.155	5.528	6.162	6.184	6.215	6.165
Bayes	6.480	6.168	5.549	6.192	6.202	6.228	6.178
Ljung-Box (5)	5.144	5.570	8.296	7.449	5.366	2.446	3.124
Engle (5)	10.644*	12.855**	11.338**	0.235	5.761	3.129	11.576**

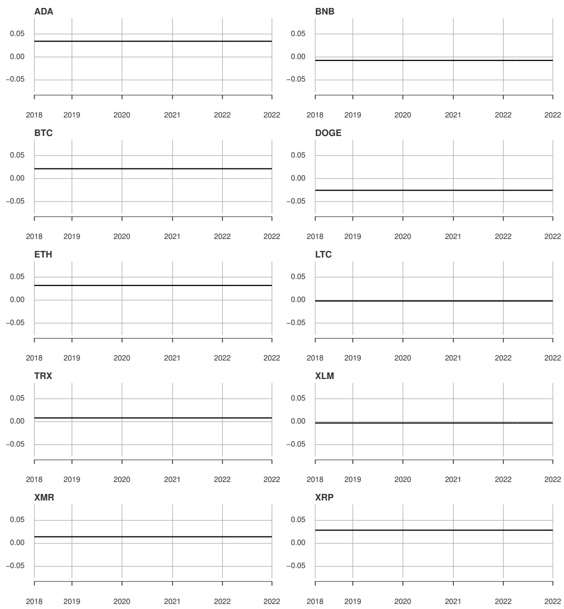
	XLM	XMR	XRP	EPU	GPR	GVZ
Model	IGARCH	EGARCH	IGARCH	GARCH	IGARCH	EGARCH
Distribution	std	std	std	sstd	snorm	sstd
ϕ_1				-0.235***	-0.322***	
ϕ_2				0.414***	0.262***	
ϕ_3				-0.322***	-0.252***	
ϕ_4				-0.336***	-0.400***	
θ_1				0.475***	0.511***	-0.134***
θ_2				-0.312***	-0.249***	
θ_3				0.485***	0.509***	
θ_4				0.837***	0.917***	
ω	6.630**	0.280	4.333**	0.627**	0.011	0.109***
α	0.292***	0.013	0.249***	0.036***	0.024**	0.122***
β	0.708	0.920***	0.751	0.950***	0.976	0.963***
γ		0.320**				0.169***
skew				1.188***	1.199***	1.400***
shape	2.783***	3.935***	2.718***	8.783***		7.509***
Akaike	6.263	6.187	6.148	6.641	6.519	5.776
Bayes	6.276	6.209	6.161	6.697	6.566	5.807
Ljung-Box (5)	6.317	1.425	5.292	42.826***	51.579***	6.023
Engle (5)	2.508	16.817***	0.996	6.064	4.411	9.544*

	OVX	USDX	VIX	VXEEM	VXEFA	VXTLT	CRIX
Model	EGARCH	GJR-GARCH	EGARCH	EGARCH	EGARCH	GARCH	IGARCH
Distribution	sstd	std	sstd	sstd	sstd	sstd	std
ϕ_1			0.938***	0.840***		0.720***	
ϕ_2				0.103***			
θ_1			-0.980***	-0.993***	-0.289***	-0.868***	
ω	0.111***	0.001**	0.566***	0.500***	0.842***	14.324***	0.764**
α	0.131***	0.069***	0.246***	0.202***	0.152***	0.334***	0.124***
β	0.966***	0.956***	0.858***	0.872***	0.829***	0.436***	0.876
γ	0.142***	-0.070***	0.135***	0.177***	0.444***		
skew	1.334***		1.598***	1.419***	1.215***	1.198***	
shape	4.000***	7.557***	6.362***	3.900***	3.239***	3.514***	3.277***
Akaike	6.176	0.359	6.675	6.558	7.482	6.381	5.700
Bayes	6.202	0.381	6.709	6.597	7.512	6.411	5.713
Ljung-Box (5)	8.117	11.387**	4.104	10.033*	5.922	3.134	7.069
Engle (5)	0.612	3.281	1.903	0.110	2.185	2.201	2.824

