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Time and frequency connectedness of uncertainties in cryptocurrency, stock, currency, energy, and precious metals markets

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ABSTRACT

This paper examines the connectedness of uncertainty in cryptocurrency, stock, currency, and commodity markets. We use the novel news-based cryptocurrency uncertainty indices of Lucey et al. (2021) and global implied volatility indices as uncertainty proxies for stock, currency, energy, and precious metals markets. We analyze weekly data between January 2014 and May 2021, employing the time and frequency connectedness measures of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018). Our results show a low degree of uncertainty connectedness between cryptocurrency and other markets. The results imply long-term diversification opportunities and highlight the distinct dynamics of the cryptocurrency markets.

1. Introduction

In the last decade, groundbreaking events such as the European sovereign debt crisis, the trade war between the US and China, Brexit, and the COVID-19 pandemic have soared uncertainty worldwide. The interest in uncertainty measures has increased since uncertainties impact the macroeconomic environment (e.g., Bashar et al., 2013; Bloom, 2014; Balcilar et al., 2016a; Barrero et al., 2017; Caggiano et al., 2017; Charles et al., 2018; Nyawo and Van Wyk, 2018; Istrefi and Mouabbi, 2018; Fontaine et al., 2017) and financial markets (e.g., Kang and Ratti, 2013; Liu and Zhang, 2015; Wu et al., 2016; Li et al., 2016; Karnizova and Li, 2014; Dakhlaoui and Aloui, 2016; Mei et al., 2018; Guo et al., 2018) adversely and increase spillovers between markets. The uncertainty indices have become essential tools for policymakers to take early precautions and develop policies to alleviate their adverse effects, for investors and portfolio managers to make decisions on asset valuation and forecasts on volatility, and to build asset allocation and hedging strategies.

This paper examines the connectedness between the uncertainties of different markets, including cryptocurrency, stock, currency, and commodities, to reveal the contribution of the uncertainty of each market to other uncertainties. In other words, we aim to unfold which uncertainty plays a dominant role in the overall uncertainty system.

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There exist only a few studies examining spillovers between the uncertainty indices. Most of them consider the economic policy uncertainties (EPU) with country-level data and sub-categories based on macroeconomic variables. Among these studies, Ajmi et al. (2015) examined the causal relationship between EPU and equity market uncertainty (EMU) in the US using daily data from January 1, 1985, to June 14, 2013. While their linear test results indicated bidirectional causality, nonlinear tests showed robust predictive power from EMU to EPU. Antonakakis et al. (2018) examined the connectedness between the macroeconomic uncertainty indices of the US, the UK, Canada, Japan, and the EU developed by Scotti (2016) using daily data from May 15, 2003, to October 2, 2017. They employed the time-varying parameter vector autoregressive (TVP-VAR) suggested by Antonakakis et al. (2020) and found a significant uncertainty transmission from the EU to the US. Thiem (2018) and Gabauer and Gupta (2018) considered categorical policy uncertainties developed by Baker et al. (2016). The former examined only the categories of the US economic policy; the latter investigated interdependence within and across the US and Japan categories. Thiem (2018) employed Diebold and Yilmaz (2012); Diebold and Yılmaz (2014) and found that while the fiscal policy was the net transmitter, trade policy was the net receiver of uncertainty. On the other hand, Gabauer and Gupta (2018) applied the TVP-VAR approach and revealed that the US trade uncertainty policy dominated that of Japan. The monetary policies of each country dominated the trade policy uncertainty of the other country. Antonakakis et al. (2019) examined the volatility transmission between the EPU index of Europe proposed by Baker et al. (2016) and the Greek categorical EPU developed by Hardouvelis et al. (2018) with monthly data between January 1998 and May 2018. The results showed a bidirectional transmission between them, and Greece was the net transmitter of uncertainty throughout the sample. In a more comprehensive study, Hasan et al. (2020) measured the time and frequency connectedness of EPU and fear among 13 countries with monthly data for January 2011 and December 2018. They employed Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) and found that the fear connectedness was much stronger than EPU connectedness. The EPU connectedness of any two countries was a strong driver of fear connectedness between their stock markets. Cipollini and Mikaliunaite (2020) examined spillovers between macroeconomic uncertainty measured by a quarterly index of uncertainty about GDP growth developed by Rossi and Sekhposyan (2017) and financial stress proxied by a monthly country-level index of Financial Stress provided by the European Central Bank by employing Global Vector Autoregression (GVAR) and found a disconnection between them.

Moreover, Gabauer and Gupta (2020) examined the spillover across real estate and financial uncertainties in addition to macroeconomic ones. They employed the TVP-VAR-based model with monthly data from July 1970 to December 2017. They found that financial uncertainty was the primary transmitter of shocks to others. Mensi et al. (2021) examined the quantile relationships among gold, silver, gold mining, oil, and energy sector uncertainty indices. Employing the quantile across-spectral approach with daily data from October 6, 2011, to September 17, 2019, their results showed that the uncertainty indices had a time and quantile-dependent structure. Foglia and Dai (2022) examined spillovers across EPU indices of 11 countries (developed by Baker et al., 2016) and the cryptocurrency uncertainty index (UCRY) (created by Lucey et al., 2021) by employing the TVP-VAR model with monthly data from December 2013 to February 2021. They revealed a cross-country spillover of EPU and the cryptocurrency uncertainty acting as a net receiver, and EPU indices could predict cryptocurrency uncertainty.

This paper contributes to the related literature in many aspects. First, there has been a plethora of studies concentrating on spillovers between uncertainty and financial markets (see the literature review part); however, there has been limited empirical investigation on the information transmission among uncertainty indices (see the above-mentioned studies). In addition, while the majority part of the related literature above considers economic uncertainty indices (proposed mainly by Baker et al., 2016), this paper follows the studies of Gabauer and Gupta (2020), Mensi et al. (2021), and Foglia and Dai (2022), which consider uncertainties other than economic policies. Moreover, it extends these studies regarding the variety of uncertainties and the methodology used. Here, we use the UCRY of Lucey et al. (2021) for cryptocurrency markets; CBOE S&P500 (VIX), Emerging Markets (EEM), and China (FXI) implied volatility indices as uncertainty proxies for stock markets; eurocurrency (EVZ) implied volatility index as an uncertainty proxy for the currency market, and the CBOE crude oil (OVX) and gold (GVZ) implied volatility indices for commodity market uncertainties. Different from these studies, we use weekly data from January 2014 to May 2021 by employing the time and frequency connectedness measures of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018).

Second, we added cryptocurrencies into our analysis since there has been a soaring tendency in cryptocurrency investments since the emergence of Bitcoin after the 2008 global financial crisis. Today, there are 305 exchanges with a total market capitalization of $ 2.08 trillion, with 6467 cryptocurrencies traded worldwide (coinmarketcap.com, September 7, 2021). Cryptocurrencies with decentralized and reliable nature attracted many investors in a way that they were recognized as safe-haven instruments, especially during financial turbulence (Bouri et al., 2017; Shahzad et al., 2019). On the other hand, their prices are highly volatile, and the market is full of uncertainties. Their values mainly depend on the beliefs and decisions of investors, who obtain information mostly from social media rather than fundamental issues (Kumar, 2021). The uncertainties of this market may transmit the others; hence, we use the most recent UCRY first to determine its contribution to the overall uncertainty.

Third, many studies argue that gold is a "safe-haven" financial asset, especially during financial turmoil (e.g., Baur and Lucey, 2010; Baur and McDermott, 2010 and 2016; Hood and Malik, 2013; Beckmann et al., 2015; Akhtaruzzaman et al., 2021). Therefore, this paper considers gold to determine whether it can still be considered a "safe haven." Additionally, we consider the crude oil market uncertainty in our analysis since it has become a highly preferable asset among investors (Bouoiyour et al., 2019) and is highly volatile because of the manipulated attracts (Al Dulaimi, 2014). Accordingly, there might be a volatility transmission from crude oil uncertainty to others. Moreover, apart from the existing literature, the currency market uncertainty proxy (i.e., CBOE Eurocurrency index, EVZ) is first considered in this context to unveil its connectedness with other uncertainties. We compare the roles (volatility transmitter or receiver) of fiat currency uncertainty with that of cryptocurrency and see which contributes more.

Fourth, different from the related literature, we examine stock market uncertainties of the US (as a developed market) and emerging markets separately since there might be substantial differences in transmitting or receiving uncertainties. Furthermore, this paper considers China's uncertainty mainly because of its large volume of trading activities compared to other emerging markets; Küfeoğlu and Özkuran (2019) argue that 70% of Bitcoin mining was performed in China to expect volatility spillover between the uncertainties of China and cryptocurrency markets.

We observed low uncertainty connectedness between cryptocurrencies and other markets, suggesting the possibility of long-term diversification and highlighting the unique characteristics of the cryptocurrency markets. The paper is organized as follows; the second section consists of literature; the third section presents the methodology; the fourth section describes data; the fifth section presents the empirical results; the last section concludes the paper and discusses policy implications.

2. Literature review

There has been abundant literature examining the impact of uncertainties on financial markets; however, not to get away from our focus here, we consider the studies trying to investigate volatility spillovers and connectedness. The first strand of the literature considers energy markets. Among them, Yang (2019) examined the causality and connectedness between EPU and oil price shocks across time scales and found that crude oil prices behaved like receivers of information from EPU regardless of the time scale. Wang and Lee (2020) examined the spillovers between the category policy uncertainty indices of Baker et al. (2016) and WTI crude oil prices for oil-importing countries (China, the US, Japan, India, Netherlands, Germany, Italy, Spain, and France) by using monthly data for the period from April 2004 to January 2019. They found that EPU was a net transmitter, and among the policy uncertainty indices, the fiscal policy uncertainty on crude oil returns was preeminent. In a more comprehensive study, Assaf et al. (2021) examined the impact of Geopolitical Risk, World Trade Uncertainty, EPU, and EMU on the dynamics of returns of energy markets, using the time-varying connectedness measures. They found that the impact of market uncertainty on energy markets was about 53%, mainly from EMU. Geng et al. (2021) examined the information transmission between stock markets, uncertainties, and natural gas in the European and North American regions. They used the CBOE's VIX, the crude oil volatility index (OVX), the US EPU, FTSE 100 volatility index, and the UK EPU index as uncertainty measures, finding that the gas market of North America impacted the energy market uncertainty and EPU. In contrast, the gas market of Europe was a net uncertainty receiver from EPU.

