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Research Article

The Dynamic Connectedness and Risk Integration of Cryptocurrency Policy Uncertainty and Cryptocurrency Price Returns

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Abstract: The basic purpose of this study to investigate the connectedness of the returns of cryptocurrencies and changes in the cryptocurrency policy uncertainty (UCRY Policy). To measure the dynamic relationship, study used Diebold and Yilmaz (2012) connectedness measurement approach to measure the returns connectedness among 7 major cryptocurrencies and UCRY Policy index. The data set encompasses the weekly frequency data of the UCRY Policy and Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Stellar (XLM), Doge (DOGE), Monero (XMR) ranging from 10 August 2015 to 15 February 2021. Empirical findings indicate that total directional connectedness measures between the UCRY policy index, XRP, NEM, Menero and ETH differentiate themselves "from" other cryptocurrencies by having very low "to" connectedness. The study has important implications, i.e., Investors should be clear now that any change in the returns of the Bitcoin, DOGE and Litecoin spillover the risk to other cryptocurrencies along with the change in the UCRY policy index.

Keywords: Cryptocurrency policy, uncertainty cryptocurrency policy index, returns
JEL Classification Codes: D4, E4

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1 Introduction

In recent years, the global financial sector has become increasingly interested in crypto currencies. Crypto currencies are virtual currencies that are built on a number of cyphers. The fact that this system is in the process of being developed to replace existing currencies and payment instruments, as well as traditional monetary theory and practices increases its importance day by day (ALPAGO, 2021). Bitcoin's viability as a payment method, its utility as a diversification tool, and its performance as a speculative asset have all been investigated in previous research. The purpose and underlying value of Bitcoin, on the other hand, continue to elicit a wide range of viewpoints (Morillon, 2022).

There are three basic purposes of Bitcoin. It is, first and foremost, a method of payment. It is also a store of value. Third, it is a tool for diversity. Morillon (2022) introduces a new function, which is its value as a short position on today's quasi-continuous expansionary monetary policies, which are still in effect in many nations. Recently, scholars and policymakers have been devoting more time and effort to gaining a better understanding of the functionality and dynamics of crypto currency. Bitcoin is the most widely used cryptocurrency in the world, when compared to other crypto currencies (Tewari, 2019). Crypto currencies have risen in popularity and mainstream acceptance after the publication of Nakamoto in 2018, which is unexpected given their immaturity (Corbet et al., 2019).Many studies have started to investigate into predictors of cryptocurrency returns due to the inefficiency of the cryptocurrency market (Bariviera, 2017; Nadarajah Chu, 2017). Cryptomarket indicators such as technical indicators (Gerritsen et al., 2019), the mean-reverting property of return (Turattia et al., 2020), the impact of attention from the media (Philippas et al., 2019), the conditional tail risk (Turatti et al., 2019) and the mean-reverting property of return (Turatti et al., 2019) have been found to predict returns (Borri Shakhnov, 2018). Furthermore, numerous studies show that macroeconomic variables have an impact on cryptocurrency returns (Cheng Yen, 2020).

Similarly, the literature focusing on the economic and financial factors of the Bitcoin return is rising in popularity. According to Matkovskyy et al. (2020), European Economic Policy Uncertainty (EPU) and the NIKKEI index have a negative impact on Bitcoin return, whereas exchange rates, interest rates, gold, and oil have a positive impact on Bitcoin return. Another body of research focuses on the time-varying market efficiency of crypto currencies. The crypto currency's time-varying market efficiency is supported by Khuntia and Pattanayak (2018); Khursheed et al. (2020); Nadarajah and Chu (2017). Several studies look into cryptocurrency bubbles (da Gama Silva et al., 2019; Fry et al., 2016), cryptocurrency herding behavior and contagion (Da Gama Silva et al., 2019), cryptocurrency return equicorrelation (Bouri et al., 2021), cryptocurrency volatility (Kinateder et al., n.d.; Liu Tsyvinski, 2018; Miglietti et al., 2020), and the impact of cryptocurrency on public policy (Morillon, 2021).