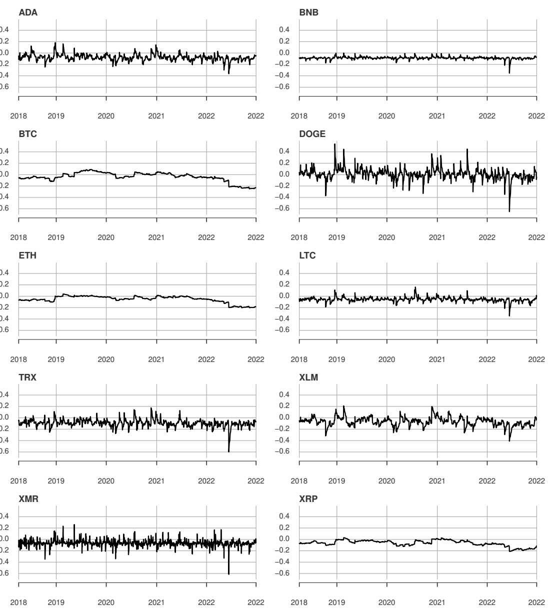
Note: Ljung–Box (5) – Ljung–Box test for autocorrelation with lag 5; Engle (5) – Lagrange multiplier test for conditiol heteroscedasticity of Engle ARCH with lag 5; Ljung–Box and Engle ARCH tests were calculated for standardized innovations. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.



