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UNCERTAINTY AND RISK IN CRYPTOCURRENCY MARKETS: EVIDENCE OF TIME-FREQUENCY CONNECTEDNESS

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Abstract

This study aims to investigate the spillover effects from geopolitical risks (proxied by the geopolitical risk index) and cryptocurrencies-related uncertainty (proxied by the Cryptocurrency Uncertainty Index) to cryptocurrencies. We utilise the Baruník and Křehlík (2018) framework to detect time-frequency connectedness. Our investigation for the period 2017 to 2022 discovers significant spillover effects from both indices to cryptocurrencies. Utilising the information transmission theory and network graphs, our findings reveal that some cryptocurrencies function as net receivers of spillovers from geopolitical risks and uncertainty in the short-term, while over longer time horizons they transform into net transmitters of spillovers to uncertainty. The study contributes to better understanding how uncertainty due to various factors (geopolitical, policy changes, regulatory changes, etc.) could affect the cryptocurrencies' markets.

Keywords: cryptocurrencies; geopolitical risk; market uncertainty; time–frequency connectedness

1. Introduction

Cryptocurrencies have undergone a dramatic transformation in recent years. Currently, the cryptocurrency market has a total capitalisation of approximately US$ 0.948 trillion. However, Bitcoin (BTC) alone had a market capitalisation of US$ 1.28 trillion in November 2021, despite experiencing many bubbles and crashes throughout its history (Thampanya et al., 2020). Bitcoin experienced a dramatic surge from US$ 1,000 to nearly US$ 20,000 in late 2017, plummeting back down to US$ 3,000 in 2019. Regulatory crackdowns have had a notable impact on cryptocurrencies' value in many countries, especially China. In 2015, Ethereum (ETH) enabled blockchain technology in smart contracts and sparked the Initial Coin Offer (ICO) boom. More recently, the rise of decentralised finance (DeFi) and decentralised exchanges (DEX) have reshaped the cryptocurrency landscape. Cryptocurrencies now exhibit similar characteristics to those of developed financial markets, such as currency markets (Drożdż et al., 2018).

Recent research has examined the safe haven properties of cryptocurrencies, particularly during the COVID-19 pandemic (Dasauki & Kwarbai, 2021; Kakinuma, 2023; Maitra et al., 2022). Several studies provide evidence that Bitcoin displays safe haven properties comparable to those of gold (Bouri et al., 2020; Shahzad et al., 2019, 2020; Thampanya et al., 2020). In contrast, other studies have found that cryptocurrency markets are highly correlated with equity markets during market downturns (Yarovaya et al., 2022). Thus, the role of cryptocurrencies as a hedge for financial investments remains a topic of hot debate, with uncertainty surrounding their effectiveness.

Our research is grounded in information transmission theory, which emphasises the importance of information in shaping the expectations of investors, traders, and policymakers and influencing the supply and demand equilibrium. In today's digital age, investors have access to a wide range of information channels, including social media, online blogs, and internet news, that can rapidly disseminate information and affect their beliefs and trading decisions. Models based on rational disagreements, such as those developed by He and Wang (1995) and Tetlock (2010), suggest that public information can lead to trade only when it helps resolve information asymmetry and results in traders' beliefs converging (Tetlock, 2014). These models provide a helpful theoretical framework for understanding how the transmission of information can impact financial markets and serve as a basis for our investigation into the relationship between information transmission and market outcomes.

The efficient functioning of financial markets, which encompasses the determination of prices and asset allocations, relies on the intricate interplay between two fundamental factors: the demand for securities by investors and the willingness of companies to supply these securities. Within the realm of finance, information transmission emerges as a pivotal and central player due to its inherent capacity to shape the expectations held by both investors and managers regarding future developments. It is this very influence that subsequently exerts a profound and far-reaching impact on the delicate equilibrium between supply and demand within these markets. Numerous scholarly endeavours have been dedicated to the exploration of information transmission, with a primary focus on the meticulous examination of stock market dynamics in response to a myriad of corporate events. These events span a wide spectrum, encompassing everything from the disclosure of earnings announcements to the dissemination of analyst forecasts. A noteworthy instance that comes to the fore is the seminal work of Fama et al. (1969), which conducted an event study that meticulously examined the trajectory of stock prices for firms following the public revelation of stock splits.

In the realm of the cryptocurrency market, characterised by its rapid pace and the continuous influx of information, these dynamics are no less relevant. Earlier studies have utilised information transmission as a theoretical basis to comprehend the intricate workings of cryptocurrencies (e.g., Akyildirim et al., 2021; Bação et al., 2018; Ji et al., 2019; Koutmos, 2018). In alignment with this existing body of research, our aim was to delve into the theory of information transmission to gain a deeper understanding of how external factors, such as geopolitical risks and regulatory uncertainties, can exert their influence on the conduct of market participants, including both investors and policymakers. At the core of this discussion lies the recognition that information stands as a fundamental driver of market behaviour within the cryptocurrency space. This encompasses a dual nature of information, encompassing both the public information domain, consisting of news reports, social media posts, and official announcements, and the realm of private information, which may be confidentially held by individual investors and insiders within the market. It is through the transmission of information that profound ripple effects are generated, directly impacting market sentiment, liquidity, and the valuation of cryptocurrency assets.