This study makes a number of significant contributions to the existing literature. For starters, earlier empirical research has looked into the relationship between various uncertainty measures (such as the VIX, NVIX, TPU, EPU, and others) and cryptocurrency returns. As an additional point of comparison to the current literature (which makes extensive use of uncertainty measures, particularly UCRY), no study has looked into the relationship between UCRY Policy and the returns of cryptocurrency assets. This study explores the time-varying association between UCRY Policy and cryptocurrency returns for the first time. That is, in contrast to previous research, this study proposes that the UCRY Policy may have a different impact on cryptocurrency returns, as well as a new research agenda for cryptocurrency market uncertainty. Second, it considers time variation in UCRY Policy and cryptocurrency returns using Engle (2002) DCC model to measure the dynamic link. As a result, by examining potential causes of cryptocurrency fluctuations, this study contributes to the increasing cryptocurrency literature. Thirdly, this research has implications for investors and policy makers. Fourth, this research is useful for investors looking for hedging or safe-haven investments, particularly in the volatile cryptocurrency markets. Finally, because there are few studies on the UCRY Policy in the finance literature, this study may be valuable for future research and fill a vacuum in the knowledge.

2 Literature review

Because of the ways that technology, communication, and globalization have changed our lives and lifestyles, the level of uncertainty is now more important than ever. Political divisions, polarization, as well as the growing importance of government spending in the economy, are the key reasons that have contributed to the recent rise in uncertainty (Baker et al., 2014). Indeed, important economic and policy events such as the global financial crisis (2007), the Greek financial crisis (2010), the Brexit vote (2016), Donald Trump's election (2016), and the UCRY Policy pandemic crisis (2020 to date) have had an impact on the world in recent years (Foglia Dai, 2022). Uncertainty in the economy and in public policy has a significant impact on the expenditure and investment of families, businesses, and governments. This prompted a large number of scholars to investigate measures of uncertainty, particularly those relevant to uncertainty in economic policies, which resulted in the formulation of various proxies for uncertainty (Shabir et al., 2021).

Demir and Ersan (2018); Iqbal et al. (2020); Kannadhasan and Das (2020) and Wu Wu (2020) have investigated how the EPU affects stock returns. They found that the EPU has a negative influence on stock returns. Uncertainties have an impact on the cryptocurrency markets in a similar way. According to Colon et al. (2021), the cryptocurrency market reacts to uncertainty in a number of ways, depending on the type of uncertainty, and that uncertainty is a significant factor determining cryptocurrency returns. Recently, the influence of uncertainty on crypto currencies has been investigated using a variety of uncertainty measures suggested in the literature.

The influence of these uncertainties and risks on cryptocurrency returns and price volatility is examined in cryptocurrency literature. W. Wu et al. (2021) looked at the relationship between Trade Policy Uncertainty (TPU) and Bitcoin returns in the United States, and concluded that TPU has a negative impact on Bitcoin returns. Similarly, Bouri et al. (2020) studied the relationship between the Bitcoin returns and TPU in the United States and concluded that the TPU has a negative impact on Bitcoin returns. Shaikh (2020) examined the effects of the EPU on Bitcoin returns in developed countries and finds that uncertainty has a negative influence on the Bitcoin market in the United States and Japan, but a positive impact in China. There is a study done by Mokni et al. (2020) that looks into the effects of EPU on Bitcoin returns. They found that EPU only affects Bitcoin returns negatively after the Bitcoin crash of December 2017. Wang et al. (2019) found that Chinese EPU has a positive effect on Bitcoin returns. Raheem (2021) compares the safe haven to uncertainty measures (VIX, EPU, and Oil Shock), and finds that the safe havens prowess is dependent on the kind of shock, with Bitcoin providing considerable protection against

EPU and VIX shocks but not Oil Shock. Karaömer (2022) studied the function of BTC, ETH, XRP, Tether, and Bitcoin Cash as a hedge and safe-haven against the EPU prior to and during the ongoing UCRY Policy issue, and concluded that crypto currencies cannot operate as a powerful hedge or safe-haven against the EPU prior to and during the crisis. The capacity of BTC to function as a safe haven against geopolitical risks index is examined by Selmi et al. (2022), and the results demonstrated that the ability of BTC to operate as a safe haven against geopolitical risks index.