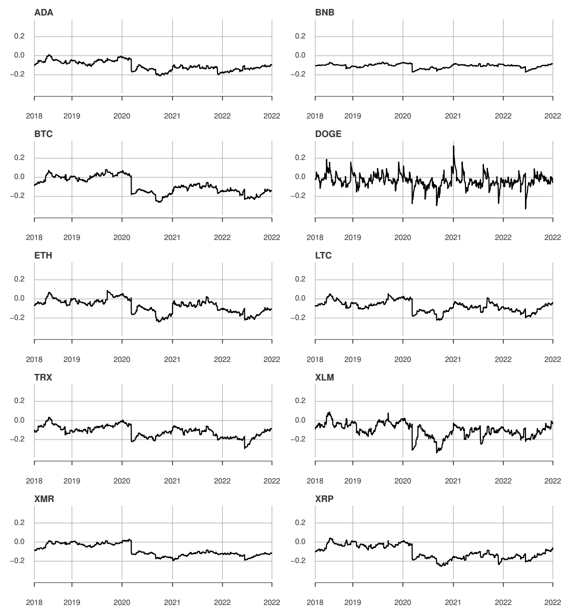
a) EPU and Coins



b) GPR and Coins

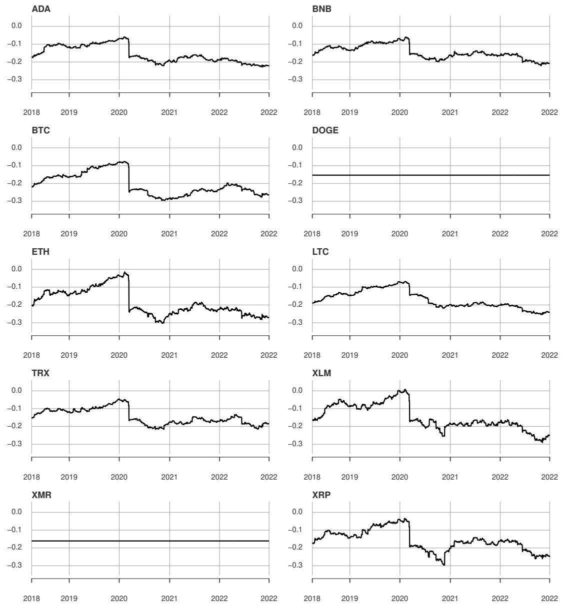


c) GVZ and Coins

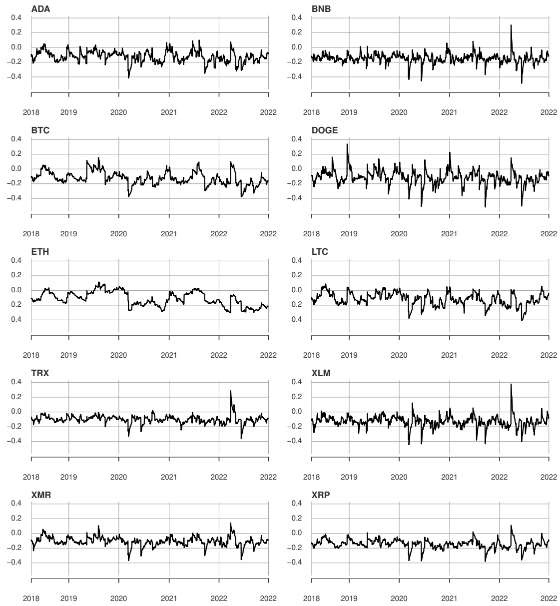


d) OVX and Coins

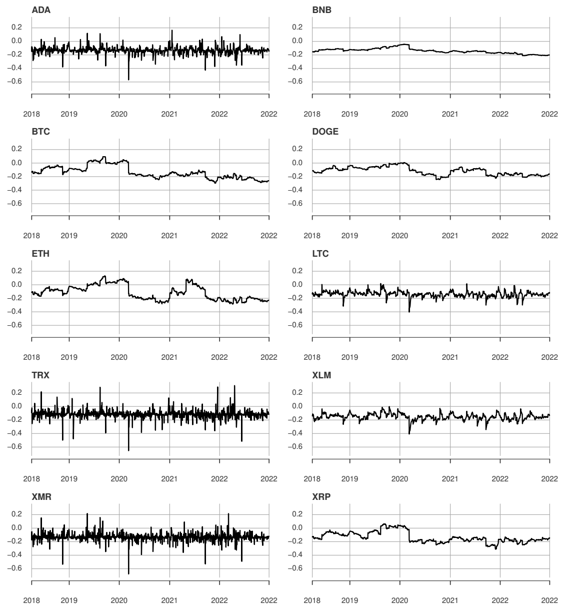
Figure 10: DCC Conditional Correlation



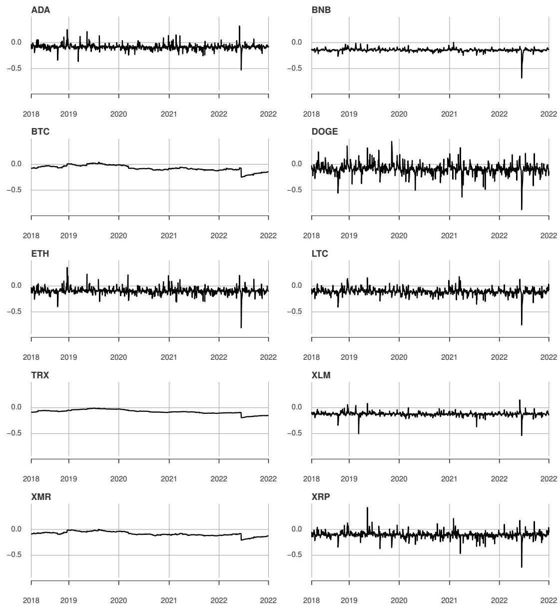
e) USDX and Coins



f) VXEEM and Coins

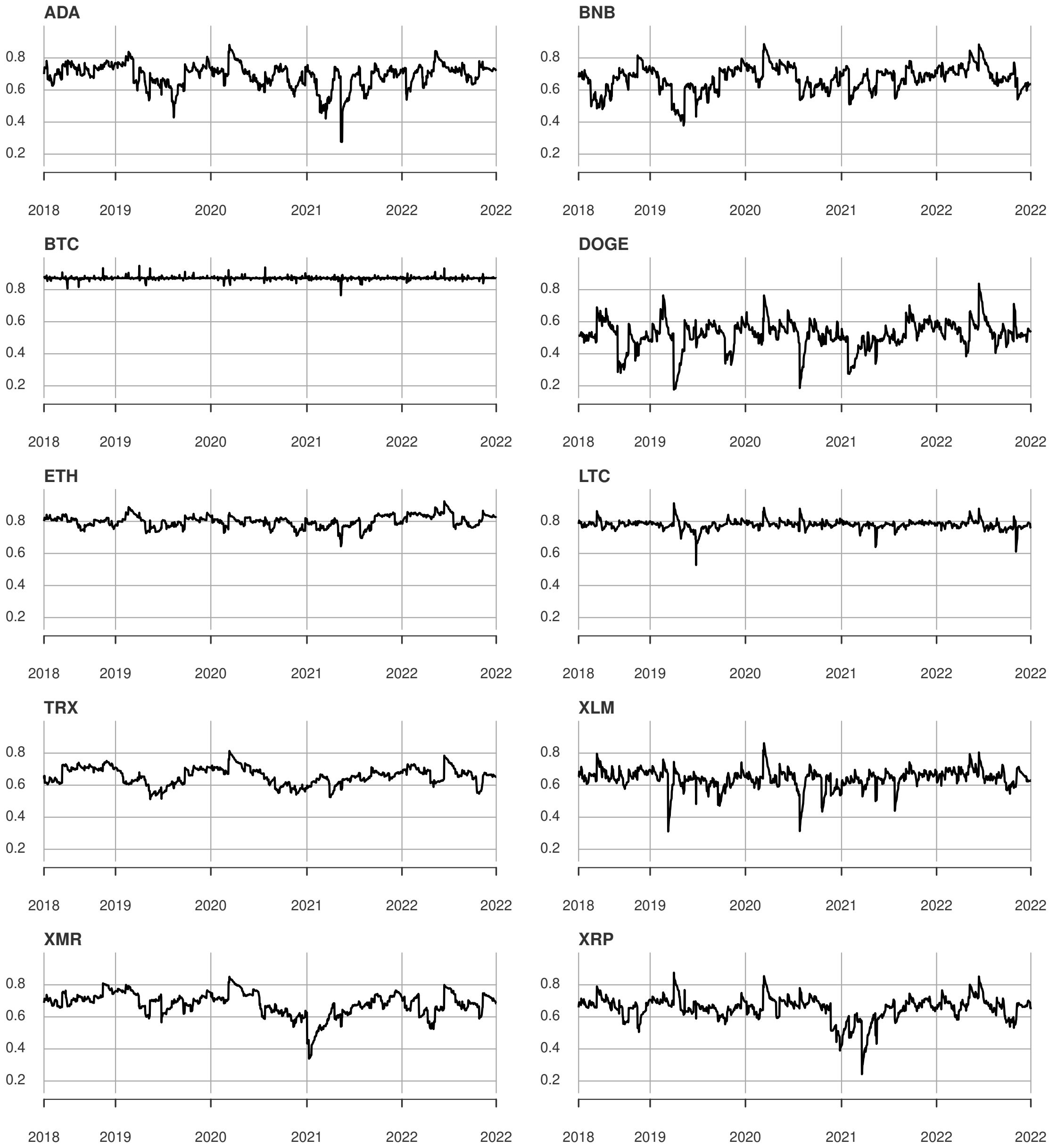


g) VXEFA and Coins



h) VXTLT and Coins

Figure 10: DCC Conditional Correlation (*continued*)



i) CRIX and Coins

Figure 10: DCC Conditional Correlation (*continued*)

Table 9: The Ranges of Values of Conditional Correlations between Uncertainty Indices and Cryptocurrencies

		ADA	BNB	BTC	DOGE	ETH	LTC	TRX	XLM	XMR	XRP
EPU	Min	-0.031	-0.273	-0.006	-0.109	0.032	-0.002	-0.306	0.034	-0.029	0.029
	Mean	0.020	0.007	-0.006	0.028	0.032	0.002	0.004	0.034	-0.029	0.029
	Max	0.092	0.254	-0.006	0.398	0.032	0.006	0.463	0.034	-0.029	0.029
	Range	0.123	0.527	0.000	0.508	0.000	0.008	0.769	0.000	0.000	0.000
GPR	Min	0.034	-0.008	0.011	-0.026	0.032	-0.002	0.008	-0.003	0.014	0.029
	Mean	0.034	-0.008	0.011	-0.026	0.032	-0.002	0.008	-0.003	0.014	0.029
	Max	0.034	-0.008	0.011	-0.026	0.032	-0.002	0.008	-0.003	0.014	0.029
	Range	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GVZ	Min	-0.363	-0.354	-0.252	-0.650	-0.204	-0.347	-0.599	-0.410	-0.613	-0.212
	Mean	-0.077	-0.087	-0.040	0.007	-0.053	-0.057	-0.093	-0.069	-0.065	-0.066
	Max	0.182	0.000	0.090	0.540	0.039	0.161	0.175	0.209	0.261	0.029
	Range	0.545	0.353	0.341	1.190	0.242	0.508	0.774	0.619	0.874	0.241
OVX	Min	-0.211	-0.172	-0.262	-0.331	-0.241	-0.222	-0.295	-0.339	-0.195	-0.255
	Mean	-0.104	-0.107	-0.084	-0.035	-0.073	-0.079	-0.115	-0.100	-0.086	-0.105
	Max	0.012	-0.067	0.081	0.329	0.088	0.055	0.034	0.089	0.031	0.042
