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"Ubiquitous uncertainties": spillovers across economic policy uncertainty and cryptocurrency uncertainty indices

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Received 8 May 2021
Revised 27 May 2021
Accepted 29 May 2021

Abstract

Purpose – The purpose of this paper is to extend the literature on the spillovers across economic policy uncertainty (EPU) and cryptocurrency uncertainty indices.

Design/methodology/approach – This paper uses cross-country economic policy uncertainty indices and the novel data measuring the cryptocurrency price uncertainties over the period 2013–2021 to construct a sample of 946 observations and applies the time-varying parameter vector autoregression (TVP-VAR) model to do an empirical study.

Findings – The findings suggest that there are cross-country spillovers of economic policy uncertainty. In addition, the total uncertainty spillover between economic policies and cryptocurrency peaked in 2015 before gradually decreasing in the following periods. Concomitantly, the cryptocurrency uncertainty has acted as the "receiver." More importantly, the authors found the predictive power of economic policy uncertainty to predict the cryptocurrency uncertainty index. This paper's results hold robust when using alternative measurement of cryptocurrency policy uncertainty.

Originality/value – This study is the first research that deeply investigates the association between two uncertainty indicators, namely economic policy uncertainty and the cryptocurrency uncertainty index. We provide fresh evidence about the dynamic connectedness between country-level economic policy uncertainty and the cryptocurrency index. Our work contributes a new channel driving the variants of uncertainties in the cryptocurrency market.

Keywords Cryptocurrency uncertainty index, Economic policy uncertainty, Spillover dynamics, Time-varying VAR

Paper type Research paper

1. Introduction

We are living in a period of great uncertainty. Indeed, in recent years, various financial and political events have shaken the world. For example, the US financial crisis (2007), the Eurozone sovereign-debt crisis (2010–13), terrorist attacks (2015), Brexit (in 2016) and the

JEL Classification — C43, C54, D80

The authors are grateful to the editors and the anonymous referees of the journal for their extremely useful suggestions to improve the quality of the article. This work is supported by China Postdoctoral Foundation (Grant No.: 2021M691015).

current health crisis due to the COVID-19 pandemic (2020-to date). This series of events has meant that uncertainty has become an important variable in modern economies, a variable that plays a key role in the transmission of fiscal and monetary policies in financial markets and then on the real economy. Given the close links between the various world markets (countries), there are many kinds of connection through which uncertainties in one market (country) can spread to others (Kang and Yoon, 2019). For example, several types of research show that the economic policy uncertainty index (EPU; Baker *et al.*, 2016) has an impact on stock markets (Antonakakis *et al.*, 2013; Liu and Zhang, 2015; Guo *et al.*, 2018; Phan *et al.*, 2018), on commodities markets (Antonakakis *et al.*, 2014; You *et al.*, 2017; Mokni *et al.*, 2020), on real estate market (Xia *et al.*, 2020) and on countries economics (Gabauer and Gupta, 2018; Kang and Yoon, 2019; Jiang *et al.*, 2019).

Therefore, this paper concerns an important issue that has emerged in the economic and financial literature, i.e. the nexus between economic uncertainty and cryptocurrency markets. In fact, the EPU is a key variable in the cryptocurrency market (Demir *et al.*, 2018; Fang *et al.*, 2019; Cheng and Yen, 2020; Wang *et al.*, 2020; Panagiotidis *et al.*, 2020; Yen and Cheng, 2021; Huynh *et al.*, 2021b) when this indicator might drive the capital flow regarding the investment opportunity of investors. Concomitantly, the strand of literature (Yuneline, 2019; Huynh *et al.*, 2020) indicates that the other the nature of money, legal, economics determinants (for instance, the ratio of gold over platinum as the aggregated market risk) and economy might have an association with the cryptocurrency market. In recent years, several studies have analyzed this nexus with different methodologies. For example, Demir *et al.* (2018), by a Bayesian Graphical structural vector autoregressive model and Quantile-on-Quantile regression, show that the EPU predicts the Bitcoin returns. Using the GARCH-MIDAS framework, Fang *et al.* (2019) study the impact of global economic policy uncertainty on Bitcoin volatility, bonds, commodities and global equities. Their results suggest that the global EPU index negatively impacts the Bitcoin-bonds correlation. On the other hand, the authors find a positive impact of EPU on Bitcoin-equities and Bitcoin-commodities correlations. Cheng and Yen (2020), by a predictive autoregressive model, analyze the relationship between EPU and Bitcoin price. The authors find that only China EPU predicts the Bitcoin returns. The same results are found by Yen and Cheng (2021). In this case, they investigate the EPU-cryptocurrencies volatility nexus. The result points out the capability of China's EPU to predict cryptocurrency volatility.