Geopolitical frictions, tensions, and events such as elections can create fluctuations or uncertainties in political environments, which can significantly impact the prices of financial assets. Balcilar et al. (2018) asserted that geopolitical risk is a crucial determinant of investment decisions, as it can alter business cycles, financial markets, and economic trajectories. The risk emanating from geopolitical tensions causes investors to reassess their portfolios taking into account the stability of government policies. For example, the recent disagreement between USA and China over the disputed island in the South China Sea had a significant indirect impact on business sentiments. Increased geopolitical risks increase asset volatility (Al Mamun et al., 2020). As a result, many studies have employed the geopolitical risk index (GPRD) as a proxy for adverse geopolitical events and associated risks (Caldara & Iacoviello, 2022).

Lucey et al. (2022) introduced a new index, the Cryptocurrency Uncertainty Index (UCRY), which captures two primary types of uncertainty: Cryptocurrency Policy Uncertainty (UCRY Policy) and Cryptocurrency Price Uncertainty (UCRY Price). This index can help assess how policy and regulatory debates influence the returns and volatility of cryptocurrencies. Studies by Al-Shboul et al. (2022), Elsayed et al. (2022), Haq and Bouri (2022) have used the UCRY to understand the dynamic connection with cryptocurrencies, equities, and gold and have established strong evidence of their connectedness.

Our research aims to investigate spillover effects from the GPRD and the UCRY to cryptocurrencies. We utilise network graphs from the frequency connectedness framework developed by Baruník and Křehlík (2018) to accomplish this goal. We aim to answer the following two research questions:

RQ 1: Does the magnitude of spillovers from the UCRY exceed those from the GPRD?

RQ 2: Are there any differences in the magnitude of the spillovers caused by UCRY and GPRD in the short, medium, and long terms?

Prior research has explored the impact of different uncertainties on cryptocurrencies, focusing on individual assets or groups of assets. For instance, Raza et al. (2023) examined the effect of financial regulatory policy uncertainty on a portfolio of six cryptocurrencies using a GARCH-MIDAS framework, finding that higher uncertainty was associated with lower volatility. Khalfaoui et al. (2023) employed a quantile cross-spectral analysis and Google Trends data to investigate the impact of the Russia-Ukraine war on cryptocurrencies. Their research revealed that investors responded to the conflict by demanding liquidity, with a resulting decline in cryptocurrency prices. Al-Shboul et al. (2023) find a negative effect of economic policy uncertainty on the total spillover among all currencies (traditional and cryptocurrencies) at all quantiles. In other words, the higher the uncertainty level, the lower the level of connectedness among currencies Tong et al. (2022) quantified the impact of attention from the search engine (Google Trends) and social media attention (Twitter) and documented bi-directional causality between these attentions and cryptocurrencies. Sawarn and Dash (2023), using a time frequency-based connectedness, concluded that US financial stress transmits uncertainty to cryptocurrencies on a net basis. Long et al. (2022) investigated the cross-sectional impact of geopolitical risk on the returns of 2000 cryptocurrencies, establishing that cryptos with higher geopolitical betas tend to underperform those with the lowest betas. Akyildirim et al. (2021) study the dynamic network connectedness between cryptocurrency returns and investor sentiments and find that information transmission is from cryptocurrency returns towards sentiments.

The remainder of the paper is structured as follows. Section 2 provides a description of the data and the methodology, while section 3 summarises the results and offers insights about the findings. Finally, section 4 concludes with some remarks.

2. Data and methodology

2.1 Data description

We use weekly data for nine major cryptocurrencies (Bitcoin, Ethereum, Basic Attention Token, Bitcoin Cash, Binance Coin, Dogecoin, Litecoin, OmiseGO, and Stellar Lumens) and two uncertainty indices, Geo-political Risk Index (GPDR)[1] and Cryptocurrency Uncertainty Index (UCYR Policy), for the period spanning November 5, 2017 to 25 December 25, 2022. We source the data of cryptocurrencies from the website of coinmarketcap.com and GPRD and UCRY data from their official websites. Table 1 provides more details about the variables and notations used, and Figure 1

[1] Geopolitical risk, as defined by Caldara and Iacoviello (2022), pertains to the potential for, occurrence of, and intensification of adverse events linked to wars, terrorism, and any strains among nations and political entities, which disrupt the peaceful progression of international relations. (https://www.matteoiacoviello.com/gpr.htm)

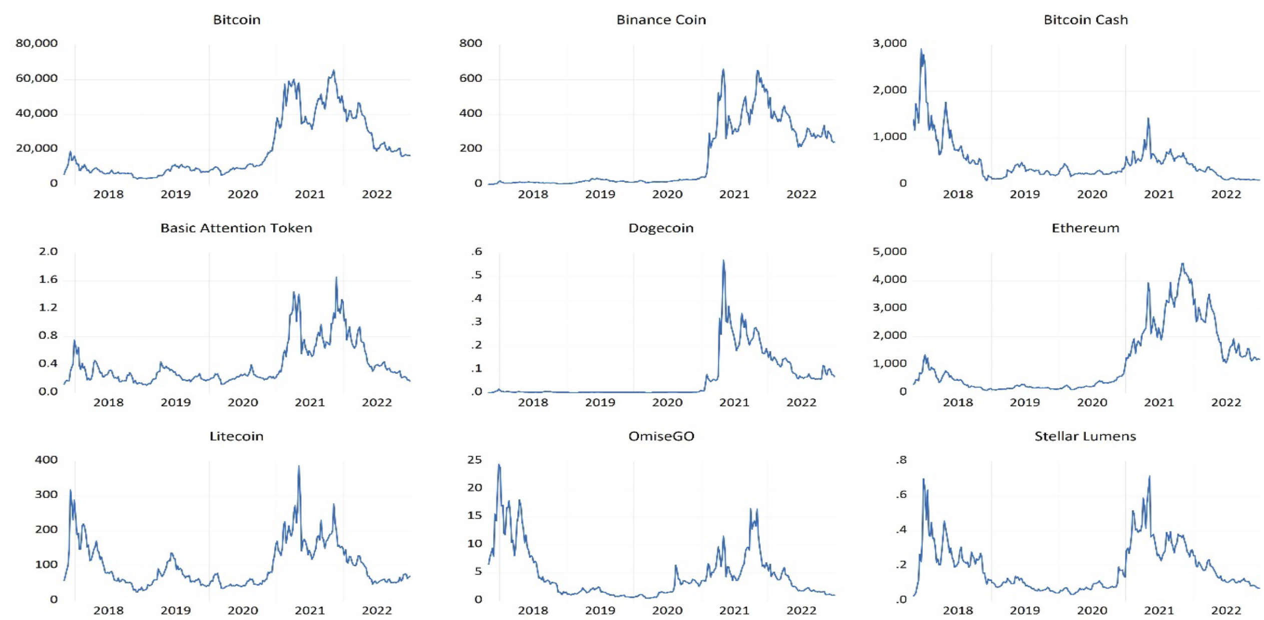
displays the time plots of the nine cryptocurrencies[2]. We calculate weekly percentage change using the formula: $\%\mathrm{Change} = \ln\left({}^{P_t}/_{P_{t-1}}\right)$; where P_t denotes the contemporaneous weekly price while P_(t-1). denotes the previous week's price.