The second strand of the literature considers metal markets. For instance, Mokni et al. (2021) examined the impact of EPU on the precious metals (gold, silver, platinum, and palladium) connectedness before and over the COVID-19 pandemic by applying the Quantile – VAR model using daily data from January 2, 2015, to December 3, 2020. They found that the precious metals connectedness was substantial, especially during extreme market conditions, and gold had a preeminent "safe-haven" role in hedging market uncertainty, implying distinct responses to COVID-19. Hasan et al. (2020) examined the time-varying correlation between precious metals and cryptocurrency uncertainty, proxied by the UCRY indices of Lucey et al. (2021), to reveal the hedging potential of precious metals against cryptocurrency uncertainty. They found that, among the precious metals, gold exhibited a consistent positive correlation with these indices, indicating a reliable safe-haven property of gold against cryptocurrency uncertainty.

The third strand of the literature consists of economic uncertainty and the stock market. Among these studies, Antonakakis et al. (2013) examined dynamic correlations among EPU introduced by Baker et al. (2016), S&P 500 returns, and the VIX index using monthly data between January 1985 and January 2013. Their results unfolded a positive relationship between the stock returns and EPU, except for the 2007–08 global financial crises. In a different paper, Behera and Rath (2022) examined Twitter uncertainty and stock market volatility in the G7 countries. Their results showed a significant volatility spillover among indices, and Twitter uncertainty was among the net receivers of shocks. In a more comprehensive study, Adekoya et al. (2021) examined the transmission of volatility between commodity markets (i.e., EU carbon market, crude oil, copper, gold, natural gas silver), the stock market (S&P 500) and the currency market (the US Dollar) along with the US EPU index. They found that the EPU was a notable driver of the connectedness of the markets. The carbon, gold, and US currency markets were net receivers of shocks.

The fourth strand of the literature focuses on the impact of uncertainties on cryptocurrency markets, investigating whether the cryptocurrency market is isolated from the current economic and financial environment, employing different techniques. Among these studies, Bouri et al. (2017) and Demir et al. (2018) found that Bitcoin was negatively correlated with the US EPU and the VIX index. In a more comprehensive study, Wang et al. (2019) added the US EMU index and examined risk spillover from these uncertainty indices to Bitcoin. They all found that the cryptocurrency market was decoupled from the traditional markets offering diversification benefits and hedging opportunities. More recent studies have added non-fungible tokens (NFTs) and examined the connectedness between NFTs and other financial assets, including cryptocurrencies. Among them, Dowling (2022) found limited volatility transmission effects between cryptocurrencies and NFTs, indicating that NFTs could potentially be considered as a low-correlation asset class distinct from cryptocurrencies. Umar et al. (2022) included other asset classes in their analysis other than the cryptocurrencies, such as equity, bond, gold, and crude oil, focusing on the influence of the pandemic on their interrelations. They found that coherence between the NFTs and other assets returns was high for the two-week-plus and low for the below-two-weeks investment horizons before and during the COVID-19 pandemic. Similarly, Aharon and Demir (2021) analyzed the connectedness between the returns of NFTs and other financial assets (equities, bonds, currencies, gold, oil, Ethereum). They showed that the overall connectedness between the returns for financial assets increased during the COVID-19 period. Their static analysis showed that the behavior of the majority of NFT returns was attributable to endogenous shocks, indicating that they were independent of shocks from these assets, including Ethereum. Their dynamic analysis revealed that the NFTs acted as transmitters of systemic risk in normal periods but acted as receivers of risk during crises.

The last strand focuses on exchange rates. Balcilar et al. (2016b) examined the spillover between returns and volatility of sixteen US dollar-based exchange rates (for both developed and developing countries) and the uncertainty indices developed by Brogaard and Detzel (2015). They employed the nonparametric causality-in-quantiles technique, using monthly data from January 1999 to March

Table 1
Descriptive Statistics.

Index	Mean	Std. Dev.	Skewness	Ex. Kurtosis	Jarque-Bera
UCRY Policy	0.0001	0.0057	0.5270*	9.1400*	1362*
UCRY Price	0.0002	0.0054	1.9750*	19.8300*	6575*
VIX	0.0105	0.1538	2.6930*	14.8110*	3995*
EEM	0.0060	0.1194	1.7200*	7.0630*	993*
FXI	0.0046	0.1008	1.3670*	4.2500*	411*
EVZ	0.0029	0.0865	0.9090*	4.5880*	392*
OVX	0.0076	0.1213	3.9810*	31.5750*	17054*
GVZ	0.0029	0.0858	1.3820*	4.1130*	395*

Note: * denotes statistical significance at the 1% level.

2012. They found that, for seven exchange rates, EPU differentials had a causal impact on the variance of exchange rate returns. In a more comprehensive study, Umar and Gubareva (2020) examined the influence of the COVID-19 pandemic on the volatility of major fiat and cryptocurrency markets using wavelet analyses. They found a high coherence between the moves of the Coronavirus Panic Index, the price moves in the Euro, British pound, and Renminbi, and the Bloomberg Galaxy Crypto Index movements. They argued that cross-currency hedge strategies might work during typical situations but might fail during the periods of global crisis, such as the COVID-19 pandemic. In another paper, Yousaf et al. (2022) examined the static and dynamic returns connectedness between DeFi assets and conventional currencies, including the Chinese Yuan, Japanese Yen, Euro, and Pound Sterling. While their static connectedness analysis results evidenced a low connection between them, their dynamic analysis showed that the return spillovers were time-varying, with an abrupt increase in connectedness between these markets in the initial period of the COVID-19 pandemic.

3. Methodology

Baruník and Křehlík (2018) extend the Diebold and Yilmaz (2012) spillover index framework, studying the frequency sources of connectedness. The connectedness measures are built upon a covariance stationary n-variate process $x_t = (x_{1t}, x_{2t}, \ldots, x_{nt})'$ at t = 1,…, T, described by the pth order vector autoregression (VAR):

$$\Phi(L)x_t = \varepsilon_t \tag{1}$$

where $\Phi(L) = [I_N - \Phi_1 L - \cdots - \Phi_p L^p]$ is $n_\times n$ lag-polynomial with I_N identity matrix and $\Phi_1, \ldots, \Phi_p$ coefficient matrices; ε_t is a white-noise covariance matrix Σ. The VAR process follows an infinite moving average specification:

$$X_t = \Psi(L)\varepsilon_t \tag{2}$$

where $\Psi(L)$ is an $n_\times n$ infinite lag-polynomial matrix, computed via $\Phi(L) = [\Psi(L)]^{-1}$. To examine the connectedness in a frequency domain, Baruník and Křehlík (2018) define the spectral density of x_t as:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E\left(x_t x_{t-h}^{'}\right) e^{-\mathrm{i}\omega h} = \Psi\left(e^{-\mathrm{i}\omega}\right) \sum \Psi'\left(e^{+\mathrm{i}\omega}\right). \tag{3}$$

The generalized causation spectrum over frequencies $\omega \in (-\pi, \pi)$ can be specified as follows:

$$(f(\omega))_{j,k} \equiv \frac{\sigma_{kk}^{-1} \left| \left(\Psi\left(e^{-\mathrm{i}\omega}\right)\Sigma\right)_{j,k} \right|^2}{\left(\Psi\left(e^{-\mathrm{i}\omega}\right)\Sigma\Psi'\left(e^{+\mathrm{i}\omega}\right)\right)_{j,j}} \tag{4}$$

where $(f(\omega))_{j,\ k}$ is the share of the spectrum of the jth variable at a given frequency ω due to shocks in the kth variable. We can weight the $(f(\omega))_{j,\ k}$ to produce a natural decomposition of generalized forecast error variance decompositions (GFEVD), using the following weighting function:

$$\Gamma_j(\omega) = \frac{\left(\Psi\left(e^{-\mathrm{i}\omega}\right)\Sigma\Psi'\left(e^{+\mathrm{i}\omega}\right)\right)_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Psi\left(e^{-\mathrm{i}\lambda}\right)\Sigma\Psi'\left(e^{+\mathrm{i}\lambda}\right)\right)_{j,j}\mathrm{d}\lambda}, \tag{5}$$

indicating the jth variable power at a particular frequency, summing through frequencies to 2π. The GFEVD on a frequency band $d = (a, b) : a,\ b \in (-\pi, \pi),\ a < b$ can be written as:

$$(\Theta_d)_{j,k} = \frac{1}{2\pi}\int_d \Gamma_j(\omega)(f(\omega))_{j,k}\mathrm{d}\omega \tag{6}$$

Exploiting the spectra depiction of GFEVD, connectedness measures on d may be expressed as follows:

$$\left(\widetilde{\Theta}_d\right)_{j,k} = (\Theta_d)_{j,k} \Big/ \sum_k (\Theta_\infty)_{j,k}; \tag{7}$$

Table 2
Unit Root Tests.

Index	ADF-Stat	ADF-2br	F-ADF
UCRY Policy	−17.56*	−18.76* [Nov-17 / Dec-17]	−17.72* (2)
UCRY Price	−16.51*	−17.52* [Dec-17 / Aug-20]	−16.70* (2)
VIX	−18.41*	−19.87* [Feb-20 / Mar-20]	−18.42* (3)
EEM	−15.70*	−18.64* [Feb-20 / Mar-20]	−15.77* (3)
FXI	−16.04*	−18.31* [Mar-20 / Mar-20]	−16.14* (3)
EVZ	−16.11*	−18.77* [Feb-20 / Mar-20]	−16.14* (3)
OVX	−17.13*	−20.91* [Mar-20 / Mar-20]	−17.15* (3)
GVZ	−14.64*	−18.19* [Feb-20 / Mar-20]	−14.65* (2)

Note: * denotes statistical significance at the 1% level. The dates in brackets are the selected break dates. The numbers in parentheses are the chosen frequency.

Table 3
Spillover Tables.