	Range	0.223	0.105	0.343	0.660	0.329	0.276	0.328	0.428	0.226	0.297
USDX	Min	-0.228	-0.221	-0.208	-0.153	-0.303	-0.254	-0.216	-0.291	-0.161	-0.297
	Mean	-0.156	-0.145	-0.208	-0.153	-0.185	-0.169	-0.145	-0.148	-0.161	-0.157
	Max	-0.059	-0.060	-0.208	-0.153	-0.015	-0.068	-0.045	0.009	-0.161	-0.034
	Range	0.169	0.161	0.000	0.000	0.288	0.186	0.171	0.300	0.000	0.263
VIX	Min	-0.499	-0.466	-0.537	-0.508	-0.590	-0.566	-0.400	-0.559	-0.409	-0.462
	Mean	-0.203	-0.213	-0.199	-0.158	-0.210	-0.201	-0.169	-0.202	-0.180	-0.204
	Max	0.046	0.022	0.205	0.358	0.172	0.095	0.118	0.111	0.147	0.057
	Range	0.545	0.488	0.742	0.865	0.762	0.661	0.518	0.671	0.556	0.520
VXEEM	Min	-0.415	-0.283	-0.372	-0.517	-0.303	-0.412	-0.360	-0.444	-0.369	-0.381
	Mean	-0.124	-0.155	-0.115	-0.114	-0.114	-0.118	-0.101	-0.129	-0.107	-0.143
	Max	0.100	0.015	0.219	0.339	0.114	0.088	0.288	0.379	0.143	0.110
	Range	0.515	0.298	0.591	0.856	0.417	0.500	0.648	0.823	0.512	0.490
VXEFA	Min	-0.569	-0.211	-0.297	-0.243	-0.285	-0.404	-0.654	-0.408	-0.677	-0.311
	Mean	-0.133	-0.140	-0.137	-0.118	-0.117	-0.139	-0.115	-0.153	-0.132	-0.135
	Max	0.166	-0.041	0.095	0.008	0.132	0.018	0.309	-0.002	0.217	0.063
	Range	0.734	0.169	0.392	0.251	0.417	0.421	0.963	0.406	0.894	0.375
VXTLT	Min	-0.529	-0.683	-0.246	-0.876	-0.807	-0.751	-0.192	-0.539	-0.207	-0.731
	Mean	-0.083	-0.144	-0.075	-0.092	-0.095	-0.109	-0.078	-0.122	-0.087	-0.104
	Max	0.322	0.006	0.038	0.443	0.358	0.181	-0.010	0.150	-0.001	0.423
	Range	0.851	0.689	0.284	1.319	1.165	0.932	0.182	0.689	0.206	1.154
CRIX	Min	0.276	0.378	0.765	0.176	0.645	0.528	0.512	0.311	0.339	0.242
	Mean	0.691	0.669	0.872	0.520	0.800	0.779	0.657	0.643	0.682	0.655
	Max	0.882	0.887	0.949	0.838	0.925	0.913	0.814	0.862	0.851	0.876
	Range	0.606	0.509	0.184	0.661	0.281	0.386	0.301	0.551	0.511	0.634