More recently, Mokni (2021), using causality across quantiles analysis, investigates the causality between Bitcoin returns (volatility) and the economic policy uncertainties. The findings show a significant causality from EPU to cryptocurrency returns. Further, Janiak *et al.* (2021) study the nexus between EPU and cryptocurrencies. Applying a quantile cross-spectral approach, the authors find that cryptocurrency markets are efficient at hedging instruments against the infectious disease EMV and EPU indexes, respectively. Huynh *et al.* (2021b) investigate the relationship between EPU and Bitcoin (returns, volume and volatility). Using the transfer entropy approach, the authors document the negative impact of EPU on Bitcoin volumes and volatilities.

However, to the best of our knowledge, no work has investigated the relationship between the cryptocurrency market uncertainty index (Lucey *et al.*, 2021) with EPU indices (Baker *et al.*, 2016). Hence, this paper investigates this important nexus and evaluates how EPU can play an important role in predicting cryptocurrency market uncertainty. Uncertainty differs from volatility in the way it is designed and measured. In fact, volatility captures the variability in the price of financial assets (in this case, cryptocurrencies). Therefore, it can be interpreted as a measure "of the present," i.e. it photographs the current situation. Uncertainty indices try to capture "the future" through the study of economic, social and political sentiment (Baker *et al.*, 2016; Lucey *et al.*, 2021). Hence, in this research, we seek to capture the relationship between two measures of uncertainty (political and financial) and how they affect each other. That is, compared to the existing literature (which uses volatility as a measure), our paper offers a view on the "future" that is more focused on political, economic and financial sentiment. For this purpose, we apply the time-varying parameter vector autoregression (TVP-VAR) model of Antonakakis *et al.* (2020). This framework is a useful method to investigate the cross-country spillovers of economic policy and cryptocurrency uncertainty. Moreover, the model employs a fixed window size; therefore, we are able to estimate the connectedness with short time-series observations.

In this study, we are interested in answering the following questions: What is the relationship between economic policy uncertainty and uncertainty in the cryptocurrency world? What role does crypto uncertainty play in shaping the connection patterns of economic policy uncertainty? Do the dynamics of economic policy uncertainty dictate the behavior in the cryptocurrency market? Our empirical findings show significant cross-country spillovers of economic policy uncertainty. We find that cryptocurrency uncertainty is a net transmitter over all the period of the analysis. The results document how the dynamics of uncertainty (EPU indexes) dictate the behavior in the cryptocurrency market.

Our study contributes to the existing literature in several ways. First, we provide empirical evidence about the dynamic connectedness between the country-level economic policy uncertainty and the cryptocurrency index. In fact, the previous literature has mainly focused on the returns and volatility of Bitcoin (Cheng and Yen, 2020; Yen and Cheng, 2021; Huynh *et al.*, 2021b). In this study, for the first time, we focus on Bitcoin and the economic policy uncertainty nexus. Second, the contribution comes from the new methodology applied. We use the TVP-VAR framework to measure spillover connectedness between EPU indexes and crypto uncertainty. This model was proposed by Diebold and Yılmaz (2014) with the new extension of TVP-VAR (Antonakakis *et al.*, 2020). This methodology, considering the structure of the network, allows us to estimate directional spillover effects without taking into account the order of variables in the vector autoregressive regression (VAR). That is, the variance decompositions of the prediction error are invariant to the ordering of the variables. Third, we show how the dynamics of uncertainty (EPU indexes) dictate the movements in the cryptocurrency market. Indeed, we find that the UCRYP index always receives more uncertainty spillover than it transmits. While these points are to examine how risk spillover has been transmitted between two types of uncertainties, our fourth contribution is the predictive power of economic policy uncertainty (EPU) to the variant of the cryptocurrency uncertainty index. Our study contributes a new channel driving the variants of uncertainties in the cryptocurrency market.

The remainder of the paper is structured as follows: After briefly commenting on data source Section 2, we discuss our main methodology in Section 3. Our empirical findings are presented in Section 4 with two main perspectives, namely dynamic connectedness and predictive regression, and Section 5 concludes.

2. Data source

We use monthly the EPU index for 11 economics: France, Germany, Italy, Spain, the UK, Russia, the US, Japan, Korea, China and India. These countries represent a sizeable portion of the global economy. The data are extracted from Baker *et al.* (2016). The economic policy uncertainty index (EPU; Baker *et al.*, 2016), based on newspaper coverage (e.g. "uncertainty"; "economy"; "regulation"), captures economic policy decisions and their related economic effects, as well as "non-economic" decisions such as military actions. The indexes are able to capture short-run and long-run uncertainties. Therefore, these indices are excellent indicators of a country's future economic and financial dynamics (Al-Thaqeb and Algharabali, 2019; Dai *et al.*, 2021a).