Panel a. (Diebold and Yilmaz, 2012) Total Connectedness, no frequency bands

	UCRY Policy	UCRY Price	VIX	EEM	FXI	EVZ	OVX	GVZ	FROM
UCRY Policy	52.99	42.38	0.79	1.59	0.80	0.12	1.22	0.11	5.88
UCRY Price	44.15	51.38	0.80	1.47	0.76	0.08	1.21	0.15	6.08
VIX	0.63	0.55	35.36	24.19	18.07	6.80	6.31	8.10	8.08
EEM	1.09	0.88	20.92	30.44	21.82	8.98	7.40	8.47	8.69
FXI	0.74	0.58	18.11	25.27	35.34	7.54	5.54	6.88	8.08
EVZ	0.19	0.08	9.07	13.18	9.43	47.35	5.44	15.28	6.58
OVX	1.16	0.94	10.38	13.60	8.68	7.08	51.94	6.22	6.01
GVZ	0.22	0.35	10.98	12.71	8.79	16.03	5.30	45.62	6.80
TO	6.02	5.72	8.88	11.50	8.54	5.83	4.05	5.65	56.20
NET	0.14	−0.36	0.8	2.81	0.46	−0.75	−1.96	−1.15	

Panel b. (Baruník and Křehlík, 2018) Frequency Connectedness with three frequency bands

	UCRY Policy	UCRY Price	VIX	EEM	FXI	EVZ	OVX	GVZ	FROM ABS	FROM WTH
Frequency Band 1: d1 ∈ (3.14, 0.79), corresponding to 1 week to 4 weeks										
UCRY Policy	47.29	37.36	0.68	1.31	0.51	0.08	1.08	0.06	5.14	6.81
UCRY Price	39.77	45.72	0.73	1.31	0.50	0.03	1.13	0.08	5.45	7.22
VIX	0.56	0.48	26.20	17.80	13.08	4.81	5.36	6.16	6.03	8.00
EEM	0.94	0.73	15.02	22.56	15.86	6.03	5.92	6.12	6.33	8.39
FXI	0.73	0.56	12.74	18.26	25.82	4.91	4.12	4.80	5.77	7.65
EVZ	0.18	0.07	6.05	9.96	7.25	31.78	4.01	10.26	4.72	6.26
OVX	0.93	0.80	6.09	8.51	5.57	4.15	37.52	4.20	3.78	5.01
GVZ	0.18	0.26	7.16	9.00	6.25	9.74	3.93	32.17	4.56	6.05
TO_ABS	5.41	5.03	6.06	8.27	6.13	3.72	3.19	3.96	41.78	
TO_WTH	7.18	6.68	8.03	10.97	8.13	4.93	4.24	5.25		55.40
NET_ABS	0.27	−0.42	0.03	1.94	0.36	−1.00	−0.59	−0.60		
Frequency Band 2: d2 ∈ (0.79, 0.00), corresponding to more than four weeks										
UCRY Policy	5.70	5.01	0.12	0.28	0.29	0.04	0.14	0.05	0.74	3.01
UCRY Price	4.37	5.66	0.07	0.16	0.25	0.04	0.07	0.07	0.63	2.56
VIX	0.07	0.07	9.15	6.38	4.99	1.99	0.95	1.94	2.05	8.33
EEM	0.15	0.14	5.90	7.89	5.96	2.96	1.48	2.34	2.37	9.62
FXI	0.01	0.01	5.36	7.01	9.52	2.64	1.42	2.08	2.32	9.42
EVZ	0.00	0.00	3.02	3.22	2.18	15.57	1.43	5.01	1.86	7.56
OVX	0.23	0.14	4.30	5.09	3.10	2.93	14.42	2.02	2.23	9.06
GVZ	0.04	0.10	3.82	3.71	2.54	6.28	1.37	13.45	2.23	9.08
TO_ABS	0.61	0.69	2.82	3.23	2.41	2.11	0.86	1.69	14.42	
TO_WTH	2.48	2.79	11.48	13.14	9.82	8.58	3.49	6.87		58.65
NET_ABS	−0.13	0.06	0.77	0.86	0.09	0.25	−1.37	−0.54		

Note: FROM_ABS (FROM_WTH) denotes the degree of uncertainty received by one market from all other markets, excluding (including) its shares. TO_ABS (TO_WTH) shows the degree of uncertainty transmission from a market to others, excluding (including) its shares. NET_ABS indicates the net uncertainty transmission, the difference between TO_ABS and FROM_ABS.

the *within* (C_d^W) and *frequency* (C_d^F) *connectedness* on the frequency band d are expressed as:

$$C_d^w = 100 \cdot \left(1 - \frac{\mathrm{Tr}\left\{ \widetilde{\Theta}_d \right\}}{\sum \widetilde{\Theta}_d} \right); \tag{8}$$

$$C_d^F = 100 \cdot \left(\frac{\sum \widetilde{\Theta}_d}{\sum \widetilde{\Theta}_\infty} - \frac{\mathrm{Tr}\left\{ \widetilde{\Theta}_d \right\}}{\sum \widetilde{\Theta}_\infty} \right) = C_d^w \cdot \frac{\sum \widetilde{\Theta}_d}{\sum \widetilde{\Theta}_\infty}, \tag{9}$$

where Tr{·} is the trace operator, and the $\sum \widetilde{\Theta}_d$ represents the sum of all elements of the $\widetilde{\Theta}_d$ matrix (Baruník and Křehlík, 2018).

4. Data

We obtain the cryptocurrency uncertainty indices (UCRY) of Lucey et al. (2021) from Professor Brian Lucey's website. The novel news- and sentiment-based indices capture the cryptocurrency policy (UCRY Policy) and price uncertainties (UCRY Price) in weekly frequency. The UCRY indices are news-based indices constructed similarly to the policy uncertainty indices in Baker et al. (2016), capturing major developments and events in the cryptocurrency markets. Lucey et al. (2021) built the policy and price uncertainty indices for cryptocurrency markets, gathering material from the LexisNexis Business Database, which covers an extensive collection of newspapers and news-wire feeds. Unlike the previous policy uncertainty measures, UCRY indices are constructed using not solely primary newspapers but also news-wire feeds, taking the social (media) part (i.e., sentiment) of cryptocurrencies into account. Lucey et al. (2021) state that the UCRY Policy (Price) is of significance for informed (amateur) investors.

Our dataset consists of the *implied* volatility indices of the conventional financial markets, including stocks, commodity, and

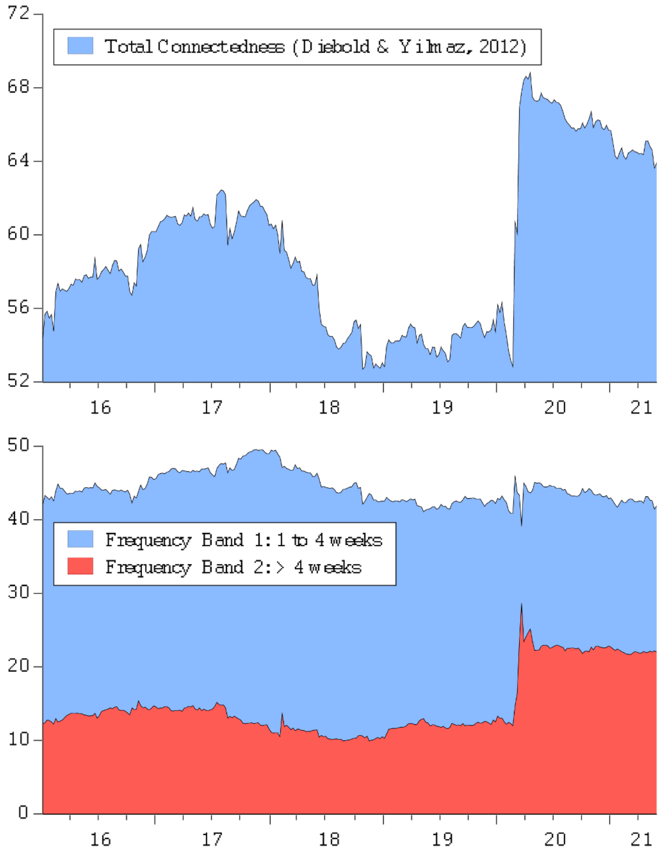
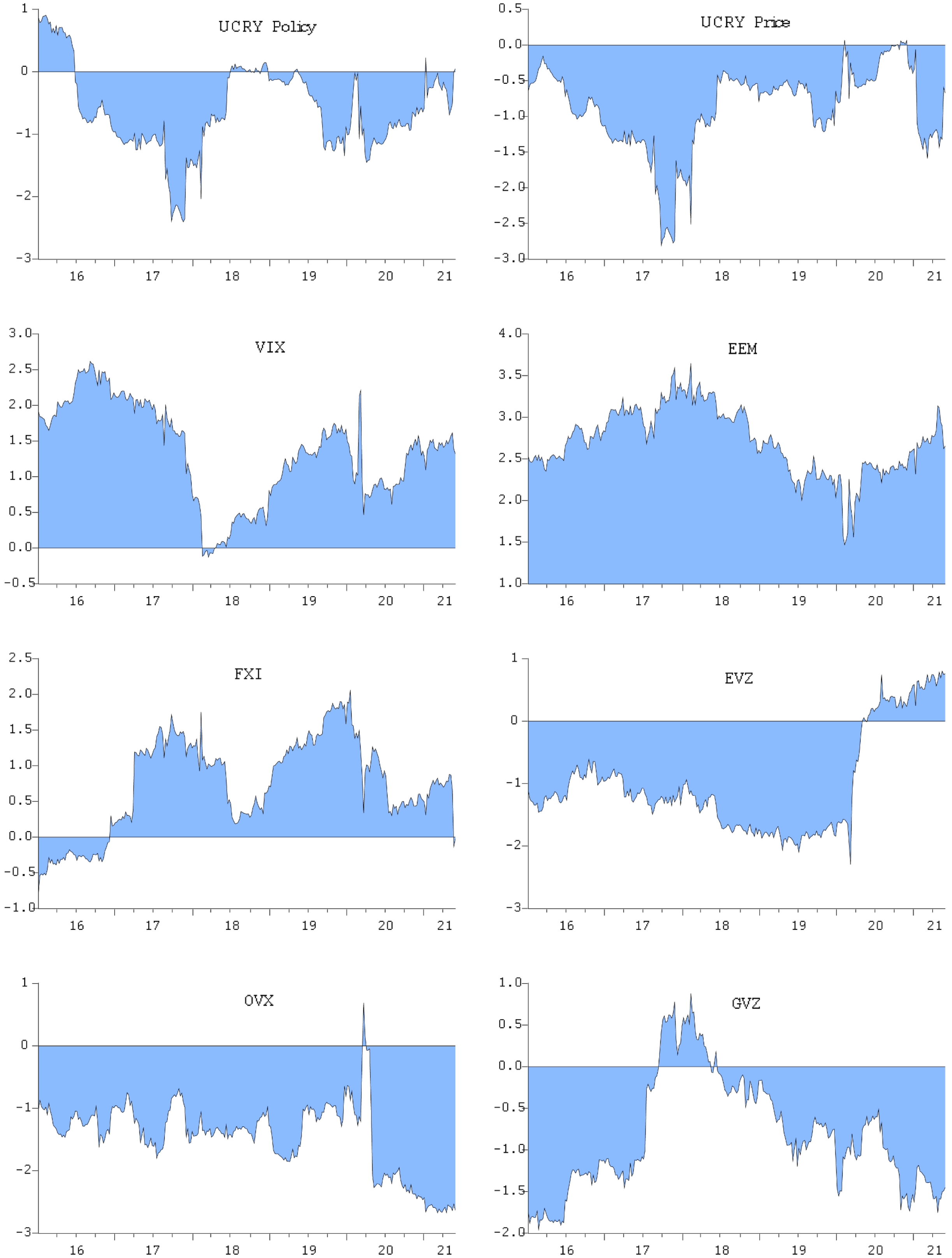