Table 10: TVP-VAR: Averaged Dynamic Connectedness between...

a) EPU and 10 Cryptocurrencies

	EPU	ADA	BNB	BTC	DOGE	ETH	LTC	TRX	XLM	XMR	XRP	FROM
EPU	72.87	3.55	1.84	2.13	0.99	1.92	2.18	4.95	3.95	3.47	2.15	27.13
ADA	0.67	22.10	8.10	9.04	6.20	10.48	9.58	7.41	10.19	8.58	7.65	77.90
BNB	0.23	7.73	31.42	8.36	4.51	9.38	9.31	7.84	6.54	8.87	5.82	68.58
BTC	0.46	8.51	8.23	24.27	6.07	10.72	10.89	6.05	7.48	12.32	4.99	75.73
DOGE	0.30	5.64	4.63	4.82	51.84	6.22	5.63	4.20	5.97	5.33	5.43	48.16
ETH	0.28	9.60	9.32	10.89	5.29	20.29	12.07	7.68	7.01	10.64	6.93	79.71
LTC	0.19	8.55	9.44	11.29	5.09	12.15	20.66	8.08	7.33	10.45	6.79	79.34
TRX	0.74	8.24	8.01	7.48	4.33	8.43	9.16	27.26	7.61	8.96	9.78	72.74
XLM	0.91	11.64	6.88	7.33	6.97	8.62	7.62	7.48	23.41	7.33	11.82	76.59
XMR	1.04	7.65	9.42	11.73	6.71	9.13	10.16	7.05	7.21	24.27	5.64	75.73
XRP	0.67	8.68	6.01	5.67	5.57	8.16	7.18	8.79	11.20	7.10	30.96	69.04
TO	5.48	79.79	71.88	78.73	51.72	85.21	83.78	69.53	74.49	83.05	67.00	TCI
NET	-21.65	1.89	3.29	3.00	3.56	5.49	4.44	-3.20	-2.10	7.32	-2.04	68.24