To measure the cryptocurrency uncertainty, we use the cryptocurrency price uncertainty index (UCRYP [1]) developed by Lucey *et al.* (2021). Using 726.9 million news from the LexisNexis database, this index is able to seize the market uncertainty (volatility) of the crypto-financial markets. The time-series data runs from December 2013 (the first observation available for the UCRYP index) to February 2021. Table 1 presents the descriptive statistics of these series. Each variable is expressed in natural logarithm returns.

As we can note, Russia exhibits the highest volatility (standard deviations), while Spain the lowest level. The means of the returns are positive during the sample period. This suggests that uncertainty shows growth in these years, i.e. the EPU indices show an upward trend. By looking at the average changes in uncertainties, we also found some highlighted economic events, which have been directed to some countries and areas (for instance, the US-China trade war (Burggraf *et al.*, 2020), the negative effects of Brexit (Nasir and Simpson, 2018), and the COVID-19 pandemic and its impacts on financial markets (Schell *et al.*, 2020; Huynh *et al.*, 2021a; Dai *et al.*, 2021b)).

3. Methodology

To evaluate the spillover dynamics between economic policy uncertainty and cryptocurrency uncertainty, we use the time-varying parameter vector autoregression (TVP-VAR) model proposed by Antonakakis *et al.* (2020). Thanks to this framework, we are able to study the dynamic connectedness between these uncertainties indexes in the context of short time series. The TVP-VAR framework can be written as follows:

$$y_t = \beta_t z_{t-1} + \varepsilon_t \quad \varepsilon_t \sim N(0, S_t) \tag{1}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + \nu_t \quad \nu_t \sim N(0, R_t) \tag{2}$$

where y_t and z_{t-1} stand for $N \times 1$ and $N_p \times 1$ variables vector, hence $z_{t-1} = [y_{t-1}, \ldots, y_{t-p}]'$. β_t represents an $N \times N_p$ time-varying parameter matrix, and ε_t is a vectors of the error terms. S_t and R_t represent the time-varying variance-covariance matrices, while $vec(\beta_t) = vec(\beta_{t-1})$ and ν_t are $N_p^2 \times 1$ dimensional vectors.

In order to compute the generalized impulse response functions (GIRF; Koop *et al.*, 1996) and generalized forecast error variance decomposition (GFEVD; Pesaran and Shin, 1998), following Antonakakis *et al.* (2020), we convert the TVP-VAR model into TVP-VMA representation, i.e.

$$y_t = \sum_{i=1}^{p} \beta_{it} y_{t-i} + \varepsilon_t = \sum_{j=0}^{\infty} A_{jt} \varepsilon_{t-j} \tag{3}$$

Variable	Mean	Median	Std. dev	Min	Max
France	0.0001	−0.0442	0.2971	−0.8301	0.7572
Germany	0.0034	0.0226	0.3622	−0.6942	1.2441
Italy	0.0043	−0.0449	0.3511	−0.8484	1.0621
Spain	0.0009	−0.0275	0.1739	−0.4194	0.6245
The UK	0.0011	−0.0211	0.3082	−0.9124	0.7117
Russia	0.0081	0.0249	0.6023	−1.483	1.3332
The US	0.0057	−0.0025	0.3022	−0.8322	0.8884
Japan	0.0020	0.0011	0.1788	−0.6386	0.5882
Korea	0.0026	−0.0022	0.3223	−0.7486	1.1617
China	0.0075	−0.0068	0.3676	−0.7972	0.8527
India	0.0081	0.0405	0.3963	−0.8031	1.0013
UCRYP	0.0006	0.0005	0.0051	−0.0065	0.0251

Note(s): This table represents the summary of descriptive statistics of 11 economies with their country's names. These figures are calculated by the logarithm changes and the terminology of Std. Dev. denotes the standard deviation

Table 1.
Descriptive statistics

where A_{jt} is a $N \times N$ dimensional matrix. From Eqn (3), we can calculate the GFEVD; that is, the variance share one variable has on other, i.e.

$$\tilde{\varphi}^{g}_{ij,t}(h) = \frac{\sum_{t=1}^{h-1} \Psi^{2,g}_{ij,t}}{\sum_{i=1}^{N} \sum_{t-1}^{h-1} \Psi^{2,g}_{ij,t}} \tag{4}$$

where $\tilde{\varphi}^{g}_{ij,t}(h)$ is the $h - step$ forecast horizon, $\Psi^{g}_{ij,t}(h) = S^{-\frac{1}{2}}_{ij,t} A_{h,t} \sum_{t} \varepsilon_{ij,t}$.

Using the GFEVD, we can build the total connectedness index (TCI) as follows:

$$C^{g}_{t}(h) = \frac{\sum_{ij=1, i \neq j}^{N} \tilde{\varphi}_{ij,t}(h)}{\sum_{ij=1}^{N} \tilde{\varphi}_{ij,t}(h)} \times 100 \tag{5}$$

The TCI indicates how the system of variables (in this case, uncertainty) is interconnected. Its dynamics concurs to us to comprise like a shock in the system that can propagate fast (high values) or slowly (low values).