Fig. 1. Time and Frequency Dynamics of Connectedness.
Note: The results are based on a rolling window of 104 weeks. The above plot shows the total connectedness measures of Diebold and Yilmaz (2012). The below plot illustrates the frequency decomposition (Baruník and Křehlík, 2018) of the total connectedness, where the blue line represents the short-term (long-term) frequency component, from one to four weeks (more than four weeks).



(caption on next page)

Fig. 2. (Diebold and Yilmaz, 2012) Net Spillovers, No Frequency Bands.
Note: The estimations are based on a rolling window of 104 weeks, illustrating the total net spillover measures of Diebold and Yilmaz (2012). The values in the positive (negative) area denote that the market is a transmitter (receiver).

currency markets. We utilize the well-known Chicago Board of Exchange (CBOE) *option-implied* volatility indices of stock (S&P500, VIX), currency (Eurocurrency, EVZ), energy (Crude oil, OVX), and precious metals (Gold, GVZ) markets, heavily analyzed in the literature. We also consider the Emerging Markets (EEM) and China (FXI) stock market volatility indices, tracking the volatility of markets where cryptocurrency trading and mining activities are considerably intense (see, inter alia, Küfeoğlu and Özkuran, 2019). Particularly, the VIX, known as the *investor fear gauge* (Whaley, 2000), expresses the investors' common belief about *expected* future stock market volatility, computed as the weighted average prices of the S&P 500 index puts and call options over a broad array of strike prices. The other indices are also calculated following the VIX's methodology; the OVX, GVZ, EVZ, EEM, and FXI are estimated using the prices of the options on the United States Oil (USO) Fund, SPDR Gold Shares ETF (GLD), and CurrencyShares Euro Trust (FXE), MSCI Emerging Markets Index, and iShares China Large-Cap ETF, respectively.

The option-implied volatility indices comprise risk and risk aversion information, reflecting market uncertainty (Bekaert et al., 2013). The level of the implied volatility indices increases when uncertainty in the markets increases, moving in the opposite direction from the underlying market index. The VIX, for instance, is used as an uncertainty measure and for the price of the risk of stock market volatility (see, inter alia, Bekaert et al., 2013; Bloom, 2009; Bloom et al., 2018; Chung and Chuwonganant, 2014, Liu et al., 2013; Lv, 2018; and the references therein). Following the above-mentioned papers and recent empirical papers in the literature (e.g., Niu et al., 2022; Pham and Nguyen, 2022), we use the VIX and other indices as a *proxy* for respective market uncertainties. The weekly dataset covering uncertainty proxies for key financial markets (i.e., stock, commodity, and currency) and cryptocurrency markets spans from January 2014 to May 2021. The UCRY indices dictate the data frequency and period.

We analyze the first differences of the series as the subsequent econometric analyses require a stationary process. Table 1 presents the descriptive statistics for the first-differenced series. According to the standard deviation statistics, the S&P500 Volatility Index (VIX) is the most volatile series, followed by the Crude Oil Volatility Index (OVX). The standard deviation statistics of the UCRY indices are among the lowest. The Jarque-Bera statistics suggest rejecting the null hypothesis that a series has a normal distribution at the 1% level. We check the integration properties of the series, estimating the ADF-type unit root tests, the conventional ADF (Dickey and Fuller, 1979), ADF with two breaks (Narayan and Popp, 2010), and Fourier-ADF (Enders and Lee, 2012). Whereas the former does not consider structural breaks, the latter two allow for unknown breaks in the data. The results are reported in Table 2. The tests suggest rejecting the null hypothesis of a unit root at the 1% level, implying that all series are stationary and suitable to the connectedness framework. Furthermore, the break dates piled around the COVID-19 epidemic in early 2020 and the collapse of the cryptocurrency markets in late 2017.

5. Empirical results

We employ the Diebold and Yilmaz (2012) framework and its extension by Baruník and Křehlík (2018) to investigate the time and frequency connectedness of the markets. We estimate a VAR model with one lag, determined by the Schwarz Information Criterion, including a constant and an exogenous variable capturing the break dates determined by the unit root tests. Panel a of Table 3 reports the (Diebold and Yilmaz, 2012) time-domain spillover results with no frequency bands. The total spillover index is 56.2%, indicating a significant degree of uncertainty connectedness. The largest pairwise uncertainty spillover is 44.15%, detected between the UCRY, followed by the spillovers among the stock market uncertainty indices, approximately 25%. The pairwise spillovers between the cryptocurrency and conventional market uncertainty indices are relatively low. The most considerable spillovers across the conventional market and UCRY uncertainty indices are from EEM to UCRY Policy (1.59%) and UCRY Price (1.47%) indices. The net spillover statistics reported in the last row show that the UCRY Price, currency, energy, and precious metals markets are net receivers of uncertainty. In contrast, the net uncertainty transmitters are the cryptocurrency policy and stock markets. The leading net source of uncertainty is the EEM, followed by the VIX, and the largest net uncertainty receiver is the OVX market.

Panel b of Table 3 presents the results of Baruník and Křehlík (2018) frequency-domain connectedness. We decompose the total connectedness into two different frequency bands, one week to four weeks ($d_1 \in (3.14, 0.79)$) and more than four weeks ($d_2 \in (0.79, 0.00)$), corresponding to short- and long-term, respectively. The absolute spillover indices reported in the penultimate column (absolute connectedness, FROM ABS) are 41.78% and 14.42% for the first and second frequency bands, respectively, implying that the total connectedness is primarily moved by the low-frequency (short-term) component. The *absolute* frequency spillover indices suggest that the markets disseminate information expeditiously; a shock to one index in the entire structure mostly significantly impacts short-term cyclical behavior. According to the last column of the table (within connectedness, FROM WTH), the *within* connectedness measures take close values, 55.40%, and 58.65%, for short- and long-term, respectively, indicating that the connectedness levels in different investment horizons do not change substantially.

For the high-frequency band ($d1$, short-term), in line with the findings reported in Panel a of Table 3, the cryptocurrency price (UCRY Price), currency, energy, and precious metals markets are net receivers of uncertainty, and the remaining are net uncertainty transmitters. However, the roles of the cryptocurrency uncertainty price (policy) and eurocurrency indices as a net uncertainty transmitter (receiver) change to a net uncertainty receiver (transmitter) in the low-frequency band ($d2$, long-term).

Besides the above-reported *static* average spillover results, we investigate the *dynamic* structure of the uncertainty connectedness using a rolling window of 104 weeks (about two years). Fig. 1 illustrates the time-varying time and frequency dynamics of