The Cryptocurrency Uncertainty Index (UCRY), developed by Lucey et al. (2022), is a novel sort of uncertainty proxy based on text content analysis. They proposed a new UCRY that encompasses two forms of uncertainty: UCRY Policy and Cryptocurrency Price Uncertainty (UCRY Price). They argued that these indexes may be used to see how policy and regulatory discussions have affected the price, return, and volatility of crypto currencies. Furthermore, they claim that the key predictor of cryptocurrency volatility is uncertainty, and that the UCRY Policy reflects the uncertainty caused by important events (e.g. China banning ICOs, hack of cryptocurrency exchanges, UCRY Policy crisis). They further claimed that, as compared to the EPU, VIX, and Global EPU index, the UCRY Policy reflects the uncertainty associated with big events in crypto currencies in better way. Furthermore, they state that it is critical to distinguish between UCRY Policy and UCRY price uncertainty in order to better understand the behavior of different investor groups in the cryptocurrency markets: amateurs will react strongly to price changes, whereas informed investors will be sensitive to policy uncertainty changes. As a result, the focus of this research is on the UCRY Policy. Hasan et al. (2021) examined the impact of the UCRY Policy on Bitcoin, Sukuk, the DJ Islamic Index, the US dollar, gold, and WTI returns, concluding that the UCRY Policy has a negative impact on BTC, WTI returns, and the US dollar, and BTC is not a safe-haven asset in the face of the UCRY Policy. The basic purpose of this study is to see the time varying return connectedness between cryptocurrency policy uncertainty (UCRY Policy) and seven major cryptocurrencies returns. More specifically, study will analyze how these currencies and their related policies from the different countries relate to each other. To achieve the objective, we used the connectedness measurement approach of Diebold and Yilmaz (2012). To the best of our knowledge, it is the first study that examines the change in UCRY policy and their interrelation with the major cryptocurrencies of the world. The study helps the market players, including brokers, investors, and regulators, to consider cryptocurrency returns connectedness with the policy related issues while their portfolio formation during such policy events.

3 Data and Methodology

3.1 Data Description

This study uses the weekly data for 7 cryptocurrencies namely Bitoin, Doge, Ethereum, Litecoin, Monero, NEM, XRP and Uncertainty Cryptocurrency (UCRY) Policy Index, ranging from 10 August 2015 to 15 February 2021. Lucey et al. (2022) build cryptocurrency uncertainty index based on the news coverage that exhibits distinct movements around major events in cryptocurrency. The UCRY Policy Index data and the cryptocurrency prices are taken in the US dollar.

3.2 Connectedness Measurement Approach

To see the connectedness of the UCRY Policy Index with the 7 major cryptocurrencies prices for the assessment of variance decomposition of the forecasted error variance, we applied Antonakakis et al. (2013); Gabauer et al. (2018), and Diebold and Yilmaz (2018) methodology. Let's Y_t be a vector matrix of (N x 1) of N cryptocurrencies returns, and the TVP-VaR model can be simply represented by the following equations;

$$Y_t = \infty_t Y_{t-1} + \mu_t; \mu_t/\Omega_{t-1} \sim N(0, S_t) \tag{1}$$

$$\infty_t = \infty_{t-1} + \nu_t; \nu_t/\Omega_{t-1} \sim N(0, S_t) \tag{2}$$

Whereas Ω_{t-1} show the information set available at one lag, Y_{t-1} is a (N_p× 1) is a lagged vector of the dependent variables whereas t is the (N × Np) matrix of the coefficient which is considered as time-varying over time. μ_t and ν_t are two (N × 1) vectors of the error terms. The technique is an extension of the familiar variance decomposition technique in which the forecasted error variance of variable i is decomposed into different parts based on the various variables available in the system. The connectedness measurement approach first fits the vector autoregressive model and then establishes a "U" period ahead forecast and, in the end, decomposes the forecasted error variance for each variable with respect to shocks from the same or other variables at time t. Study use $d^U_{i,j}$ to denote the ij-tu U-step forecasted error variance. In other words, $d^U_{i,j}$ represents the fraction of variable i's U-step forecast error variance due to shocks in variable j, where ij = 1. . . .N and I $\neq$ j, which emphasizes that connectedness measures are usually more emphasized for the other entities of interest for seeing their cross connectedness with each other instead of their own.