Table 1: Definition of Variables

Variable	Label	Frequency
Geopolitical Risk Index	GPRD	Weekly*
Cryptocurrency Uncertainty Index	UCRY	Weekly
Bitcoin	BTC	Weekly
Ethereum	ETH	Weekly
Basic Attention Token	BAT	Weekly
Bitcoin Cash	BCH	Weekly
Binance Coin	BNB	Weekly
Dogecoin	DOGE	Weekly
Litecoin	LTC	Weekly
OmiseGO	OMG	Weekly
Stellar Lumens	XLM	Weekly

*Note: * GPRD index was converted from daily to weekly frequency by using averages.*

Figure 1: Weekly closing prices of cryptocurrencies



[2] Descriptive statistics for the variables and diagnostic test results are found in the Appendix

2.2 Methodology

Baruník and Křehlík (2018) proposed a frequency connectedness method to measure the directional connectedness between two sets of variables in a frequency domain. Let us denote the two variable sets as X and Y. The frequency connectedness measure is defined as:

$$FC_{X\to Y}(\omega) = \sum_{j=1}^{p_Y} \left| \frac{\sum_{i=1}^{p_X} \gamma_{XY,ij}(\omega)}{\sum_{i=1}^{p_X} \gamma_{XX,ii}(\omega)} \right| \qquad (1)$$

Where $\gamma_{XX,ii}(\omega)$ is the auto-covariance of the i-th variable in set X, $\gamma_{XY,ij}(\omega)$ is the cross-covariance between the i-th variable in set X and j-th variable in set Y, and ω is the frequency.

The measure $FC_{X\to Y}(\omega)$ represents the proportion of the variation in set Y that can be explained by setting at frequency ω, after controlling for the variation within set Y at the same frequency. The measure ranges between 0 and 1, where 0 indicates no connectedness, and 1 indicates complete connectedness.

To measure the total frequency connectedness from set X to set Y, the measure is integrated across all frequencies:

$$FC_{X\to Y} = \int_{-\pi}^{\pi} FC_{X\to Y}(\omega) d \qquad (2)$$

Similarly, the frequency connectedness from set Y to set X can be defined as:

$$FC_{Y\to X}(\omega) = \sum_{i=1}^{p_X} \left| \frac{\sum_{j=1}^{p_Y} \gamma_{YX,ji}(\omega)}{\sum_{j=1}^{p_Y} \gamma_{YY,jj}(\omega)} \right| \qquad (3)$$

And the total frequency connectedness from set Y to set X is derived as:

$$FC_{Y\to X} = \int_{-\pi}^{\pi} FC_{Y\to X}(\omega) d \qquad (4)$$

3. Empirical Results

Figure 2 displays the spillovers between GPRD and the selected set of cryptocurrencies.[3] The 1st, 2nd, and 3rd sub-figures (left to right) in figure 2 refer to (1 week), frequency 2 (1 to 4 weeks), and frequency 3 (4 weeks to infinity), respectively. GPRD is a net transmitter of spillovers to DOGE for all three frequency bands, indicating that changes in GPRD are causing spillover effects that are impacting

[3] The corresponding spillovers table can be found in the Appendix.

the price and market dynamics of DOGE. This finding suggests that DOGE is highly sensitive to policy and regulatory risk changes.

Moreover, for frequency 3, BNB, BCH, and ETH are net receivers of spillovers from GPRD, suggesting that changes in GPRD are causing spillover effects impacting these cryptocurrencies' price and market dynamics. The fact that these cryptocurrencies are net receivers of spillovers from GPRD for the long-term frequency band indicates that they may be more sensitive to policy and regulatory risk over a longer time horizon. Overall, these results suggest spillover effects from changes in policy and regulatory risk, as captured by GPRD, to the selected set of cryptocurrencies and that these spillover effects can occur over different time horizons.