Further, we can calculate four measures of directional connectedness: to-connectedness, from-connectedness, net-connectedness and net-pairwise directional connectedness.

The to-connectedness is defined as:

$$C^{g}_{i \to j,t}(h) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\varphi}_{ji,t}(h)}{\sum_{ij=1}^{N} \tilde{\varphi}_{ji,t}(h)} \times 100 \tag{6}$$

The *to-connectedness* measures how a shock in variable (country) i spillover to all other variables j (countries).

The *from-connectedness* is given by

$$C^{g}_{i \leftarrow j,t}(h) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\varphi}_{ij,t}(h)}{\sum_{ij=1}^{N} \tilde{\varphi}_{ij,t}(h)} \times 100 \tag{7}$$

The *from-connectedness* quantifies the directional uncertainty spillover of variable (country) i from all other variables (countries) j

Third, we calculate the net-*connectedness*. This measure is given by the difference between *to-connectedness* and *from-connectedness*.

$$C^{g}_{i,t} = C^{g}_{i \to j,t}(h) - C^{g}_{i \leftarrow j,t}(h) \tag{8}$$

The index identifies the main net transmitters and receivers of uncertainty spillovers.

In the end, to examine the bidirectional connection between uncertainty indexes, we compute the *net pairwise directional connectedness* (NPDC):

$$NPDC_{ij}(h) = \frac{\tilde{\varphi}^{g}_{ji,t}(h) - \tilde{\varphi}^{g}_{ij,t}(h)}{N} \times 100 \tag{9}$$

We would like to highlight our main reason for choosing this approach. First, an advantage of using this model is that we can mitigate the likelihood of losing valuable observations during the computational process. Furthermore, by incorporating the dynamic process, our variables do not strictly rely on the size of the rolling window. Therefore, our chosen approach could quickly adapt to specific events (or sudden shocks). Eventually, the TVP-VAR connectedness model can accommodate low-frequency and short-horizon time-series dataset, which supports our findings to not disrupt the changes in uncertainties on the onset of the COVID-19 pandemic.

4. Empirical results

4.1 Dynamic connectedness between EPU and crypto-uncertainties

Table 2 summarizes the static estimates of the TVP-VAR model. The value of the total spillover index is on overage 47%, implying that countries' uncertainty is not independent of each other. Focusing on the directional spillover "to," France transmits the highest level of uncertainty (69%), followed by the US (64%). Regarding the "NET" spillover, France is the largest net transmitter of spillovers (15.43%), followed by India (12.87%) and China (10.19%). On the other hand, the UK and Spain are net recipients of spillovers (−20.68%, −11.54%, respectively). The findings corroborate the work of Kang and Yoon (2019), which finds that the UK is a net contributor to uncertainty spillovers.

To better visualize the connection structure, we plot the net pairwise spillover network in Figure 1. The figure helps to understand the direction of economic uncertainty shocks across countries and the UCRYP index. The direction of the arrows shows the "to" and "from" connection, while the size of the arrow represents the degree of the connection. In blue are the countries that are net-receiver, while in red are the countries that are uncertainty emitters. It is interesting to note the importance of France, India and China. These countries play a crucial role in economic uncertainty spillovers. Moreover, it is noteworthy to point out that the crypto market uncertainty index is a net receiver for every country. Overall, the figure shows the significant transmission of shocks in the system and how these shocks affect uncertainty in the cryptocurrency world.

Figure 2 displays the dynamic of the total spillover index [2]. The figure suggests that the information spillover changes over time. From the first analysis, we can observe the bearish trend of the dynamics from its highest peak in 2015 (87%). This suggests that in this period, there was a high interaction level between the countries' uncertainty and the cryptocurrency world. The main reason driving the highest level of total connectedness is the European immigration crisis before 2016. In addition, the global economy was concerned about the Chinese economy in 2015. Moreover, the event of the Brexit referendum was mentioned in late 2015. These aforementioned reasons were discussed in the current literature (Davis, 2016). Concomitantly, Demir *et al.* (2018) found that the multivariate instantaneous dependence structures are relatively higher in the period of 2015. Furthermore, we also elaborate on the interesting dynamics connectedness between 11 economies and cryptocurrency uncertainty over the period 2013 to 2021. When it comes to the cryptocurrency market from 2013 to 2017, this is the bubble period, which attracts a huge amount of capital flow from other conventional assets to this new market before the Bitcoin crash in 2017 (Makarov and Schoar, 2020).