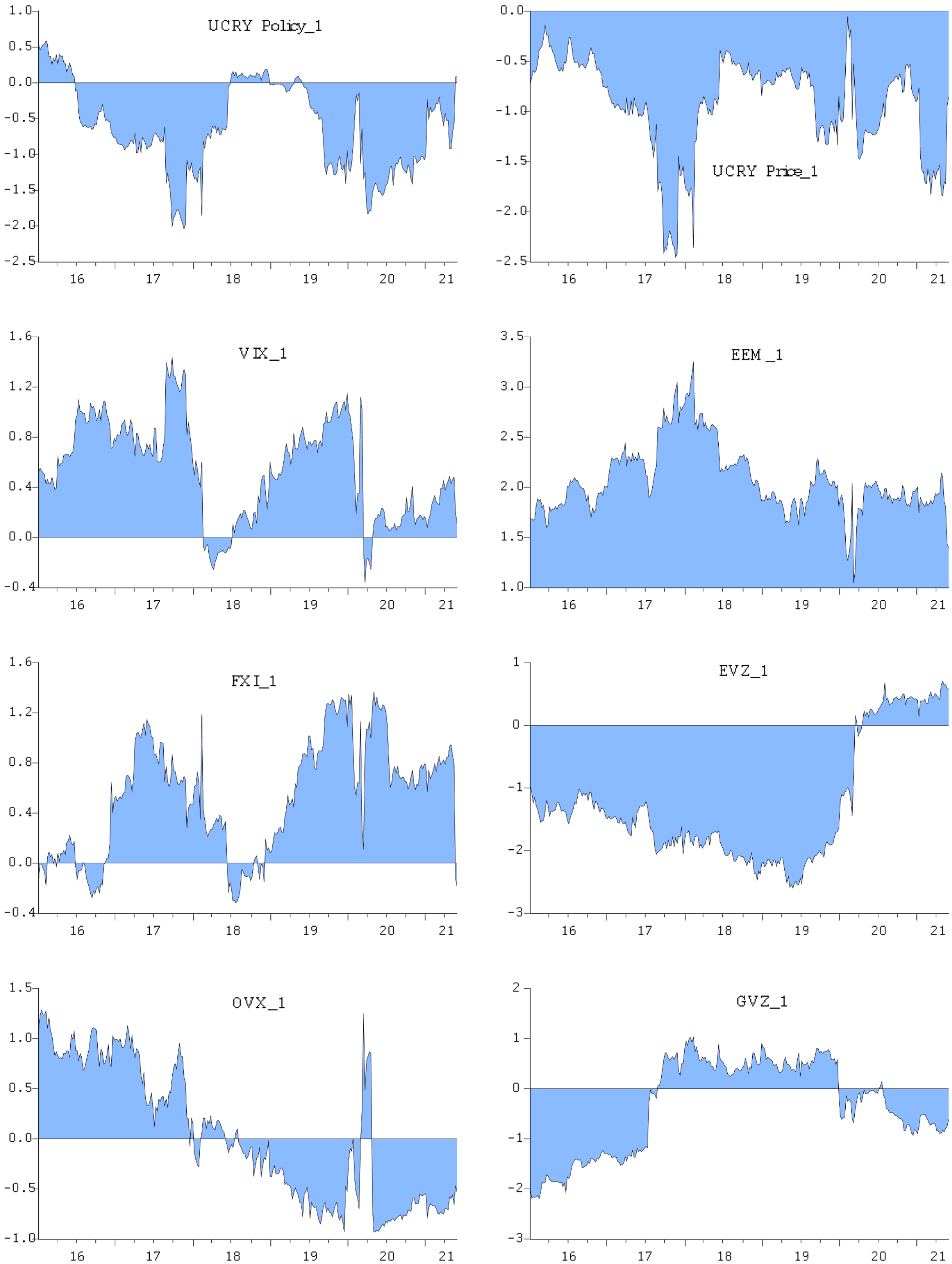


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Fig. 3. (Baruník and Křehlík, 2018) Net Spillovers, Frequency Band 1: d1 ∈ (3.14, 0.79).
Note: The estimations are based on a rolling window of 104 weeks, illustrating the net spillover measures of Baruník and Křehlík (2018) for the short-term frequency component. The values in the positive (negative) area denote that the market is a transmitter (receiver).

connectedness. The total connectedness measure of Diebold and Yilmaz (2012) ranges from 52% to 62% between January 2016 and March 2020. By the COVID-19 outbreak in mid-March 2020, the total connectedness index sharply increased to 69% and took a value of no less than 62%. The high-frequency component (short-term, Frequency 1) takes a value between 39% and 49%, exhibiting a relatively stable behavior over the whole sample period. We observe two different regimes in the low-frequency component (long-term, Frequency 2); the long-term component of total connectedness ranges from 10% to 16% between January 2016 and March 2020; however, it increases to 29% by the COVID-19 and takes a value between 22% and 28%. Consistent with the static analysis, the high-frequency (short-term) component is dominant and drives the total connectedness index. A shock to one uncertainty index in the entire system mostly significantly impacts short-term cyclical behavior (Baruník and Křehlík, 2018, p. 16). The figures imply that the COVID-19 pandemic has a permanent effect that is persistent over the long term; the shocks during that period are transmitted for more extended periods and are more persistent than those in shorter periods.

Fig. 2 illustrates the time-varying net spillover measures of Diebold and Yilmaz (2012) with no frequency bands. The cryptocurrency indices are mostly net uncertainty receivers, reaching the lowest levels in late 2017 when Bitcoin prices crashed and lost almost 50% value in one month. The net spillover of the stock market uncertainties remains mainly in the positive area, indicating that they transmit uncertainty to other markets during the sample period, except for the Chinese stock market in 2016. The currency, energy, and precious metals markets are mostly uncertainty receivers; their net spillover measures remain mostly in the negative area. Notably, the gold market was a net uncertainty transmitter in late 2017 when the net uncertainty receipts of cryptocurrency deepened. The role of the eurocurrency market as an uncertainty receiver changes to an uncertainty transmitter during the COVID-19 pandemic.

Figs. 3 and 4 illustrate the time-varying net spillovers of Frequency bands 1 and 2, respectively. The time-varying evolution of net directional spillovers at the high frequency (Frequency band 1) is identical to that of the time-based net spillover measures, except for uncertainty in the energy and precious metals markets. While the energy market is a net uncertainty transmitter until late 2017, it becomes an uncertainty receiver later. The gold market is an uncertainty receiver, except during the mid-sample period (2018–2019). Furthermore, the net directional spillovers at the low-frequency (Frequency band 2) component identify a different pattern in all markets, except the stock and energy markets, compared to the time-based spillover measures. The cryptocurrency market became an uncertainty transmitter in 2019, more perceptible by the COVID-19 outbreak. The eurocurrency market is a net uncertainty transmitter until 2020, and then it becomes an uncertainty receiver during the COVID-19 period. The role of the gold market as an uncertainty receiver becomes more evident after the beginning of 2018.

Finally, we report the net pairwise directional spillovers in Figs. 5 to 10, focusing solely between UCRY indices and other markets. Figs. 5 and 6 illustrate the net pairwise spillovers based on the Diebold and Yilmaz (2012) measures with no frequency bands. Consistent with the prior analyses above, the magnitude of net pairwise uncertainty spillovers is relatively small, indicating a low degree of connectedness between UCRY indices and other markets. UCRY Policy and Price indices are mostly net receivers of uncertainty from stock (i.e., VIX, EEM, FXI) and crude oil (OVX) markets. The currency market transmits uncertainty to UCRY indices, except for two episodes earlier in the sample period and between 2018 and 2019. Towards the midpoint of the data period, the roles for the pairwise net spillover between the UCRY indexes and the gold market change. The UCRY indices, net uncertainty receivers from GVZ until 2018, become net uncertainty transmitters until the end of the sample period.

Figs. 7 to 10 illustrate net pairwise spillovers at short-term and long-term frequency components. We evidence similar patterns in the net pairwise spillovers in the short-term frequency component, reported in Figs. 7 and 8, to those of the Diebold-Yilmaz measures in Figs. 5 and 6. However, the UCRY indices become net uncertainty transmitters to the other markets after 2019, with the degree of spillovers increasing by the COVID-19 outbreak.

Overall results show mediocre (averaged) connectedness among cryptocurrency, stock, currency, energy, and precious metals markets. Notably, the UCRY indices exhibit distinct spillover patterns and a low connectedness with the other financial markets, implying some diversification opportunities. By decomposing the total connectedness index into frequency components, we evidence the altered behavior of markets, specifically the cryptocurrency markets, in the long term. Furthermore, uncertainty shocks fade out swiftly in the short term, as we find that the short-term component drives total connectedness. However, the COVID-19 pandemic, a black-swan event, has a long-term impact on total connectedness, causing the financial markets to respond to the uncertainty impulses differently in a longer investment horizon.

6. Concluding remarks and policy implications

This paper investigates volatility transmission among the uncertainty indices of various markets, including cryptocurrency, stock, currency, energy, and precious metals, for different investment horizons. Our results suggest that stock market uncertainty contributes to the uncertainty of other markets, regardless of the investment horizon. As uncertainty transmitters or receivers, the role of the cryptocurrency, currency, energy, and precious metals markets changes over time, especially across investment horizons. Moreover, the COVID-19 epidemic has a significant long-term effect on the dynamic structure of the uncertainty connectedness of the markets. Our finding on cryptocurrency is consistent with the study of Foglia and Dai (2022), indicating that the UCRY Price index is a net receiver. Closely examining the averaged pairwise measures suggests a weak connection between cryptocurrency uncertainty and other markets' uncertainties. This finding highlights cryptocurrency markets' distinct dynamics and unique characteristics,