Figure 2: GPRD spillover

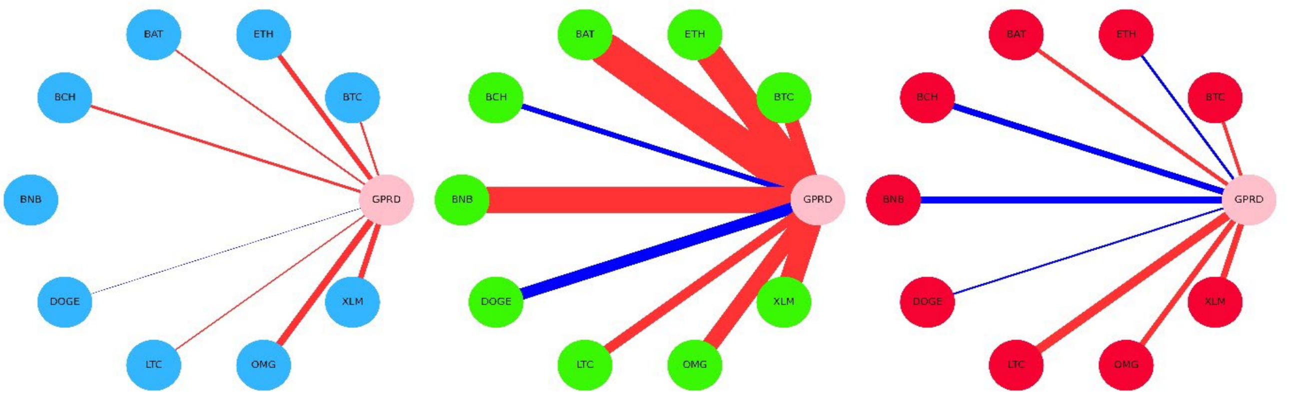
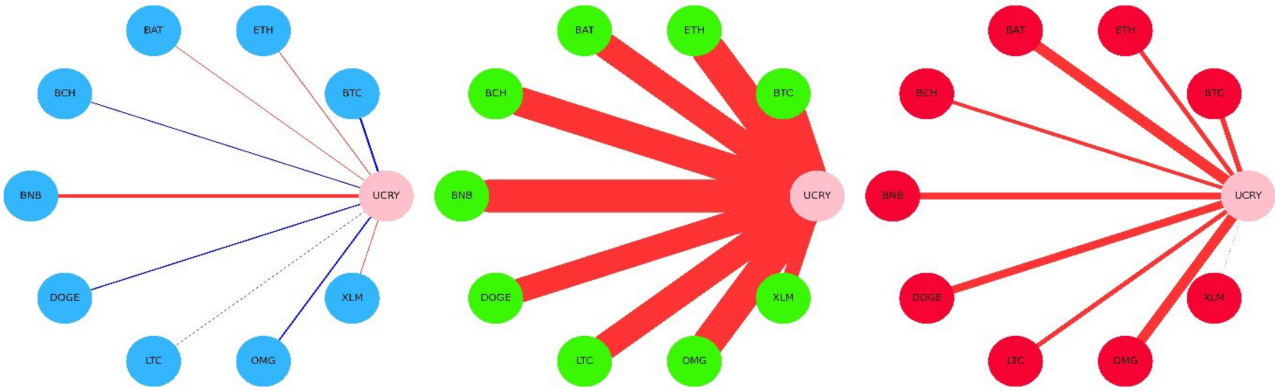


Figure 3 illustrates the spillovers between UCRY and the selected set of cryptocurrencies.[4] The three sub-figures (left to right) show frequency 1 (1 week), frequency 2 (1 to 4 weeks), and frequency 3 (4 weeks to infinity), respectively. For frequency 1, OMG, LTC, DOGE, BCH, and BTC receive net spillovers from UCRY, but none of the cryptocurrencies receive spillovers at frequencies 2 and 3. The results indicate that uncertainty about specific cryptocurrency policies affects the weekly prices of BTC, BCH, DOGE, OMG, and LTC in the short term (frequency 1), as investors react to policy changes by becoming more risk-averse and selling off their holdings. However, this uncertainty does not seem to have a longer term effect (>1 week). Interestingly, these cryptocurrencies become net spillover transmitters over longer horizons to UCRY, suggesting their price and market dynamics impact overall uncertainty in the cryptocurrency market.

[4] The corresponding spillovers table can be found in the Appendix.

Figure 3: UCRY spillover



Figures 4 and 5 provide a visualisation of the total connectedness between GPRD and cryptocurrencies and between UCRY and cryptocurrencies. The results indicate that the magnitude of total connectedness increases as the time horizon extends from short- to medium- to long-term. For the case of GPRD and cryptocurrencies, the total connectedness for frequency 1 (1 week), frequency 2 (1 to 4 weeks), and frequency 3 (4 weeks to infinity) are 68.90%, 72.05%, and 74.98%, respectively. These results suggest that changes in GPRD are highly connected to changes in the selected set of cryptocurrencies and that this connection becomes stronger as the time horizon extends.

Similarly, for the case of UCRY and cryptocurrencies, the total connectedness for frequency 1, frequency 2, and frequency 3 are 69.35%, 70.36%, and 74.65%, respectively. This result suggests that changes in UCRY are also highly connected to changes in the selected set of cryptocurrencies and that this connection becomes stronger as the time horizon extends. These findings highlight the importance of understanding the interconnectedness and spillover effects within the cryptocurrency market and the potential impact of policy and regulatory changes on the overall level of uncertainty in the market. The fact that total connectedness increases with the time horizon suggests that investors and market participants should be mindful of longer-term trends and potential spillover effects when making investment decisions.

It is important to note here that the differing impact of GPRD and UCRY on cryptocurrencies stems from the multifaceted nature of geopolitical risks, the unique attributes of individual cryptocurrencies, the role of market sentiment, and the specific focus of each index. While GPRD casts a wide net over global political events, UCRY delves into the inherent uncertainties specific to the cryptocurrency sector.