Table 1: Schematic of a connectedness table

	x1	x2	......	XN	From Others
x1	$d^U_{1,1}$	$d^U_{1,2}$	......	$d^U_{1,N}$	$\sum_{j=1}^{N} d^U_{1,j}, j \neq 1$
x2	$d^U_{2,1}$	$d^U_{2,2}$	......	$d^U_{2,N}$	$\sum_{j=1}^{N} d^U_{2,j}, j \neq 2$
⋮	⋮	⋮	⋮	⋮	⋮
xN	$d^U_{N,1}$				$\sum_{j=1}^{N} d^U_{1,j}, j \neq 1$
To Others	$\sum_{i=1 \atop \neq 1}^{N} d^U_{i,1}, i$	$\sum_{i=1}^{N} d^U_{i,2}, i \neq 2$	......	$\sum_{i=1 \atop \neq N}^{N} d^U_{i,N}, i$	$\frac{1}{N}\sum_{i=1}^{N} d^U_{1,N}, i \neq j$

To get the variances decomposition (DH) matrix the measure used in study focuses more on the off-diagonal. These elements are known as pairwise connectedness and are part of the N forecasting error variance decomposition of significance. The pair wise directional connectedness from j to I is defined as follows:

$$C^U_{i\leftarrow j} = d^U_{i,j} \tag{3}$$

In general, $C^U_{i,j} \neq d^U_{i,j}$, so there are (N2 – N) different sets of pairwise directional connectedness measures. So, in the same line, we can define the net pairwise directional connectedness as follows;

$$C^U_{i,j} = C^U_{j\leftarrow i} - C^U_{i\leftarrow j} \tag{4}$$

Now let's assume that the off-diagonal column and row have a sum of DU. The off-diagonal row sum is labelled as "from others" in the resultant connectedness table, which gives the share of U-step forecast error variance of variable xi coming from the shocks arising from all other variables. So the total directional connectedness forms the other variables to the i as,

$$C^U_{i\leftarrow \blacksquare} = \sum_{j=1,j\neq 1}^{N} \times d^U_{i,j} \tag{5}$$

And now the reverse total connectedness to the others from j as;

$$C^U_{\blacksquare\leftarrow j} = \sum_{j=1,j\neq 1}^{N} \times d^U_{i,j} \tag{6}$$

So, there are two N total directional connectedness measures. Just as for net pairwise directional connectedness, we define net total directional connectedness of variable i as,

$$C^U_i = C^U_{\blacksquare\leftarrow i} - C^U_{i\leftarrow \blacksquare} \tag{7}$$

Finally, the sum of "from" columns or "to" rows measures total connectedness, which is the grand total of the off-diagonal entries in DU. We define total connectedness as;

$$C^U = \frac{1}{N} \sum_{j=1,j\neq 1}^{N} \times d^U_{i,j} \tag{8}$$

So, the resultant CU measure which calculates the total connectedness into a single measure. In the case of orthogonal shocks, variance decomposition will be measured as variance of the weighted sum of all variances of different series. While in the case of non-orthogonal shocks, the variance decomposition cannot be calculated easily because tractional methods such as Cholesky-factor identification may be sensitive to ordering. This issue is addressed by Demirer et al. (2018) by introducing the vector autoregression (VAR) decompositions that are invariant to ordering, same as suggested by Koop et al. (1996). The U-step generalized variance decomposition (GVD) matrix $D^{g^U} = [d^{g^U}_{i,j}]$ with entries, which is:

$$d^{g^U}_{i,j} = \frac{\sigma^{-1}_{jj} \sum_{h=0}^{U-1} (e'_i \ominus_U \sum e_j)^2}{\sum_{h=0}^{U-1} (e'_i \ominus_U \sum \ominus'_h e_i)} \tag{9}$$