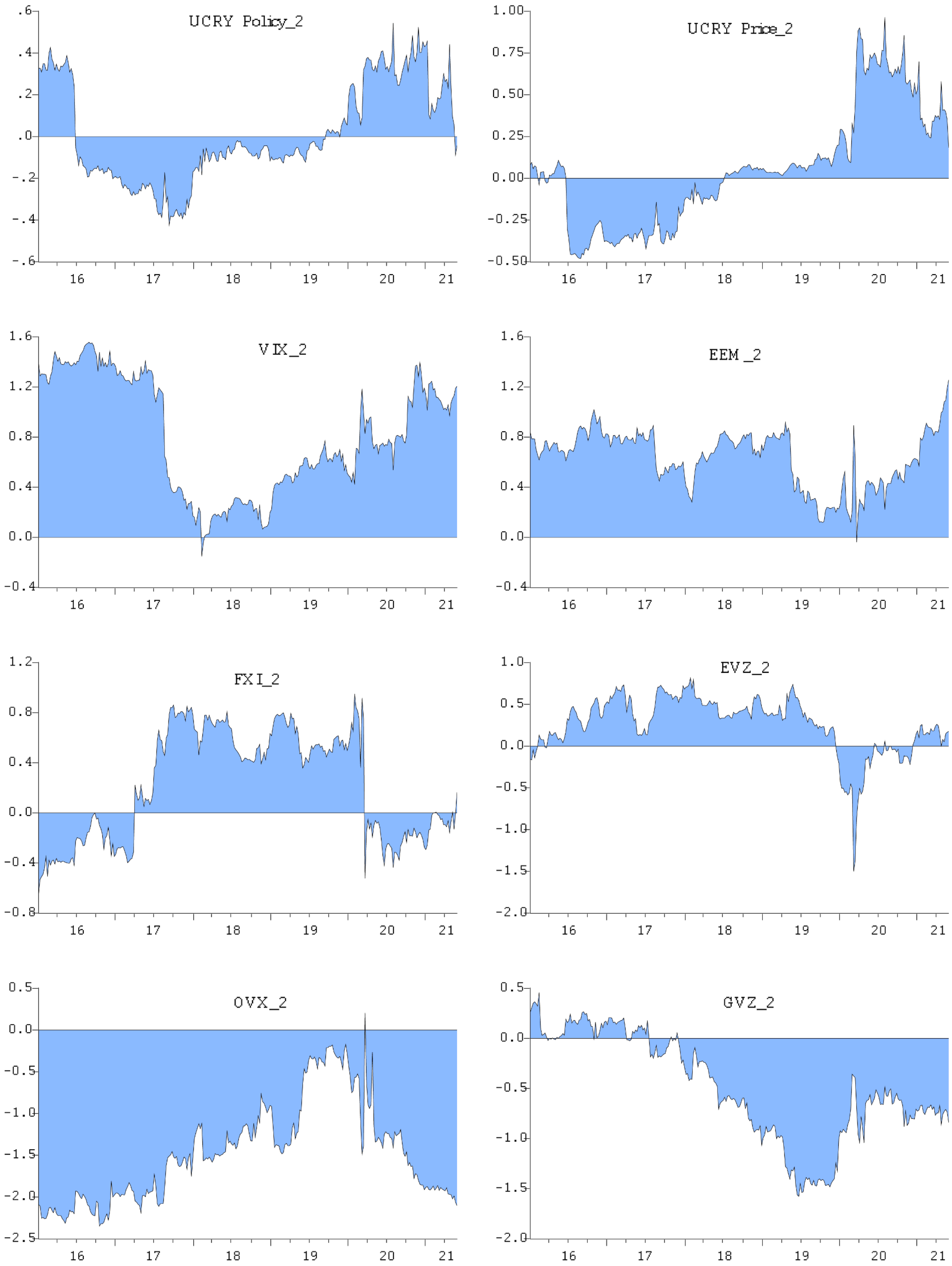

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Fig. 4. (Baruník and Křehlík, 2018) Net Spillovers, Frequency Band 2: d1 ∈ (0.79, 0.00).
Note: The estimations are based on a rolling window of 104 weeks, illustrating the net spillover measures of Baruník and Křehlík (2018) for the long-term frequency component. The values in the positive (negative) area denote that the market is a transmitter (receiver).

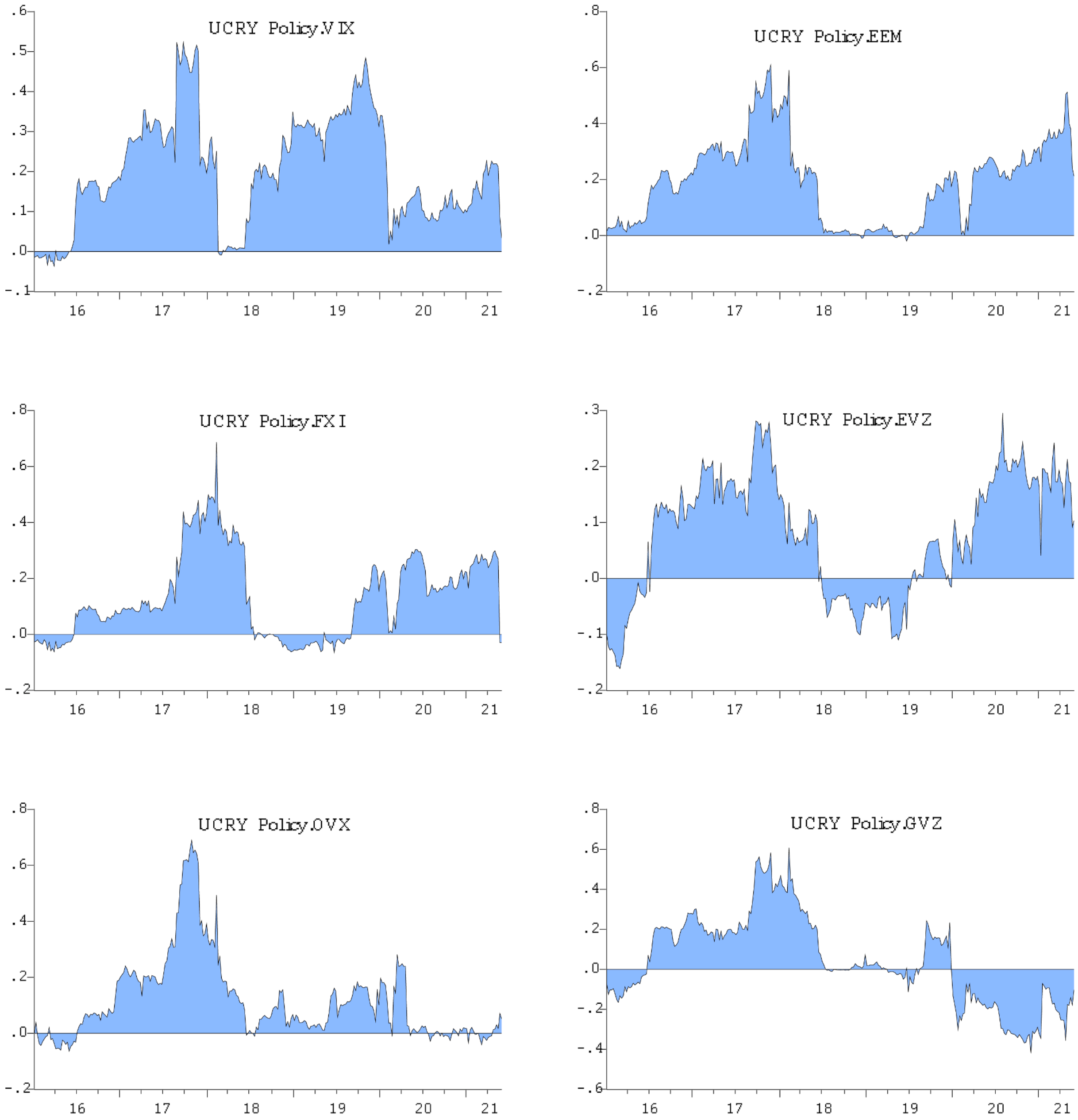

Fig. 5. Net Pairwise Directional Connectedness, UCRY Policy, No Frequency Bands.
Note: The estimations are based on using a rolling window of 104 weeks, illustrating the total net pairwise spillover measures of Diebold and Yilmaz (2012). The values in the positive (negative) area denote that the UCRY Policy is a net uncertainty receiver (transmitter) from (to) the other market.

distinguishing them from conventional financial markets and providing evidence of diversification opportunities for investors.

From the dynamic perspective, the total connectedness abruptly increases by the COVID-19 outbreak, a *black-swan* event causing financial and cryptocurrency market uncertainties to amplify. When we decompose the total connectedness into short-term and long-term components, the results suggest that short-term uncertainty shocks predominantly impact the total connectedness, denoting that uncertainty shocks do not persist in the long term and fade out within the short term. However, the COVID-19 outbreak has long-term

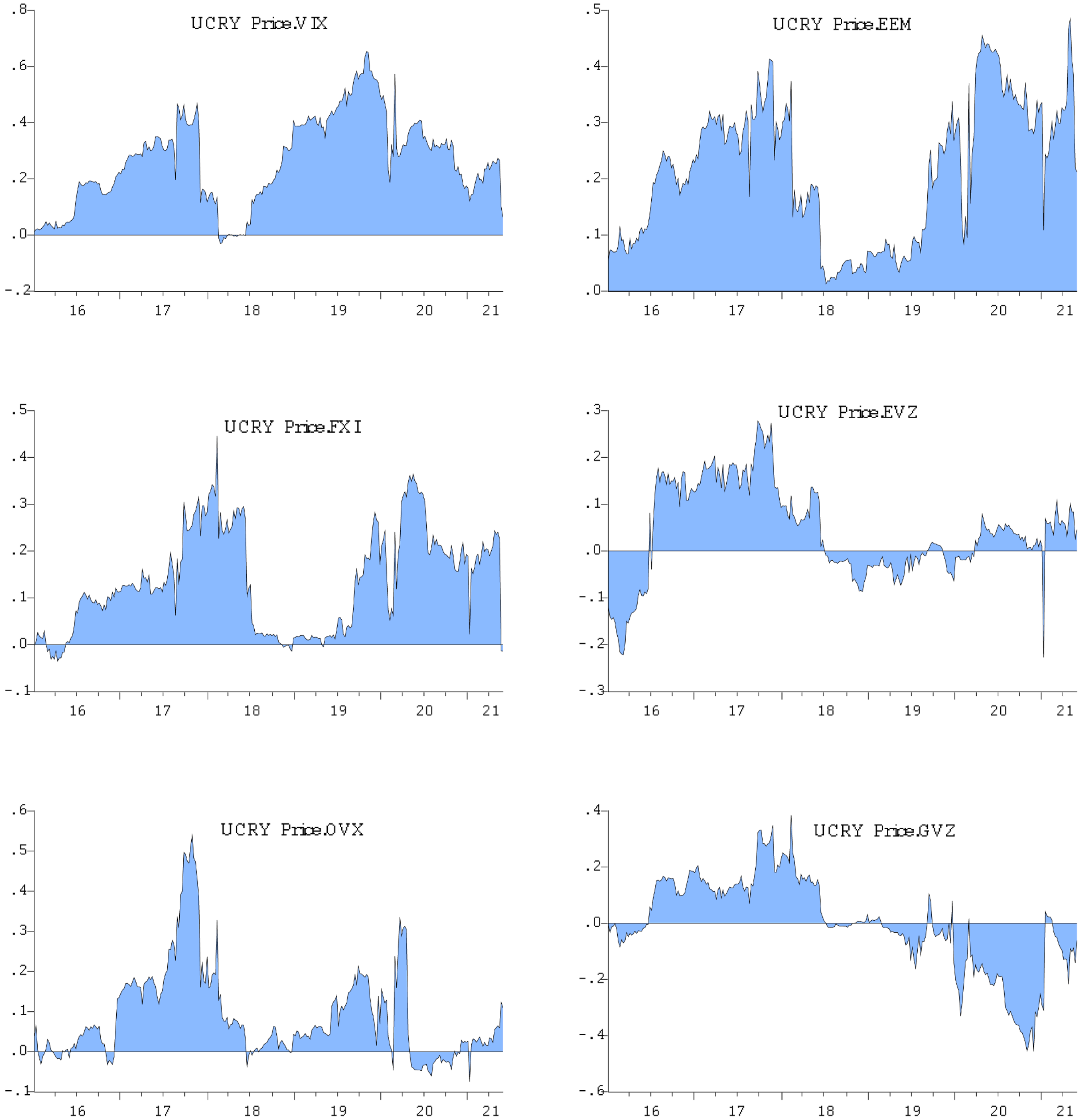

Fig. 6. Net Pairwise Directional Connectedness, UCRY Price, No Frequency Bands.
Note: The estimations are based on using a rolling window of 104 weeks, illustrating the total net pairwise spillover measures of Diebold and Yilmaz (2012). The values in the positive (negative) area denote that the UCRY Price is a net uncertainty receiver (transmitter) from (to) the other market.

persistence in the connectedness of the entire system. The shocks during the COVID-19 pandemic are transmitted for extended periods, escalating the total connectedness trend to the upper level. Particularly, the role of the cryptocurrency markets in the long-term changes; they have become a limited source of uncertainty after the COVID-19 outbreak. In contrast, the crude oil and gold markets begin receiving long-term uncertainty shocks from the others.