Figure 4: Connectedness between GPRD and cryptocurrencies

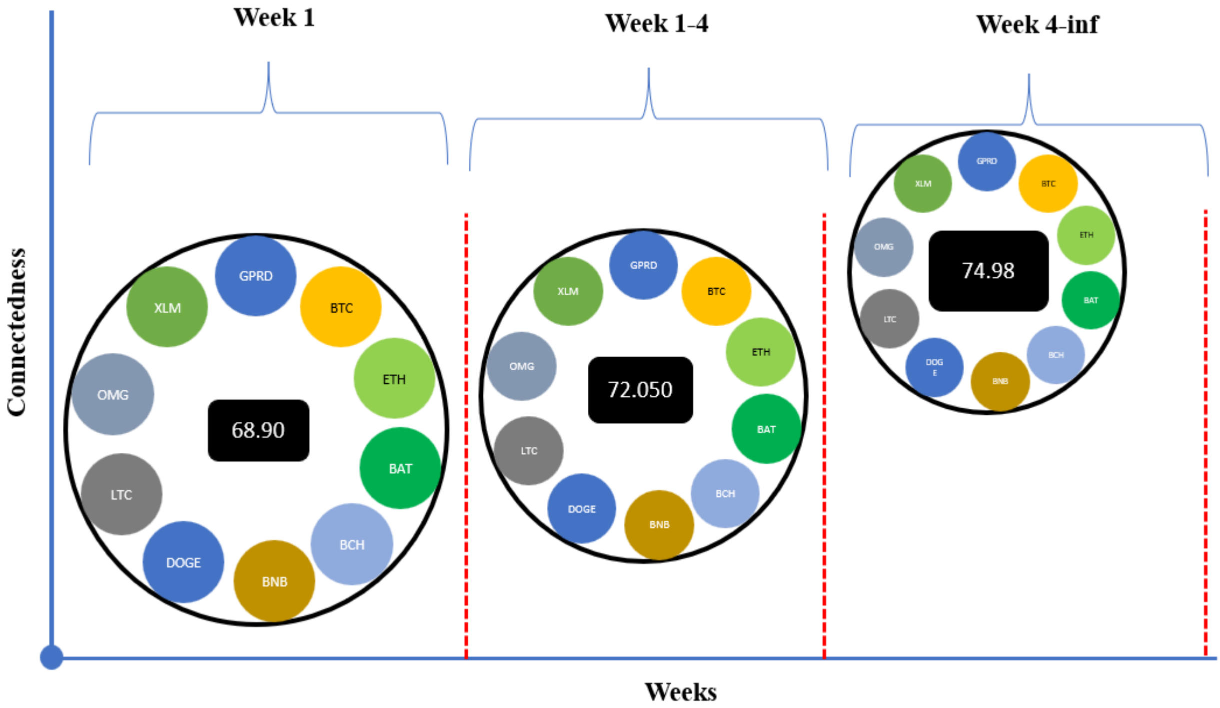
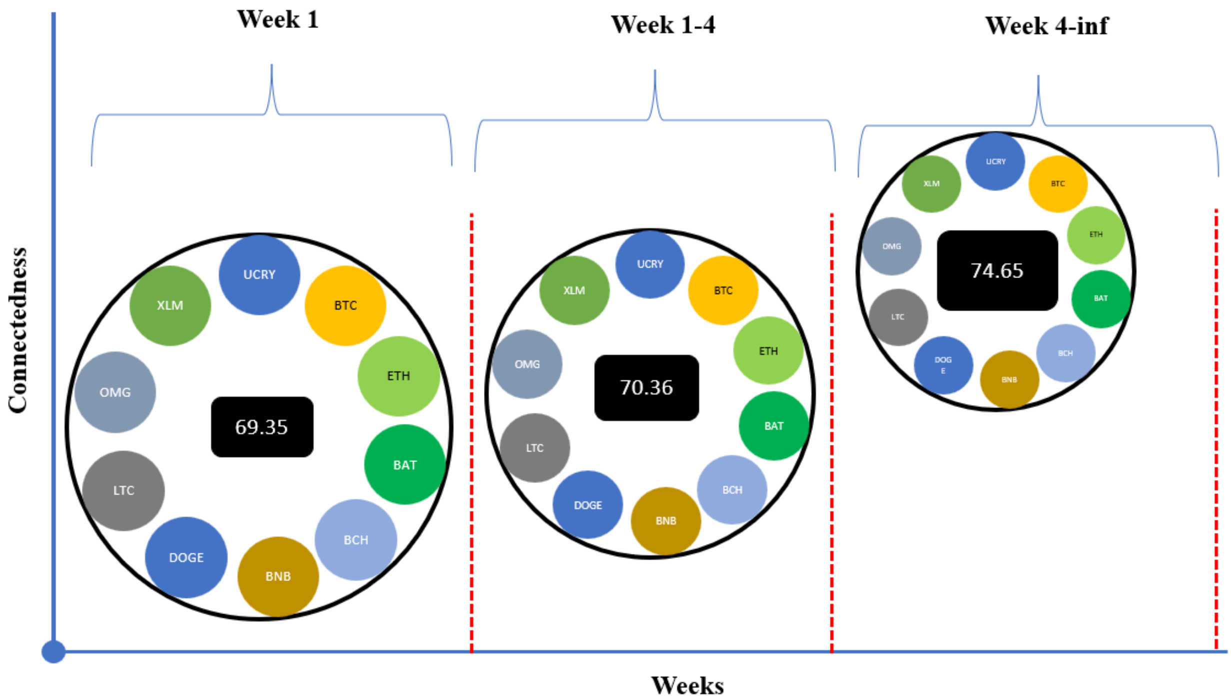


Figure 5: Connectedness between UCRY and cryptocurrencies



4. Concluding Remarks

The present study sheds light on the spillover effects and interconnectedness between geopolitical risk, uncertainty related to cryptocurrencies, and prices of a selected set of major cryptocurrencies: Bitcoin, Ethereum, Basic Attention Token, Bitcoin Cash, Binance Coin, Dogecoin, Litecoin, OmiseGO, and Stellar Lumens.