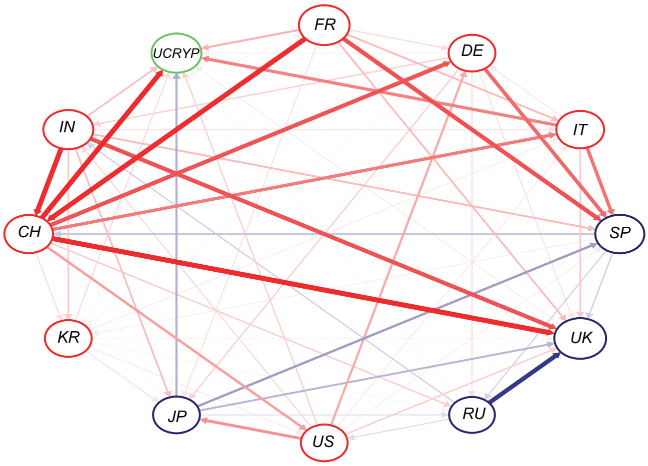
After 2015, we can see several three main peaks: 2016, 2018 and 2020. The dynamics of TC follow the events that have occurred in recent years. For example, terrorist attacks at Charlie Hebdo (in 2015), the China stock market crash, the Brexit vote (in 2016), Donald Trump's victory in the 2016 US presidential election, the BTC bubble in 2017 and COVID-19 from 2020. However, the results are quite surprising, showing that the events of 2015 had a higher prominence in uncertainty connections. What is surprising is that these events also had a greater impact than the COVID-19 outbreak. Although we can observe a peak in the series, the level remains much lower than in 2015.

To further analyze the transmission of uncertainty, in Figure 3, we plot the net dynamic total connectedness. We find that the European countries and the US spread more spillovers during 2015, while other economics were net transmitters of spillovers. However, the situation has reversed since 2017 where European countries have become risk receivers (except France). It is interesting to note the role played by China, India and the US, which have emitted more spillovers from 2016 to date. One possible explanation is that these countries (the US and China) are a major source of spreading uncertainty about other countries (Kido, 2018; Su *et al.*, 2019; Zhang *et al.*, 2019). Turning our attention to crypto market uncertainty, we find that UCRYP is always a net receiver of shock.

Table 2.
Static connectedness

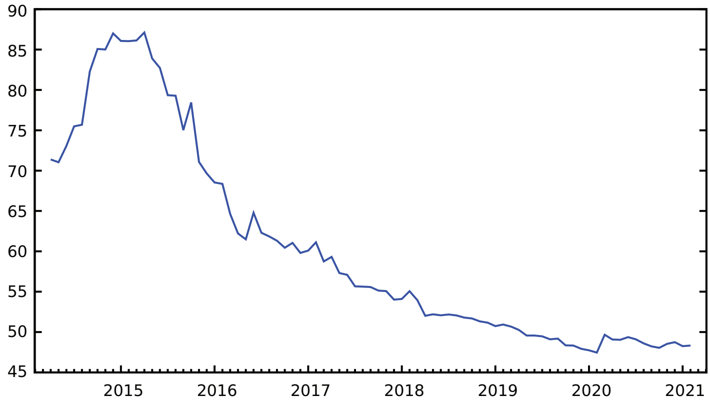
	France	Germany	Italy	Spain	The UK	Russia	The US	Japan	Korea	China	India	UCRYP	From
France	46.45	13.46	7.25	4.00	5.51	1.71	5.63	6.76	5.54	1.35	2.17	0.18	53.55
Germany	14.29	40.34	4.56	2.22	4.45	0.18	9.13	9.76	5.66	4.47	4.88	0.21	59.66
Italy	8.84	3.93	53.01	6.74	2.79	0.15	2.69	4.58	5.09	5.17	6.52	0.49	46.99
Spain	8.18	5.77	10.02	55.52	1.78	4.05	1.83	4.81	2.22	0.95	4.68	0.19	44.48
The UK	7.05	5.09	4.05	2.82	46.81	5.34	5.07	4.29	2.44	10.64	6.17	0.21	53.19
Russia	1.68	1.00	0.41	4.98	1.00	75.12	1.09	2.53	1.13	1.82	3.23	2.51	24.88
The US	5.52	7.13	2.13	1.33	3.93	1.17	41.74	8.07	18.00	3.66	6.36	0.96	58.26
Japan	7.42	10.77	4.56	2.73	2.68	1.85	10.71	43.27	7.02	0.52	7.49	1.00	56.73
Korea	5.81	5.98	4.56	2.62	2.12	0.79	17.45	6.33	39.93	1.48	11.87	1.09	60.07
China	6.34	0.32	2.06	2.17	5.58	0.67	1.39	0.72	0.64	73.31	6.45	0.39	26.69
India	1.87	5.97	5.85	3.12	2.05	4.23	7.26	5.97	10.64	1.46	49.29	2.31	50.71
UCRYP	2.00	0.61	3.47	0.22	0.63	2.73	2.04	2.77	1.97	5.42	3.78	74.35	25.65
TO	68.98	60.03	48.93	32.94	32.51	22.87	64.27	56.52	60.36	36.88	63.58	13.85	560.00
TOTAL	115.43	100.37	101.94	88.46	79.32	97.99	106.01	99.79	100.28	110.19	112.87	87.35	*TCI*
NET	15.43	0.37	1.94	−11.54	−20.68	−2.01	6.01	−0.21	0.28	10.19	12.87	−12.65	46.74