Where e_j is the selection vector with jth as unity element and zeros elsewhere, $\ominus_U$is the coefficient matrix in the moving averaging method with non-orthogonal rotation of VAR. is the sum of the covariance matrix of the shock vector, and jj is the jth diagonal element. Due to the non-orthogonal nature of the VAR framework, shocks are not necessary to be unit, as it normalized each entry through generalized variance decomposition (GVD) matrix by summing up the row to obtain pairwise directional connectedness from j to I, which is:

$$\hat{d}^g_{i,j} = \frac{d^g_{i,j}}{\sum_{j=1}^{N} d^g_{i,j}} \tag{10}$$

By construction of $\sum_{j=1}^{N} \hat{d}^g_{ij} = 1$ and $\sum_{ij}^{N} \hat{d}^g_{ij} = N$, study can calculate the connectedness measuring using $\hat{D}^g_{ij}$

4 Empirical results

Descriptive analysis has been performed and reported in Table 1. The results indicate that the highest return is earned by the NEM cryptocurrency holders during the sample period and the lowest return belongs to the XMR while the highest standard deviation belongs to the XRP and the lowest standard deviation belongs to the BTC variable. Thus, BTC provides lesser returns in terms of the risk-return profile but possesses the lowest risk compared to other cryptocurrencies. The variables' high kurtosis values show the fat tails or outliers. This situation may have occurred due to non-continuous price jumps. Thus, it can be said that the rate of return of cryptocurrencies has a much higher probability of gain or loss than the normal distribution.

Table 2: Summary Statistics of Cryptocurrency and UCRY Policy returns

	Mean	SD	Skewness	Kurtosis
BITOIN	0.018	0.088	-0.009	4.292
DOGE	0.02	0.163	1.771	10.262
ETH	0.027	0.15	1.116	6.335
LTC	0.014	0.125	1.539	11.905
MONERO	0.021	0.14	1.298	9.08
NEM	0.028	0.167	1.156	5.456
XRP	0.014	0.171	2.175	11.346
UCRY POLICY	0.0003	0.006	0.844	5.787

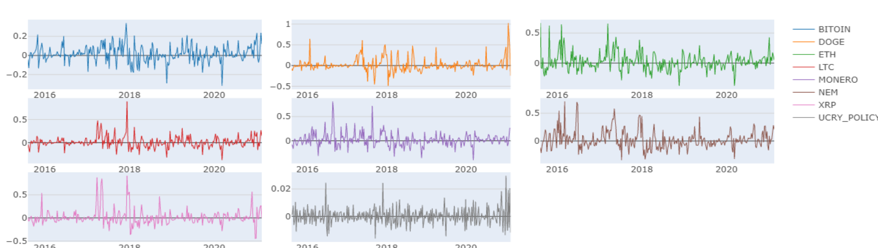

Figure 1: Line Graph of Cryptocurrency and UCRY Policy returns

Table 3: Average Dynamic Connectedness Analysis of Cryptocurrency and UCRY Policy returns

	BIT	DOGE	ETH	LTC	MONERO	NEM	XRP	UCRY_POLICY	FROM
1	**40.51**	11.25	7.31	16.64	10.52	7.15	6.35	0.28	59.49
2	10.8	**39.31**	8.45	12.66	6.61	9.48	12.66	0.02	60.69
3	8.67	9.84	**47.1**	8.97	10.43	8.69	6.25	0.09	52.94
4	15.47	11.71	7.53	**37.9**	8.14	6.12	12.4	0.72	62.1
5	12.54	7.95	10.55	10.39	**46.38**	6.94	5.22	0.04	53.62
6	8.78	11.02	8.93	8.91	7	**43.4**	11.92	0.01	56.58
7	7.47	13.44	7.45	14.35	5.3	10.77	**41.1**	0.08	58.86
8	0.83	1.02	0.8	2.42	0.79	1.34	0.78	**92.01**	7.99
TO others	64.56	66.23	51.02	74.34	48.8	50.49	55.58	1.24	**412.3**
Inc. own	105.1	105.54	98.08	112.2	95.18	93.91	96.72	93.26	TCI
NET	5.08	5.54	-1.92	12.24	-4.82	-6.09	-3.28	-6.74	**51.53**
NPDC	2	1	3	0	4	6	5	7	

TVP-VAR: Antonakakis, Chatziantoniou, and Gabauer (2020, JRFM), QVAR: Chatziantoniou, Gabauer and Stenfors (2021, EL) (Extended) Joint Connectedness: Balcilar, Gabauer, and Zaghum (2021, RP) Bitcoin (1), Doge (2), Ethereum (3), Litecoin (4), Monero (5), NEM (6), Ripple (XRP) (7), UCRY Policy Index