Our findings indicate that among the nine cryptocurrencies examined, Dogecoin is the most sensitive to policy and regulatory risk changes, as spillover effects from changes in geopolitical risk impact it over all three horizons. Moreover, Binance Coin, Bitcoin Cash, and Ethereum are net receivers of spillovers from geopolitical risk over longer time horizons, indicating their time-dependent sensitivity to policy and regulatory risk. We also find that short-term uncertainty related to cryptocurrencies affects the prices of BTC, BCH, DOGE, OMG, and LTC, with investors and traders displaying a knee-jerk reaction to policy changes. However, over longer time horizons, all cryptocurrencies become net transmitters of spillovers to uncertainty related to cryptocurrencies. Our study highlights the importance of understanding the interconnectedness and spillover effects within the cryptocurrency market and the potential impact of policy and regulatory changes on the overall level of uncertainty in the market. These findings significantly impact investors, policymakers, and regulators in managing risks in cryptocurrencies' rapidly evolving and interconnected world.

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Appendix

Appendix Table A1: Descriptive Statistics

Time-series	Mean	Median	Max	Min	Std. Dev.	Skew	Kurt.	JB
GPRD	0.0012	-0.0069	1.0157	-0.7316	0.2445	0.0354	4.0977	13.5108*
UCRY	0.0003	-0.0005	0.0512	-0.0796	0.0130	-0.2127	10.6109	648.8605*
BTC	0.0038	0.0090	0.3111	-0.4079	0.1081	-0.4791	4.4455	33.5831*
ETH	0.0051	0.0104	0.4885	-0.5310	0.1423	-0.3687	4.8469	44.1605*
BAT	0.0011	0.0019	0.6095	-0.7069	0.1640	-0.0603	5.4772	68.6847*
BCH	-0.0099	-0.0029	0.8843	-0.7427	0.1751	0.1348	7.7988	257.9619*
BNB	0.0190	0.0069	0.8408	-0.7610	0.1671	0.8249	10.1160	595.8502*
DOGE	0.0157	-0.0166	1.4570	-0.5288	0.2199	2.8491	17.5008	2710.6051*
LTC	0.0007	0.0058	0.7626	-0.7260	0.1521	0.0948	6.7433	156.8731*
OMG	-0.0069	-0.0051	0.8312	-0.7690	0.1850	0.2727	6.1481	113.9918*
XLM	0.0035	-0.0127	0.8045	-0.6638	0.1712	1.0162	7.8477	308.5498*

*Note: * p value < 0.01*

Appendix Table A2: Diagnostic Test Results

	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM
Panel A: Normality test results									
Bartels Test	-1.485	-1.771***	-0.581	-0.76	-0.049	-1.952**	-0.564	-0.892	-1.102
Robust Jarque Bera Test	76.157*	85.031*	121.089*	652.294*	2020.692*	22351.26*	272.775*	234.769*	831.527*
Test of normality SJ Test	6.762*	6.536*	7.01*	11.615*	15.246*	25.969*	8.229*	8.722*	12.032*
Bootstrap symmetry test	-1.15	-0.898	-0.119	-1.041	1.952	4.525*	-0.828	-0.234	2.455**
Difference sign test	0.317	-1.162	0.95	-1.373	0.528	-0.95	-1.162	-1.795*	1.162
Mann-Kendall rank test	-0.859	0.087	-0.82	-0.036	-1.063	-0.752	0.235	-0.016	-0.587
Runs Test	0.612	-0.857	0.367	-0.49	0.122	-2.081	-0.245	-1.224	-0.857
Panel B: Nonlinearity test results									
Teraesvirta NN test	4.0039	3.7089	2.272	3.6997	7.560**	0.5619	4.2773	10.583**	4.799*
White NN test	3.419	2.946	2.2196	6.162**	5.967*	0.788	4.1088	11.159**	3.168
Keenan test	3.953**	6.3290**	0.738	1.084	2.536	0.064	0.0233	0.232	0.617
Tsay test	3.954**	0.395	0.402	0.059	2.537	0.064	0.953	0.496	0.872

*Note: * = 0.01; ** = 0.05; *** =0.10*

Appendix Table A3: Unit Root Tests (Cryptocurrencies)

TS	adf.pvalue	kpss.pvalue	pp.pvalue	adf.statistic	kpss.statistic	pp.statistic
BTC	0.0100	0.1000	0.0100	-5.6874	0.1377	-232.6082
ETH	0.0100	0.1000	0.0100	-6.3772	0.1370	-246.9336
BAT	0.0100	0.1000	0.0100	-7.0004	0.1179	-275.4860
BCH	0.0100	0.1000	0.0100	-7.1474	0.0807	-248.2890
BNB	0.0100	0.1000	0.0100	-6.4622	0.1379	-252.2678
DOGE	0.0100	0.1000	0.0100	-6.5073	0.1000	-230.5368
LTC	0.0100	0.1000	0.0100	-7.2543	0.0619	-252.4033
OMG	0.0100	0.1000	0.0100	-6.5326	0.1101	-251.3423
XLM	0.0100	0.1000	0.0100	-7.5310	0.1833	-256.9216