b) GVZ and 10 Cryptocurrencies

	GVZ	ADA	BNB	BTC	DOGE	ETH	LTC	TRX	XLM	XMR	XRP	FROM
GVZ	79.31	1.54	1.86	2.91	2.27	2.67	2.51	1.85	1.50	1.69	1.89	20.69
ADA	1.18	21.81	7.97	8.67	6.43	10.41	9.42	7.52	10.34	8.58	7.68	78.19
BNB	1.00	7.63	30.94	8.09	4.70	9.43	9.23	7.71	6.51	8.82	5.94	69.06
BTC	1.59	8.21	8.19	23.79	6.41	10.57	10.99	5.87	7.36	12.01	5.01	76.21
DOGE	0.90	5.76	4.78	4.88	50.36	6.40	5.73	4.27	5.86	5.63	5.42	49.64
ETH	1.85	9.33	9.12	10.41	5.51	19.99	11.93	7.50	7.09	10.29	6.99	80.01
LTC	1.13	8.34	9.19	10.99	5.21	11.92	20.79	7.90	7.30	10.30	6.94	79.21
TRX	0.95	8.33	8.01	7.27	4.56	8.36	9.09	27.10	7.68	8.87	9.78	72.90
XLM	0.58	11.78	6.89	7.26	6.98	8.93	7.62	7.57	23.22	7.46	11.70	76.78
XMR	1.18	7.59	9.51	11.30	7.03	9.02	10.01	7.24	7.28	24.23	5.62	75.77
XRP	0.71	8.65	5.99	5.58	5.59	8.21	7.25	8.74	11.19	6.98	31.12	68.88
TO	11.07	77.15	71.51	77.36	54.70	85.92	83.77	66.16	72.09	80.63	66.98	TCI
NET	-9.62	-1.04	2.45	1.15	5.06	5.91	4.56	-6.74	-4.70	4.86	-1.90	67.94

c) OVX and 10 Cryptocurrencies

	OVX	ADA	BNB	BTC	DOGE	ETH	LTC	TRX	XLM	XMR	XRP	FROM
OVX	87.21	1.25	0.86	1.30	0.76	0.94	1.16	1.30	1.55	2.32	1.35	12.79
ADA	2.79	22.38	7.48	8.32	6.50	10.23	8.98	7.57	9.94	8.17	7.65	77.62
BNB	4.24	7.35	31.86	7.22	4.54	8.76	8.48	7.80	5.82	8.24	5.69	68.14
BTC	4.78	7.80	7.21	24.18	6.61	10.15	9.99	5.79	6.73	11.88	4.87	75.82
DOGE	1.16	5.41	4.60	4.69	51.70	6.20	5.51	4.25	5.81	5.39	5.29	48.30
ETH	2.57	9.40	8.58	10.28	5.44	20.69	11.47	7.70	6.64	10.21	7.02	79.31
LTC	2.91	8.38	8.51	10.67	5.24	11.66	20.72	8.07	6.93	10.10	6.81	79.28
TRX	1.85	8.09	7.36	7.07	4.40	8.12	8.74	28.63	7.15	8.66	9.94	71.37
XLM	2.95	11.35	6.16	6.62	7.16	8.33	7.15	7.46	23.73	7.12	11.97	76.27
XMR	2.24	7.33	8.84	11.32	7.24	8.80	9.69	7.12	6.78	25.04	5.60	74.96
XRP	1.44	8.27	5.66	5.21	5.53	7.77	7.00	8.88	10.85	6.63	32.75	67.25
TO	26.94	74.64	65.27	72.68	53.41	80.95	78.17	65.94	68.22	78.73	66.18	TCI
NET	14.14	-2.99	-2.87	-3.14	5.11	1.64	-1.11	-5.43	-8.05	3.77	-1.08	66.47

d) USDX and 10 Cryptocurrencies

	USDX	ADA	BNB	BTC	DOGE	ETH	LTC	TRX	XLM	XMR	XRP	FROM
USDX	68.29	2.40	3.74	3.16	1.66	4.55	3.75	2.78	3.01	3.83	2.84	31.71
ADA	1.13	22.25	8.25	8.97	5.51	10.49	9.61	7.60	10.32	8.65	7.22	77.75
BNB	1.44	7.74	30.74	8.33	4.14	9.55	9.48	7.67	6.35	8.78	5.79	69.26
BTC	1.58	8.63	8.18	24.03	5.85	10.51	10.98	5.98	7.38	12.01	4.88	75.97
DOGE	1.55	5.48	4.66	5.00	50.46	6.00	5.73	4.38	5.87	5.84	5.02	49.54
ETH	1.54	9.61	9.40	10.64	4.89	20.24	12.05	7.96	6.86	10.27	6.54	79.76
LTC	1.27	8.55	9.41	11.32	4.92	11.98	20.70	8.15	7.05	10.17	6.48	79.30
TRX	1.28	8.56	7.65	7.29	4.22	8.53	9.21	27.23	7.59	8.85	9.59	72.77
XLM	1.10	11.72	6.85	7.19	6.59	8.54	7.45	7.64	23.84	7.44	11.63	76.16
XMR	1.40	7.79	9.45	11.45	6.34	8.97	10.04	7.26	7.15	24.68	5.46	75.32
XRP	1.74	8.60	6.14	5.67	4.83	7.94	7.13	9.12	11.17	6.96	30.69	69.31
TO	14.04	79.08	73.73	79.03	48.95	87.06	85.43	68.54	72.74	82.79	65.46	TCI
NET	-17.66	1.33	4.47	3.06	-0.59	7.30	6.13	-4.22	-3.43	7.47	-3.86	68.80