Note(s): This table summarizes the static connectedness. The TVP-VAR model estimation is computed using 10-days-ahead forecasts. Schwarz Bayesian information criterion is used to select the lag length of the VAR model (= 1). Column "from" indicates the received spillovers from the system, while the row "to" presents the transmitted spillovers to the system. The row "NET" is computed by the difference between row "to" and the column "from,"" i.e. indicates the net spillovers from one country to the system. Finally, the TCI is the total connectedness (spillover) index



Note(s): This figure plots the Pairwise spillover network between 11 countries and the UCRYP index. Node size represents the degree of the net-pairwise spillover. Node colour denotes whether a country is a net transmitter (red) or net receivers (blue) of spillover

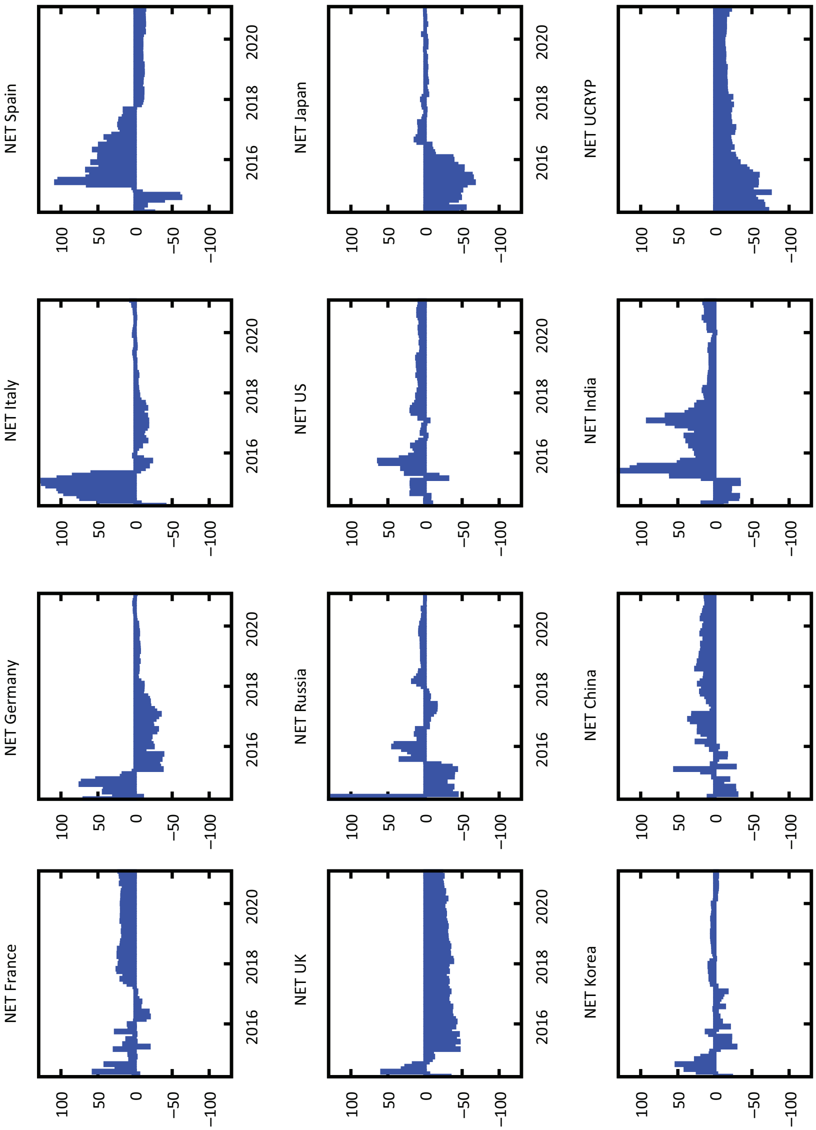
Figure 1.
Pairwise spillover network



Note(s): This figure summarizes the total connectedness between 11 country-level Economic Policy Uncertainties and Cryptopcurrency uncertainty index over the period from December 2013 to February 2021