Our findings have valuable implications for both policymakers and investors. Investors and portfolio managers should pay more attention to markets that primarily receive uncertainty from others. The tenuous connection between cryptocurrency and other markets implies that the uncertainty in the conventional financial markets may be alleviated by including the uncertainties in the cryptocurrency markets. However, investors should build dynamic asset allocation strategies as the uncertainty transmission changes across investment horizons and the connectedness of uncertainty spikes during economic downturns (e.g., COVID-19) when industrial production halts due to supply chain bottlenecks. Thus, investors should cautiously construct portfolios and hedging strategies to avoid losses since long-term

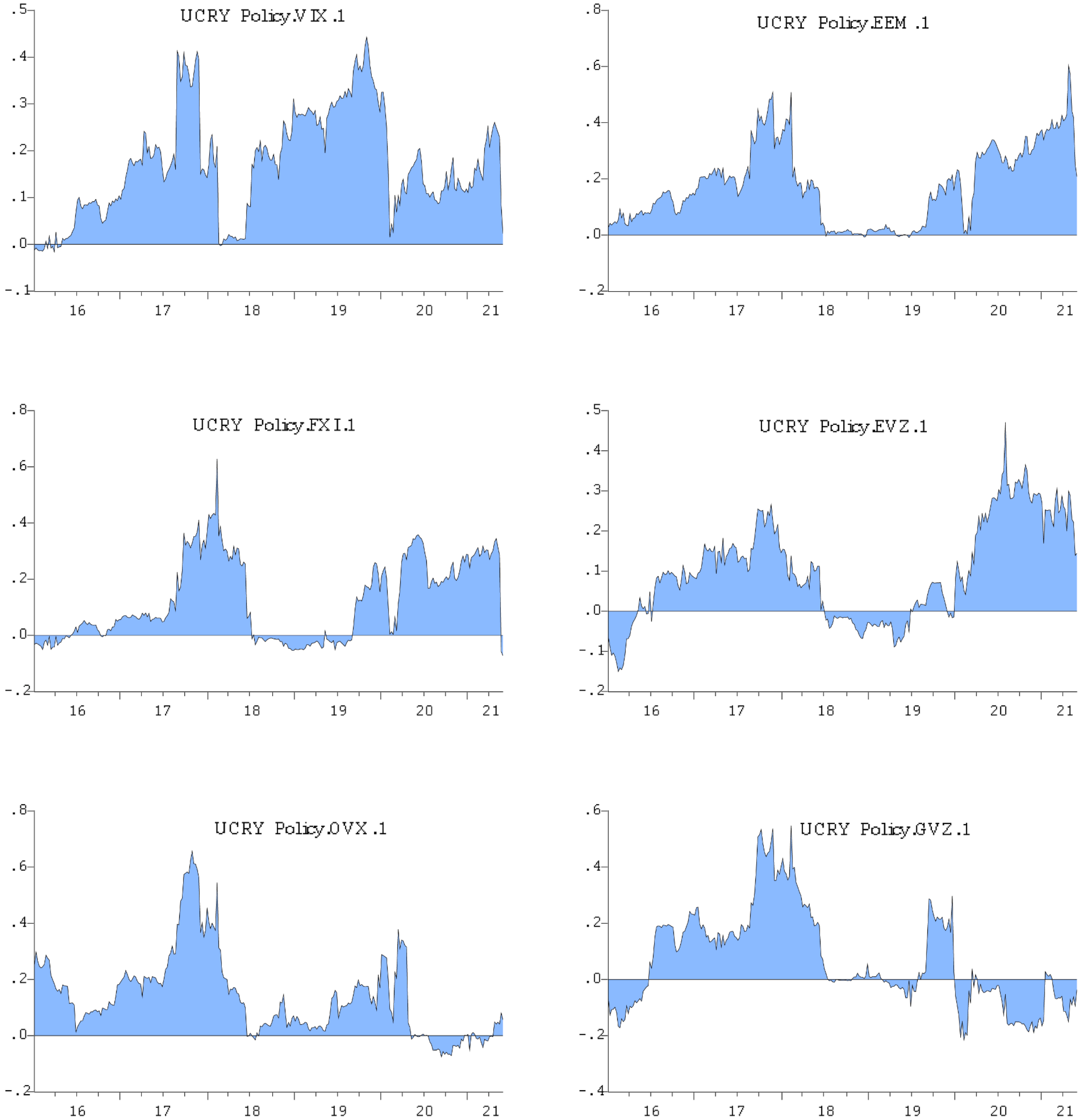

Fig. 7. Net Pairwise Directional Connectedness, UCRY Policy, Frequency Band 1.
Note: The estimations are based on a rolling window of 104 weeks, illustrating the total net pairwise spillover measures of Baruník and Křehlík (2018) for the short-term frequency component. The values in the positive (negative) area denote that the UCRY Policy is a net uncertainty receiver (transmitter) from (to) the other market.

uncertainty shocks persist for longer periods during such turbulent times (Yarovaya et al., 2021). They should diversify their portfolios and use hedging instruments dynamically to reduce the adverse effects of uncertainties stemming from particular markets.

Policymakers should try to calm down the markets by making the necessary regulations regarding each asset group that may increase the instability in financial markets, notably in nascent cryptocurrency markets. During turbulent times such as the COVID-19 pandemic, governments might develop sound strategic plans to prevent further uncertainty (Sharif et al., 2020). While monetary policy actions should be of assistance to market participants in the short and medium term, policymakers are responsible for not creating an additional uncertainty source that persists for a longer duration, such as inflation. Regulators should pave the way for creating clear regulatory laws in cryptocurrency markets to avoid cryptocurrency platform-related issues and concerns, lack of transparency, liquidity, and investor protection, which might provoke uncertainty. Regulatory collaborations at the international level may help

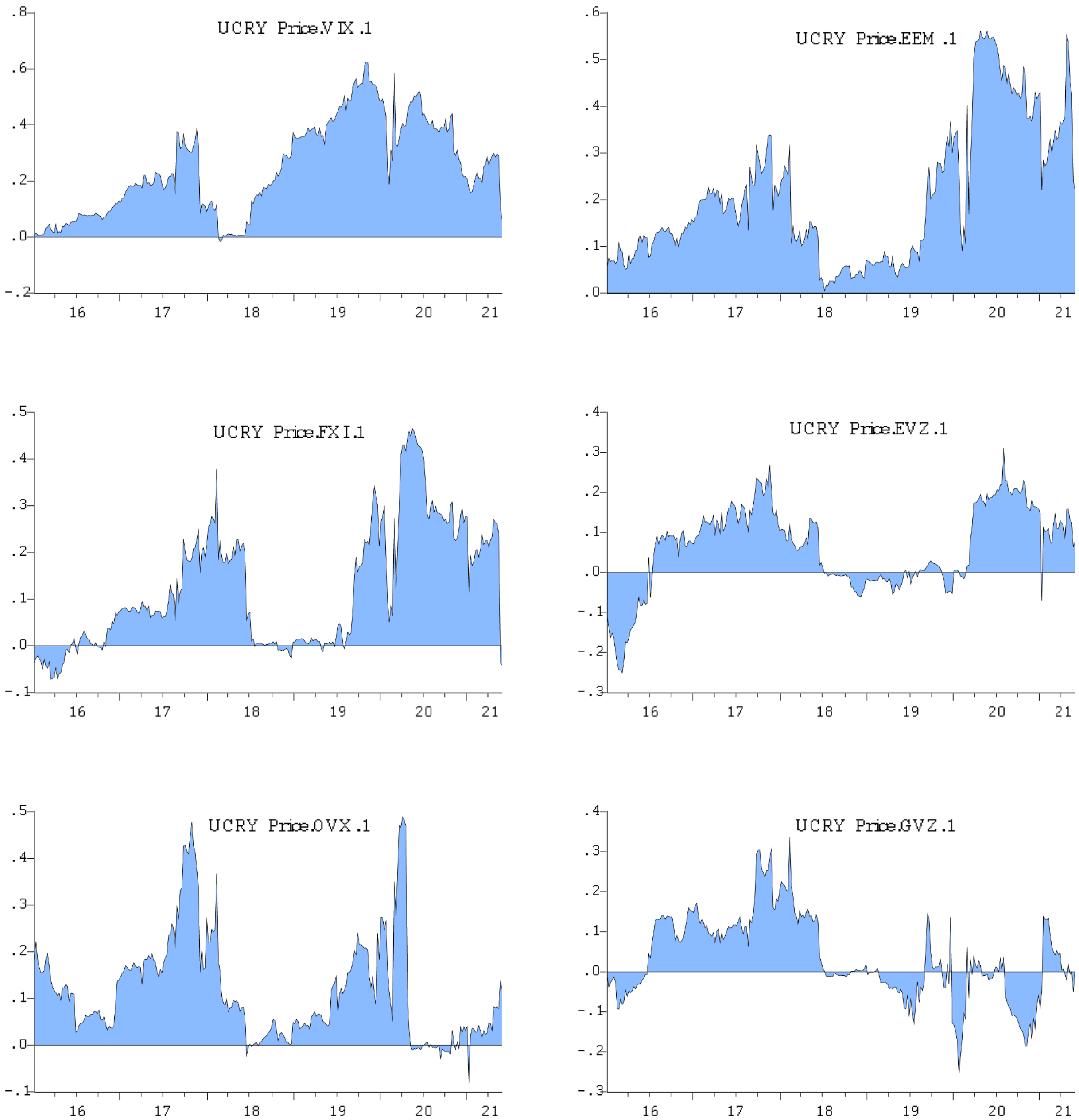

Fig. 8. Net Pairwise Directional Connectedness, UCRY Price, Frequency Band 1.
Note: The estimations are based on a rolling window of 104 weeks, illustrating the total net pairwise spillover measures of Baruník and Křehlík (2018) for the short-term frequency component. The values in the positive (negative) area denote that the UCRY Price is a net uncertainty receiver (transmitter) from (to) the other market.

protect investors and lessen uncertainties by reducing market frictions and irrational trading activities (e.g., overconfidence, herding). Furthermore, well-designed derivatives contracts are beneficial to increasing hedging capabilities and liquidity, which limit financial losses during distressing times (Cuny, 1993).