Table 10: TVP-VAR: Averaged Dynamic Connectedness between... (*continued*)

e) VIX and 10 Cryptocurrencies

	VIX	ADA	BNB	BTC	DOGE	ETH	LTC	TRX	XLM	XMR	XRP	FROM
VIX	76.60	3.27	2.06	2.71	1.46	2.44	2.26	2.36	2.21	2.51	2.13	23.40
ADA	1.08	22.07	7.92	8.95	6.43	10.33	9.35	7.51	10.25	8.59	7.53	77.93
BNB	1.61	7.57	30.63	8.29	4.57	9.14	9.22	7.88	6.39	8.86	5.85	69.37
BTC	1.43	8.25	8.05	24.32	6.06	10.53	10.89	5.96	7.35	12.15	5.00	75.68
DOGE	0.71	5.55	4.62	4.59	51.69	6.02	5.54	4.29	5.98	5.52	5.50	48.31
ETH	1.73	9.39	8.98	10.81	5.30	20.04	11.87	7.67	6.91	10.47	6.82	79.96
LTC	1.19	8.42	9.18	11.19	5.15	11.86	20.58	7.99	7.20	10.44	6.82	79.42
TRX	0.94	8.27	7.98	7.51	4.54	8.40	9.07	27.21	7.51	9.02	9.55	72.79
XLM	0.65	11.69	6.81	7.30	7.38	8.61	7.50	7.57	23.25	7.51	11.73	76.75
XMR	1.27	7.59	9.39	11.53	6.85	8.93	10.04	7.17	7.24	24.35	5.64	75.65
XRP	1.19	8.40	5.89	5.62	5.86	7.92	7.14	8.79	11.13	7.02	31.05	68.95
TO	11.79	78.40	70.88	78.49	53.59	84.19	82.88	67.19	72.16	82.08	66.57	TCI
NET	-11.61	0.47	1.51	2.82	5.27	4.23	3.46	-5.60	-4.59	6.43	-2.38	68.02

f) VXEEM and 10 Cryptocurrencies

	VXEEM	ADA	BNB	BTC	DOGE	ETH	LTC	TRX	XLM	XMR	XRP	FROM
VXEEM	73.56	3.88	1.80	2.97	1.50	2.57	3.10	2.82	3.00	3.39	1.41	26.44
ADA	1.33	22.02	8.00	8.94	6.28	10.36	9.41	7.46	10.22	8.58	7.40	77.98
BNB	1.40	7.59	30.44	8.34	4.54	9.28	9.20	7.94	6.45	8.95	5.87	69.56
BTC	1.32	8.25	8.22	24.31	6.04	10.71	10.89	5.90	7.26	12.20	4.90	75.69
DOGE	1.74	5.43	4.65	4.74	50.90	6.15	5.60	4.18	5.91	5.39	5.31	49.10
ETH	0.99	9.41	9.25	10.90	5.34	20.24	11.94	7.61	6.97	10.60	6.75	79.76
LTC	0.99	8.42	9.22	11.16	5.20	11.89	20.51	8.04	7.26	10.45	6.86	79.49
TRX	0.91	8.25	8.01	7.53	4.35	8.39	9.14	27.31	7.59	9.04	9.50	72.69
XLM	0.95	11.64	6.93	7.23	7.17	8.62	7.52	7.54	23.28	7.39	11.72	76.72
XMR	1.23	7.62	9.61	11.59	6.62	9.05	10.15	7.16	7.18	24.25	5.54	75.75
XRP	1.77	8.34	5.92	5.69	5.49	8.03	7.24	8.76	11.18	7.08	30.50	69.50
TO	12.63	78.82	71.60	79.08	52.54	85.04	84.18	67.41	73.03	83.07	65.25	TCI
NET	-13.80	0.84	2.04	3.39	3.45	5.28	4.69	-5.28	-3.69	7.33	-4.24	68.43