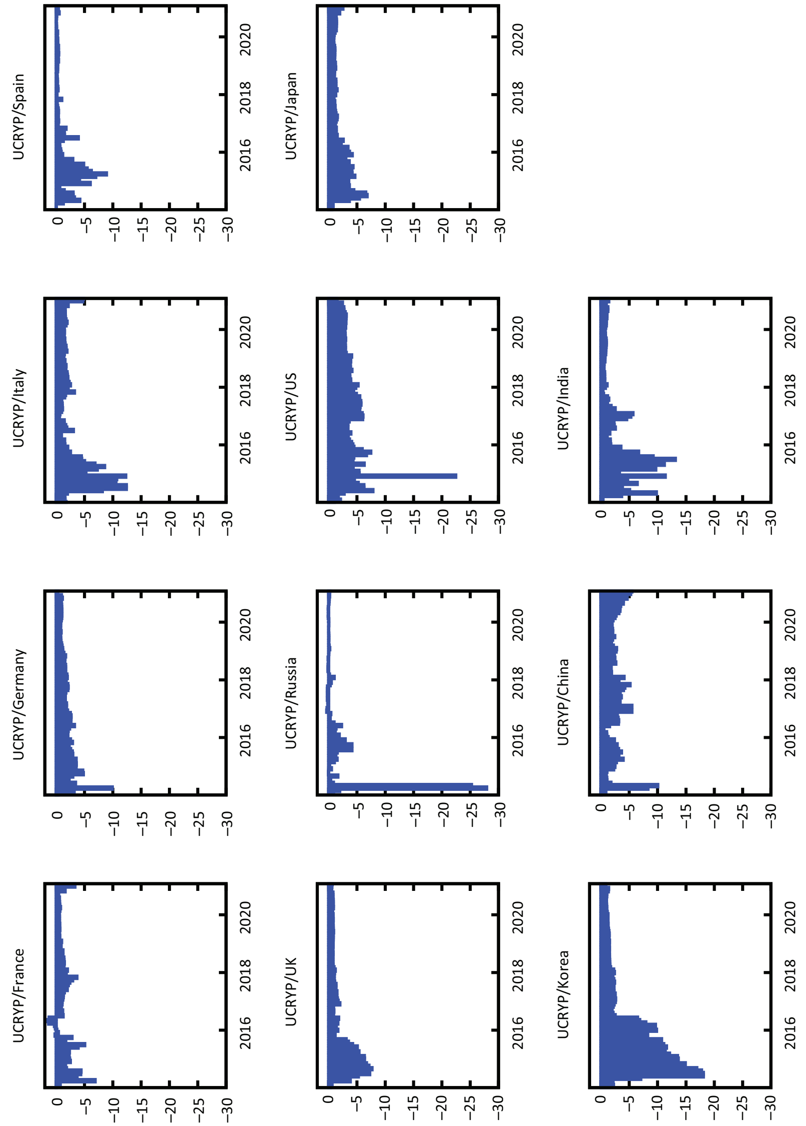
Figure 2.
The total connectedness index

Figure 4 further illustrates the dynamic relationship between net pairwise time-varying spillover effects [3]. We focus our analysis only on the relationship between UCRYP and each of the country-level measures of uncertainty. The graph helps us to understand which countries mainly transmit or receive uncertainty spillover effects in net terms. The figure shows that the UCRYP index always receives more spillover effects than it transmits (especially in 2015). This relationship suggests that it is the dynamics of uncertainty (EPU indexes) dictate the movements in the cryptocurrency market. Our findings shed an



Note(s): Net directional spillovers

Figure 3.
Net connectedness



Note(s): Net pairwise directional spillovers

Figure 4.
Net pairwise connectedness

important light that the sensitivity of the cryptocurrency market would stem from the economic shocks in these 11 economies. More noticeably, the effects are more pronounced in Asian countries such as China and India. Although the current literature highlights that these Asia countries are likely to be conservative of blockchain and cryptocurrencies by introducing the banned regulations (Zhou and Kalev, 2019), these countries still embrace trading activities and investment in this digital market (Hileman and Rauchs, 2017; Hendrickson *et al.*, 2016). From a financial perspective, this can be explained by the co-movement between EPU and cryptocurrency volatility (Demir *et al.*, 2018; Fang *et al.*, 2019; Cheng and Yen, 2020; Yen and Cheng, 2021; Mokni, 2021). In order to test this hypothesis, in the next section, we employ a regression analysis between EPU and UCRYP indices.

4.2 The impact of EPU on cryptocurrency uncertainty

In this section, we follow Huynh *et al.* (2021b), and we apply a panel pooled OLS model to investigate whether the EPUs indexes can predict cryptocurrency uncertainty (UCRYP). We compute the following regression model:

$$\Delta UCRYP_{it} = c + \beta_1 \Delta EPU_{it} + \Delta X_{it} + \varepsilon_{it} \tag{10}$$

where $\Delta UCRYP_{it}$ is the log change of cryptocurrency uncertainty price index (Lucey *et al.*, 2021) at time t, ΔEPU_{it} is the log return of the EPU indexes, X_{it} is the $N \times N$ matrix of control variables [4], while $\varepsilon_{i,t}$ is the error term.