Appendix Table A4: Spillover Table Between GPRD and Cryptocurrencies

Frequency 1~ 1 Week											
	GPRD	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM	FROM_ABS	FROM_WTH
GPRD	1.430	0.010	0.030	0.010	0.010	0.010	0.000	0.000	0.050	0.040	0.020	0.880
BTC	0.000	0.370	0.310	0.190	0.270	0.240	0.140	0.250	0.170	0.200	0.180	9.710
ETH	0.000	0.170	0.330	0.160	0.230	0.200	0.100	0.180	0.160	0.180	0.140	7.660
BAT	0.000	0.140	0.230	0.460	0.260	0.180	0.090	0.180	0.150	0.200	0.140	7.930
BCH	0.000	0.180	0.240	0.180	0.420	0.130	0.110	0.190	0.140	0.140	0.130	7.180
BNB	0.010	0.160	0.250	0.200	0.170	0.420	0.130	0.180	0.190	0.220	0.150	8.350
DOGE	0.000	0.120	0.170	0.090	0.180	0.090	0.470	0.110	0.080	0.100	0.090	5.150
LTC	0.000	0.180	0.250	0.190	0.290	0.170	0.110	0.330	0.140	0.170	0.150	8.180
OMG	0.000	0.170	0.270	0.210	0.240	0.280	0.120	0.230	0.420	0.220	0.170	9.560
XLM	0.000	0.140	0.200	0.200	0.160	0.210	0.120	0.160	0.160	0.410	0.130	7.440
TO_ABS	0.000	0.130	0.190	0.140	0.180	0.150	0.090	0.150	0.130	0.150	1.310	
TO_WTH	0.100	6.930	10.690	7.790	9.930	8.260	5.090	8.170	6.930	8.150		72.050

Frequency 1~ 1- 4 weeks											
	GPRD	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM	FROM_ABS	FROM_WTH
GPRD	80.33	0.56	1.53	2.17	0.46	1.66	0.08	0.58	0.93	1.06	0.9	1.26
BTC	0.17	14.55	9.89	5.73	7.84	7.94	3.55	9.31	6.33	7.41	5.82	8.12
ETH	0.22	7.8	12.9	6.12	8.15	6.88	3.34	7.96	6.8	6.42	5.37	7.49
BAT	0.16	5.7	8.19	16.3	7.28	7.03	2.85	6.75	8.13	7.77	5.38	7.51
BCH	0.54	7.32	9.87	6.21	15.6	5.49	3.56	9.02	7.1	6.22	5.53	7.72
BNB	0.35	6.95	8.58	6.59	5.5	14.9	2.96	7.16	6.82	6.76	5.17	7.21
DOGE	0.38	5.65	7.03	4.65	6.63	5.21	22.7	6.54	4.96	6.01	4.71	6.57
LTC	0.36	8.35	9.62	6.37	9.29	7.34	3.75	14.43	7.31	6.57	5.9	8.23
OMG	0.41	6.04	8.65	7.7	7.75	7.83	3.01	7.73	16.07	6.82	5.6	7.81
XLM	0.16	6.38	7.31	7.29	5.94	6.95	3.37	6.6	6.19	15.16	5.02	7
TO_ABS	0.28	5.48	7.07	5.28	5.88	5.63	2.65	6.16	5.46	5.5	49.39	
TO_WTH	0.38	7.64	9.86	7.37	8.21	7.86	3.69	8.6	7.61	7.68		68.9

Frequency 3~ 4 Weeks to inf												
	GPRD	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM	FROM_ABS	FROM_WTH
GPRD	8.27	0.06	0.06	0.13	0.04	0.08	0.01	0.22	0.08	0.1	0.08	0.29
BTC	0.03	6.32	3.03	1.84	2.73	1.96	1.87	3.47	1.96	1.94	1.88	7.11
ETH	0.08	4.17	5.62	2.96	3.69	2.87	2.59	3.89	3.04	2.77	2.61	9.84
BAT	0.09	2.73	2.74	6.3	2.2	3.02	1.97	2.79	2.89	3.23	2.17	8.17
BCH	0.14	3.52	3.41	2.46	5.03	1.98	2.38	3.83	2.55	2.05	2.23	8.42
BNB	0.21	3.52	2.75	2.98	2.28	6.71	3.66	3.38	2.9	3.11	2.48	9.35
DOGE	0.02	2.48	2.43	1.93	1.9	2.15	10.39	3.22	1.85	2.47	1.84	6.96
LTC	0.03	4.06	2.7	1.8	2.57	2.15	1.99	5.1	2.12	2.27	1.97	7.43
OMG	0	2.87	2.9	2.88	2.31	2.16	1.76	2.72	5.87	2.34	1.99	7.53
XLM	0.01	3.84	3.63	3.3	2.79	2.92	3.24	3.47	2.99	6.69	2.62	9.88
TO_ABS	0.06	2.73	2.36	2.03	2.05	1.93	1.95	2.7	2.04	2.03	19.87	
TO_WTH	0.23	10.29	8.92	7.65	7.73	7.28	7.35	10.18	7.69	7.66		74.98