Table 2 reports the variance decomposition of the TVP-VAR model for change in the UCRY Policy index and returns of 6 different cryptocurrencies. Variance decomposition is based on the 10 step ahead forecast using a lag length of 1 lag for the TVP-VAR. The word "TO" denotes the degree to which a particular variable I transmits its shock to all other variables "j" in a directed manner. The term "From" refers to the degree of directional "connectedness" with which a given variable I receives shocks from all other variables "j." TCI stands for total connectedness index, while "net spillovers" refers to the difference between the two directional "connectedness."

Table 2 indicates the estimated values generated by the TVP-VAR model and average dynamic connectedness measures for the UCRY index and 6 cryptocurrency's returns. We observed that change in Uncertainty cryptocurrency policy index spillover and cryptocurrency's returns had explained the highest share of the forecast error variance because the variance of the diagonal elements receives higher values than the off-diagonal elements. Similarly, the value of TCI is 51.53, which indicates that more than half (51.53%) of the forecast error variance in returns of cryptocurrencies and change in Uncertainty cryptocurrency policy index comes from connectedness. Therefore, connectedness is important for cryptocurrencies returns and change in the UCRY Policy index.

From net connectedness perspective, the first three highest spillover from other was received by Litecoin as 62.1%, Doge as 60.59% and Bitcoin as 59.49%. On the other hand, the contribution of the risk transmission to the counter cryptocurrencies and UCRY policy is also high for the Litecoin, Doge, and Bitcoin which is 74.34%, 66.23 and 64.56%, respectively. In comparison, the lowest transmission was observed on UCRY policy index in both ways. The most interesting result of the total directional connectedness measures is that

UCRY policy index, XRP, NEM, Menero and ETH differentiate themselves from other cryptocurrencies by having very low "to" connectedness, ranging between 1.24% and 55.58%. They also have low "from" connectedness, but it is not as low as their "to" connectedness. As a result, their net connectedness measures are all negative and range between -1.92% and -6.74%. The net spillovers indicate that these cryptocurrencies along with UCRY Policy Index are the net receiver of the spillover while all the other cryptocurrencies are net risk transmitters.

The same can be seen in the figure 2, yellow color is the indication of the net receiver of the risk, while the blue color indicate the net risk transmitter.

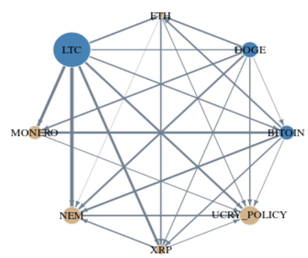

Figure 2: Network Diagram of Cryptocurrency and UCRY Policy returns

5 Conclusion

This study used UCRY Policy Index as developed by Lucey et al. (2022) with the 7 major cryptocurrencies prices for the assessment of variance decomposition of the forecasted error variance, we applied Antonakakis et al. (2013); Gabauer et al. (2018), and Diebold and Yilmaz (2018) connectedness methodology. Empirical findings indicate that total directional connectedness measures between UCRY policy index, XRP, NEM, Menero and ETH differentiate themselves “from” other cryptocurrencies by having very low "to" connectedness. The net spillovers indicate that these cryptocurrencies along with UCRY Policy Index are the net receiver of the spillover while all the other cryptocurrencies are net risk transmitters.

The result of this study provides potential implications for the investors and other stakeholders. Investors should be clear now that any change in the returns of the Bitcoin, DOGE and Litcoin will be observed in the price change of other cryptocurrencies along with the change in the UCRY policy index. It means, all the other cryptocurrencies are the potential receivers of the risk transmitted by these three main cryptocurrencies. Moreover, the findings regarding the hedging and safe haven properties of cryptocurrencies can provide valuable information for policymakers as they determine the position of the cryptocurrency market in their financial systems and set relevant regulatory policies on cryptocurrencies. Each cryptocurrency is impacted differently by the UCRY Policy, especially salient events. Finally, considering the empirical findings of this study, they would benefit by diversifying their portfolios against the UCRY policy arising from the cryptocurrency markets.

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