Table 3 reports the estimation results of the panel pooled OLS model. Our findings are robust whether we maintain the control variables in our model or not. The β_1 coefficient is significant and positive. This suggests that EPU influences the UCRYP index, i.e. EPUs have positive predictive power for cryptocurrency uncertainty. These findings are perfectly in line with the literature (Demir *et al.*, 2018; Fang *et al.*, 2019; Yen and Cheng, 2021; Mokni, 2021), who find that EPU indexes predict the volatility (returns) of the cryptocurrency markets.

However, in adding new evidence from considering cryptocurrency uncertainty price, the results are of interest to policymakers and investors concerned about the spread of uncertainty among the various financial markets and, thus, on the real economy. While the novel study of Lucey *et al.* (2021) confirms the risk pass-through from fiscal policies to the cryptocurrency uncertainty index, our study contributes a new channel driving the variants of uncertainties in the cryptocurrency market.

4.3 Robustness check

Lucey *et al.* (2021) introduced two indices measuring cryptocurrency uncertainties, namely policy and price uncertainty. We employed the cryptocurrency price uncertainty index for our TVP-VAR model as well as the predictive model. In our robustness check, we replace the

Y = UCRYP	Model (1)	Model (2)
C	0.001*** [0.000]	0.001*** [0.000]
β_1	0.013*** [0.002]	0.011*** [0.004]
Control variables	No	Yes
R^2	0.011	0.023
Obs	946	946

Note(s): * < 0.1; ** < 0.05; *** < 0.01. Control variables are log return of crude oil WTI, log return of the iBoxx bond index and log return of gold prices. The parameter c and β_1 explicitly indicate the constant term and predictive power of EPU, respectively

Table 3. The predictive power of EPU on the cryptocurrency uncertainty index

proxy measuring price uncertainties as to the policy one. After that, we apply the previous approaches to a new alternative variable, and our results still hold robust [5]. Finally, we can come to the conclusion that there exist spillovers across the economic policy uncertainty and the cryptocurrency uncertainty index. Furthermore, the cryptocurrency policy uncertainty exhibits a good predictor of the economic policy uncertainty index.

5. Concluding remarks

The work investigates the nexus between economic uncertainty and cryptocurrency markets in a time-varying framework. Accordingly, we implement the dynamic connectedness model developed by Antonakakis *et al.* (2020). The empirical results show significant cross-country spillovers of economic policy uncertainty. Moreover, we figure out how the cryptocurrency uncertainty is a net receiver throughout the period. Therefore, this finding suggests that it is the dynamics of uncertainty (EPU indexes) dictate the behavior in the cryptocurrency market. To test this nexus, we computed a regression analysis between EPU and UCRYP indexes. Our empirical regression reveals that EPU influences the UCRYP index, i.e. EPUs have positive predictive power for cryptocurrency uncertainty. Our findings provide the robust and clear evidence that there exists a pass-through between two indices. There are two main policy implications that can be drawn from this study. First, the investors should be cautious when diversifying their portfolio between the conventional assets, impacted by socio-economic news and policy changes, and the cryptocurrency uncertainty index highlighted the fluctuation regarding the unpredictable prices' movements. Second, cryptocurrency is also considered a part of conventional investment channel because we found pass-through mechanisms between economy and digital markets. It implies that the investors who are likely to invest or trade in the cryptocurrency market should keep their eyes on the regular news, including economic growth, policy changes or any crises. In the same vein, the stability of cryptocurrency markets should be done when stabilizing the economic system and policies.

Our study has two limitations. First, the data represent the monthly format that might not reflect the immediate and continuous features of these markets. Therefore, future research could construct the high-frequency data, for example, tick-by-tick or 5-min intervals, to examine the jumps of uncertainties. Second, the uncertainty index has been constructed based on the "sentimental words," which does not fully reflect the market structure. For example, the cryptocurrency uncertainty index was retrieved with specific keywords "uncertainty" or "uncertain" while there might be a huge number of missing words representing sentimental uncertainties in the markets. Thus, the future direction could apply state-of-art methodologies, namely machine-learning, deep-learning, to generalize the different sentiments in the public. Another possible extension of our research could be to test how market conditions (bearish or bullish) can change the network connection, thus the uncertainty spillovers. To this end, a network connection model that takes into account quantiles would be desirable. This would provide insight into the dynamics of uncertainty spillovers and different propagation mechanisms during bad and good conditions. In doing so, the understandings of the market structure for conventional investment and cryptocurrency will be clearer. These are our limitations and are left for future research.

Notes

1. To robustness check, we also use the cryptocurrency uncertainty index policy. The results are qualitatively the same, and they are available upon request.
2. We also estimated the TVP-VAR model with log variables (not on returns). The dynamic connectedness shows a similar trend.

3. For brevity reasons, we have not included the net pairwise time-varying spillover effects between EPUs. However, they are available upon request.
4. Control variables are: log return of crude oil WTI, log return of the iBoxx bond index and log return of gold prices.
5. The results are available upon request.

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