Appendix Table A5: Spillover Table Between UCRY and Cryptocurrencies

Frequency 1~ 1 Week												
	UCRY	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM	FROM_ABS	FROM_WTH
UCRY	2.1300	0.0000	0.0100	0.0000	0.0000	0.0400	0.0000	0.0000	0.0000	0.0000	0.0100	0.3600
BTC	0.0100	0.3600	0.3000	0.1800	0.2600	0.2400	0.1400	0.2500	0.1700	0.2000	0.1700	9.3300
ETH	0.0100	0.1600	0.3200	0.1500	0.2300	0.2000	0.1000	0.1800	0.1600	0.1900	0.1400	7.3400
BAT	0.0000	0.1400	0.2300	0.4600	0.2600	0.1800	0.0900	0.1900	0.1600	0.2100	0.1500	7.8600
BCH	0.0000	0.1800	0.2300	0.1700	0.4000	0.1300	0.1100	0.1900	0.1500	0.1500	0.1300	6.9500
BNB	0.0100	0.1600	0.2500	0.1900	0.1600	0.4100	0.1400	0.1800	0.2000	0.2300	0.1500	8.0900
DOGE	0.0100	0.1100	0.1600	0.0900	0.1700	0.0800	0.4600	0.1000	0.0800	0.1100	0.0900	4.8700
LTC	0.0000	0.1800	0.2500	0.1900	0.2800	0.1700	0.1100	0.3300	0.1400	0.1800	0.1500	8.0400
OMG	0.0100	0.1600	0.2600	0.2100	0.2300	0.2800	0.1200	0.2300	0.4300	0.2300	0.1700	9.2500
XLM	0.0000	0.1400	0.2000	0.2000	0.1500	0.2100	0.1200	0.1600	0.1700	0.4300	0.1400	7.2600
TO_ABS	0.0100	0.1200	0.1900	0.1400	0.1700	0.1500	0.0900	0.1500	0.1200	0.1500	1.3000	
TO_WTH	0.3000	6.5600	10.1900	7.4500	9.3100	8.1200	5.0500	7.8400	6.6200	7.8900		69.3500

Frequency 1~ 1- 4 weeks												
	UCRY	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM	FROM_ABS	FROM_WTH
UCRY	69.7100	2.0500	2.3500	1.9900	1.8800	2.6900	1.3500	1.7700	2.3200	0.5000	1.6900	2.3700
BTC	0.3000	14.5500	9.9500	5.7700	7.8700	7.9900	3.4800	9.3300	6.3800	7.3200	5.8400	8.1700
ETH	0.3600	7.7800	12.8400	6.1000	8.2000	6.9300	3.2800	8.0000	6.8100	6.3500	5.3800	7.5300
BAT	0.7500	5.7100	8.2600	16.1600	7.2700	7.0100	2.8200	6.6900	8.1000	7.7000	5.4300	7.6000
BCH	0.2800	7.2900	9.9700	6.1300	15.6600	5.6600	3.5600	9.1200	7.2100	6.1700	5.5400	7.7500
BNB	0.7300	6.8600	8.5500	6.4500	5.5600	14.7400	2.9600	7.1700	6.8000	6.7200	5.1800	7.2500
DOGE	0.1900	5.4700	6.8900	4.6200	6.5800	5.3200	22.7700	6.6600	4.9900	6.1900	4.6900	6.5600
LTC	0.4500	8.2600	9.6700	6.2700	9.3400	7.4200	3.8300	14.3500	7.3600	6.5600	5.9200	8.2800
OMG	0.6300	6.0100	8.6700	7.6000	7.8500	7.8800	3.0000	7.7800	15.9500	6.8000	5.6200	7.8600
XLM	0.0900	6.2800	7.2600	7.2500	5.8700	6.9700	3.4600	6.6200	6.2100	15.1700	5.0000	7.0000
TO_ABS	0.3800	5.5700	7.1600	5.2200	6.0400	5.7900	2.7800	6.3100	5.6200	5.4300	50.2900	
TO_WTH	0.5300	7.7900	10.0100	7.3000	8.4600	8.0900	3.8800	8.8300	7.8600	7.6000		70.3600

Frequency 3~ 4 Weeks to inf												
	UCRY	BTC	ETH	BAT	BCH	BNB	DOGE	LTC	OMG	XLM	FROM_ABS	FROM_WTH
UCRY	9.9300	0.1000	0.0900	0.3100	0.0700	0.1600	0.1600	0.0700	0.2700	0.0100	0.1200	0.4700
BTC	0.0400	6.3000	3.0200	1.8800	2.6800	1.9400	1.7900	3.4400	1.9500	1.9000	1.8600	6.9900
ETH	0.0400	4.1800	5.6100	3.0200	3.6900	2.8800	2.5100	3.9200	3.0600	2.7400	2.6000	9.7800
BAT	0.0600	2.7200	2.7100	6.2600	2.1600	2.9500	1.9500	2.7600	2.8400	3.1900	2.1300	8.0100
BCH	0.0300	3.5400	3.4300	2.5100	5.0100	2.0200	2.2700	3.8500	2.5700	2.0000	2.2200	8.3500
BNB	0.0600	3.5400	2.7800	3.0100	2.3600	6.6900	3.6200	3.4500	2.9200	3.1000	2.4800	9.3200
DOGE	0.0100	2.4700	2.4500	1.9600	1.9500	2.2100	10.2300	3.3100	1.8800	2.4900	1.8700	7.0300
LTC	0.0200	4.0500	2.7000	1.8100	2.5700	2.1500	1.9500	5.0700	2.1100	2.2400	1.9600	7.3500
OMG	0.0500	2.8800	2.8900	2.9000	2.3000	2.1500	1.7000	2.7200	5.7900	2.3000	1.9900	7.4700
XLM	0.0100	3.8400	3.6500	3.3400	2.8000	2.9600	3.2300	3.5200	3.0100	6.6700	2.6400	9.9000
TO_ABS	0.0300	2.7300	2.3700	2.0700	2.0600	1.9400	1.9200	2.7000	2.0600	2.0000	19.8900	
TO_WTH	0.1200	10.2500	8.9000	7.7800	7.7300	7.2900	7.2000	10.1500	7.7400	7.5000		74.6500