g) VXEFA and 10 Cryptocurrencies

	VXEFA	ADA	BNB	BTC	DOGE	ETH	LTC	TRX	XLM	XMR	XRP	FROM
VXEFA	82.24	1.99	1.90	2.11	1.03	1.55	2.36	1.89	1.67	1.34	1.91	17.76
ADA	0.48	22.29	8.10	8.96	6.37	10.45	9.44	7.54	10.32	8.57	7.49	77.71
BNB	0.81	7.77	31.27	8.24	4.58	9.34	9.28	7.85	6.41	8.84	5.62	68.73
BTC	0.76	8.41	8.21	24.33	6.22	10.68	10.95	5.98	7.43	12.21	4.84	75.67
DOGE	0.57	5.76	4.70	4.76	51.02	6.18	5.65	4.39	6.00	5.60	5.38	48.98
ETH	0.65	9.63	9.28	10.86	5.44	20.25	12.07	7.62	7.03	10.55	6.62	79.75
LTC	0.41	8.49	9.40	11.22	5.15	12.07	20.82	8.01	7.24	10.45	6.75	79.18
TRX	1.34	8.41	7.93	7.58	4.55	8.36	9.14	27.34	7.52	9.01	8.81	72.66
XLM	0.50	11.90	6.86	7.33	7.16	8.62	7.51	7.59	23.34	7.45	11.75	76.66
XMR	0.65	7.73	9.53	11.57	6.87	9.06	10.15	7.17	7.29	24.44	5.54	75.56
XRP	3.37	8.58	5.83	5.56	5.93	7.73	7.17	8.53	11.13	6.94	29.22	70.78
TO	9.54	78.66	71.75	78.18	53.30	84.04	83.72	66.58	72.03	80.95	64.70	TCI
NET	-8.22	0.95	3.02	2.51	4.32	4.29	4.54	-6.08	-4.62	5.39	-6.08	67.59

h) VXTLT and 10 Cryptocurrencies

	VXTLT	ADA	BNB	BTC	DOGE	ETH	LTC	TRX	XLM	XMR	XRP	FROM
VXTLT	81.17	1.48	1.71	2.10	1.69	1.61	1.91	2.04	1.62	2.62	2.05	18.83
ADA	0.58	22.13	8.10	8.91	6.37	10.51	9.40	7.52	10.33	8.59	7.54	77.87
BNB	0.99	7.67	30.96	8.24	4.60	9.40	9.23	7.81	6.46	8.84	5.79	69.04
BTC	0.90	8.32	8.20	24.42	6.26	10.61	10.72	5.98	7.44	12.23	4.93	75.58
DOGE	1.11	5.56	4.70	4.72	51.23	6.12	5.61	4.19	5.92	5.42	5.41	48.77
ETH	1.07	9.45	9.21	10.72	5.38	20.23	11.96	7.67	6.98	10.46	6.88	79.77
LTC	0.91	8.34	9.36	11.16	5.10	12.05	20.71	7.99	7.21	10.37	6.79	79.29
TRX	1.20	8.29	8.07	7.42	4.39	8.47	9.01	26.94	7.59	8.97	9.64	73.06
XLM	0.73	11.71	6.89	7.24	7.24	8.61	7.40	7.60	23.40	7.41	11.77	76.60
XMR	1.02	7.63	9.53	11.51	6.83	9.03	9.98	7.19	7.28	24.37	5.63	75.63
XRP	0.62	8.55	5.90	5.49	5.72	8.09	7.11	8.86	11.18	7.02	31.46	68.54
TO	9.14	77.00	71.67	77.50	53.59	84.50	82.33	66.84	72.01	81.94	66.45	TCI
NET	-9.70	-0.87	2.64	1.92	4.82	4.73	3.04	-6.21	-4.59	6.32	-2.10	67.54

Table 10: TVP-VAR: Averaged Dynamic Connectedness between... (*continued*)

i) CRIX and Various Risk Indices

	CRIX	EPU	GPR	GVZ	OVX	USDX	VIX	VXEEM	VXEFA	VXTLT	FROM
CRIX	67.53	1.00	0.83	4.29	9.44	3.38	4.52	3.59	1.72	3.69	32.47
EPU	2.36	81.32	1.02	3.04	1.41	0.98	2.43	3.60	1.87	1.97	18.68
GPR	2.38	1.12	78.15	3.69	5.16	1.32	2.53	2.03	1.57	2.05	21.85
GVZ	2.49	1.50	0.80	59.45	5.21	3.23	13.01	8.05	1.91	4.36	40.55
OVX	1.35	2.14	0.54	2.85	74.87	1.71	8.30	3.17	2.84	2.23	25.13
USDX	4.40	0.80	1.38	5.15	3.79	66.09	6.41	5.65	1.93	4.39	33.91
VIX	1.54	0.84	0.89	7.41	6.95	2.17	49.89	19.68	7.35	3.26	50.11
VXEEM	1.77	1.97	0.77	5.53	3.25	3.99	20.30	56.92	4.00	1.50	43.08
VXEFA	1.45	0.97	0.58	3.07	3.67	0.96	10.76	6.01	69.53	2.99	30.47
VXTLT	3.00	0.75	0.94	4.79	1.20	4.13	8.58	5.21	2.17	69.23	30.77
TO	20.74	11.08	7.76	39.83	40.09	21.87	76.84	56.98	25.38	26.44	TCI
NET	-11.72	-7.60	-14.08	-0.73	14.96	-12.04	26.74	13.90	-5.09	-4.33	32.70