Future work may exceed the limits of this paper to gather further insights. Our study may be extended to include additional uncertainty measures of the (emerging) stock markets, individual commodities, and crypto-assets (e.g., non-fungible tokens). Moreover, specific portfolio weighting (Kroner and Ng, 1998) and hedging strategies (Kroner and Sultan, 1993), along with their hedging effectiveness statistics (Ederington, 1979), may be provided as complementary to the connectedness framework. The minimum connectedness portfolio framework of Broadstock et al. (2022) may reveal additional insight into particular portfolio strategies. Finally, the potential determinants of the uncertainty connectedness might be investigated.

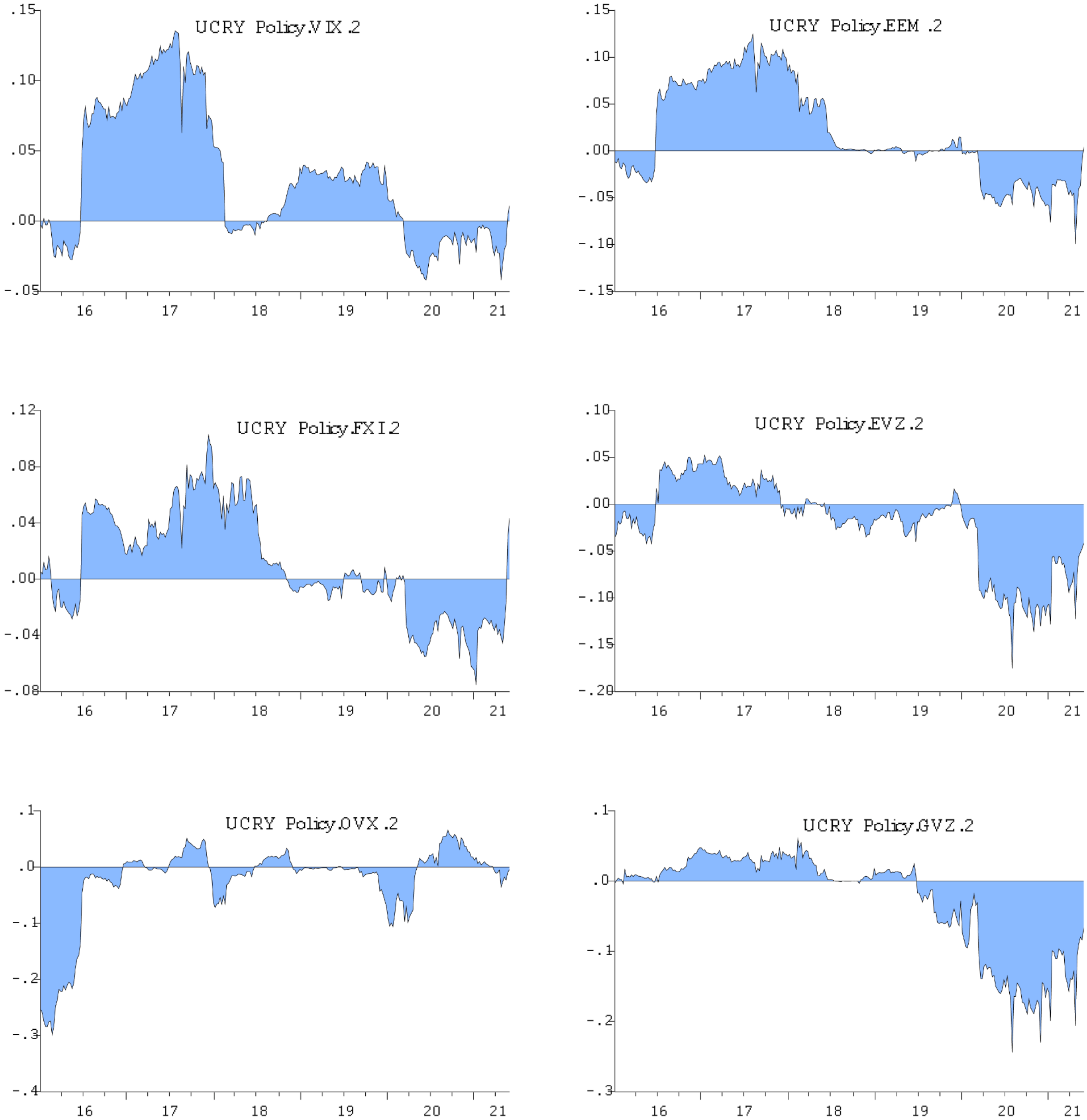

Fig. 9. Net Pairwise Directional Connectedness, UCRY Policy, Frequency Band 2.
Note: The estimations are based on a rolling window of 104 weeks, illustrating the total net pairwise spillover measures of Baruník and Křehlík (2018) for the long-term frequency component. The values in the positive (negative) area denote that the UCRY Policy is a net uncertainty receiver (transmitter) from (to) the other market.

CRediT authorship contribution statement

Efe Caglar Cagli: Writing – original draft, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Conceptualization, Validation, Visualization, Writing – review & editing. **Pinar Evrim Mandaci:** Writing – original draft, Formal analysis, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

None.

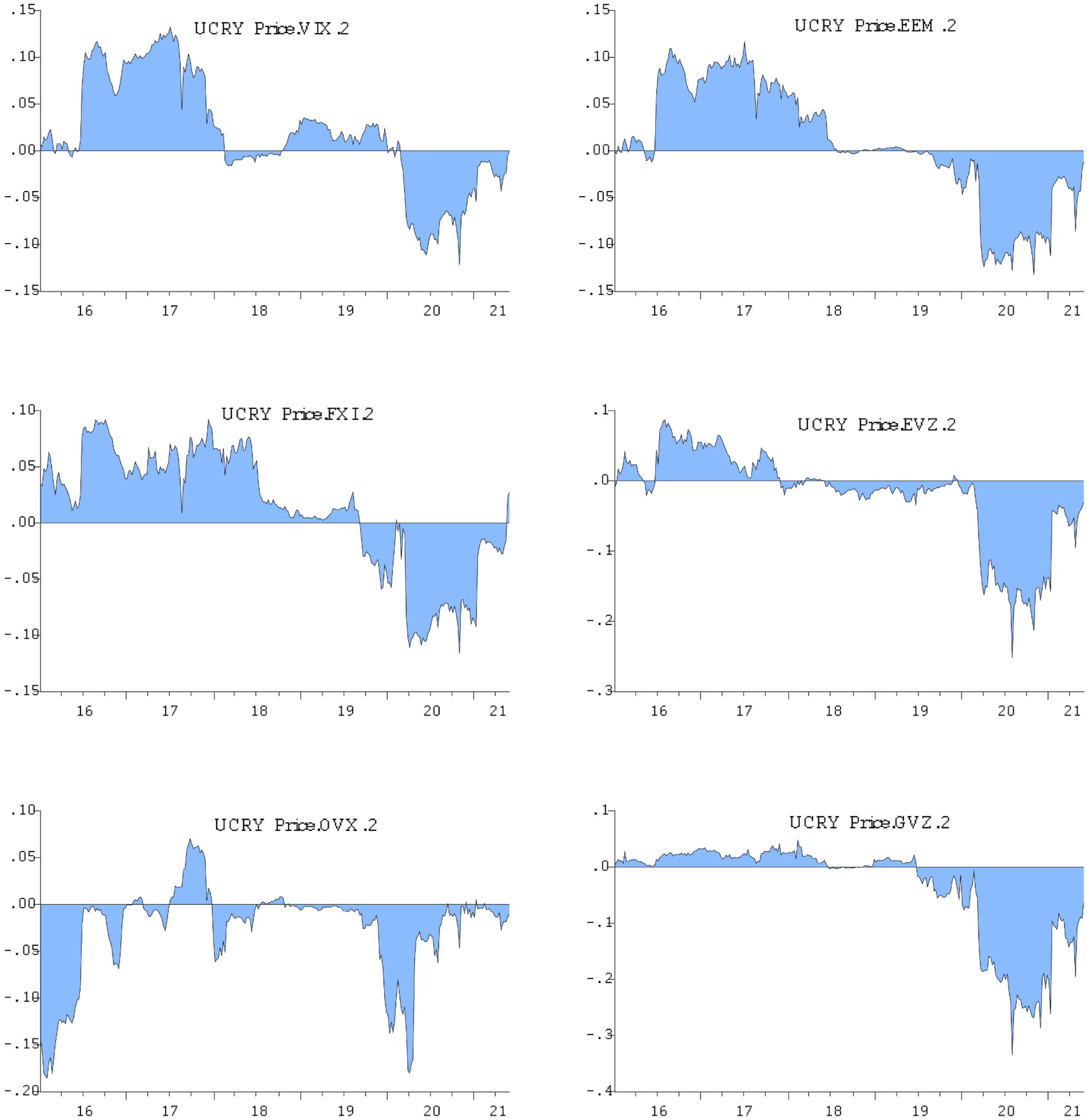

Fig. 10. Net Pairwise Directional Connectedness, UCRY Price, Frequency Band 2.
Note: The estimations are based on a rolling window of 104 weeks, illustrating the total net pairwise spillover measures of Baruník and Křehlík (2018) for the long-term frequency component. The values in the positive (negative) area denote that the UCRY Price is a net uncertainty receiver (transmitter) from (to) the other market.

Data availability

Data and Code: https://doi.org/10.17632/m8cy5xw3dc.1

Time and Frequency Connectedness of Uncertainties in Cryptocurrency, Stock, Currency, Energy, and Precious Metals Markets (Original data) (Mendeley Data)

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