Frequency connectedness between DeFi and cryptocurrency markets

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Abstract.
This study investigates the time-frequency spillovers across four main DeFi (BAT, Link, Maker, and SNX) and four leading cryptocurrency markets (Bitcoin, Ethereum, Litecoin, and Ripple). Employing the spillover metrics by Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), we show Ripple and the four DeFi assets are net receivers of spillovers in the system and other cryptocurrencies are contributors. Furthermore, the short-run spillovers largely predominate both mid- and long-run spillovers. The spillover size jumps during the first and the fourth COVID-19 waves. Finally, a strong frequency connectedness observed during COVID-19, implying contagion effects and decline in the diversification benefits.

JEL Classification: DeFi assets, cryptocurrency, spillovers, frequencies, COVID-19

Keywords: G14

1. Introduction

Decentralized Finance (DeFi) assets are the emerging digital financial service in the modern finance. The growing capital flow of DeFis and the upside trend of the DeFi prices have engendered a deep reflection of market participants and research communities regarding these new assets as an alternative or a substitute investment to cryptocurrencies.[1] Operated on public blockchains. DeFi asset enables users to earn interest or borrow against their cryptocurrency holdings. They are traded on the Ethereum network. Similarly, cryptocurrencies showed a rapid grow in the last decade where the market capitalization reaches $ 3 trillion in November 2021.[2] The important number of cryptocurrencies and their fast growth explain the attention of retailers and fund managers to these digital assets. As a store value, Bitcoin is the largest cryptocurrency in terms of trading volume and market capitalization. In contrast to DeFi assets, Bitcoin is traded on its own blockchain. This blockchain technology eliminates the need of government agency and central banks, expands the reach of transactions and empowers new business models. Moreover, the interest rates for DeFi assets are more attractive than those offered by traditional financial system. The high connections among cryptocurrencies (Katsiampa et al., 2019; Borr and Shakhnov, 2020; Umar and Gubareva, 2020; Caporale et al., 2021; Moratis, 2021; Raza et al., 2021; Xu et al., 2021) turn the attention of investors to move to other digital assets such as DeFi and Non-Fungible Tokens (NFTs).

The literature addressed the linkages between DeFi assets with other asset classes, especially cryptocurrencies are limited. Yousaf et al. (2022) examine the dynamic spillovers between DeFi (Basic Attention Token, Chainlink, Maker, and Synthetix) and currency markets

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[1] In March 17, 2022, the market capitalization of Synthetix (SNX) is $509,896,836, Basic Attention Token (BAT) $1,285,253,386, Maker (MKR) $1,938,950,146, and Chainlink (LINK) $6,847,038,856.

[2] https://www.consultancy-me.com/news/4692/determining-the-real-market-capitalization-of-crypto-assets#:~:text=And%20the%20answer%20is%20quite,highs%20of%20about%20%243%20trillion.

(Yuan, Yen, Euro, and GBP). Karim et al. (2022) examine the risk transmission between DeFi tokens, NFTs, and cryptocurrencies using the methodology of Ando et al. (2018). The results reveal significant spillovers within blockchain markets and that NFTs provide a diversification benefits. Maouchi et al. (2021) investigate the bubbles in NFTs and DeFi assets. The results show persistent bubble in DeFi markets in summer 2020. The bubbles are less pronounced and more frequent in cryptocurrencies than DeFi and NFTs.

Motivated by the above emerging studies, it is evident that there is a linkage between cryptocurrency and DeFi markets. However, the previous studies did not address how these markets are connected and how much DeFi/cryptocurrency asset contributes the forecasting variance of cryptocurrency/DeFi asset. Our study fills this gap in the literature by examining the frequency volatility spillover size and directions between main DeFi and cryptocurrency assets. As far as we know this research represents a pioneering attempt in this domain of the frequency connectedness studies, as our analysis is carried out across frequencies as well as prior and during the pandemic, caused by the COVID-19 virus.

Our findings demonstrate that the time-varying spillovers between DeFi and cryptocurrency markets intensify during the first wave of COVID-19 crisis and during times of COVID-19 variants. The short-run spillovers largely predominate over the mid- and long-run spillovers. This reveals that the financial contagion effects are more pronounced within one week. DeFi and XRP markets behave as the net receivers of spillovers whereas BTC, ETH, and LTC play role of the net contributors in the system across different frequencies. Furthermore, we observe significant connections between DeFi and cryptocurrencies before and during the COVID-19 pandemic irrespective of frequencies, limiting the diversification benefits.

Our notable contributions are in the following ways. First, the Bitcoin price crash early 2018 has increased the uncertainty in cryptocurrency marketplace, generating a panic of crypto investors. Alongside with the ongoing COVID-19 pandemic, the apparition of a DeFi asset may intensify the turbulence in cryptocurrency markets. Thus, it is worthy of investigation to analyze how these two emerging markets are interconnected. We use both the time spillover metrics by Diebold and Yilmaz (2012; hereafter DY-12), along with the spillover metrics of by Baruník and Křehlík (2018; hereafter BK-18) in the time-frequency space, allowing to explore the extent and the direction of dynamic spillovers between DeFi and cryptocurrency assets. We further examine how these 8 markets are connected (in terms of magnitude and direction) simultaneously before and during the pandemic and across frequencies. This study provides useful insights to crypto investors concerning management of investment portfolios and efficient funds allocation.

The remainder of this article is structured in the following manner. Section 2 discusses the methodology. Section 3 presents the data and descriptive statistics. Section 4 reports the results while Section 5 presents conclusions.

2. Methodology

2.1. DY-12 spillover index method

To quantify the directional spillover across the DeFi and cryptocurrency markets, we first employ the generalized VAR methodology proposed by Diebold and Yilmaz (2012; hereafter DY-12). Following DY-12 spillover index methodology, a covariance stationary n-variable VAR(p) is assumed as:

$$y_t = \sum_{i=1}^{\rho} \Phi_i y_{t-1} + \varepsilon_t \quad (1)$$

where y_t is an $n * 1$ vector of endogenous variables, Φ_i, represents the $n * n$ autoregressive coefficient matrices and ε_t is a vector of error terms without serial correlation.

With the VAR process based on the assumption of covariance stationarity, a moving average form follows:

$$y_t = \sum_{j=0}^{\infty} A_j \varepsilon_t \tag{2}$$

where A_j is an $n * n$ coefficient matrix in line with the recursion of the form, $A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2} + \cdots . \Phi_\rho A_{j-\rho}$, where A_0 is the $n * n$ identity matrix and $A_j = 0$ or $j < 0$. Tackling the problem of orthogonal innovation, DY-12 utilize the generalized VAR set up for the H-step forecast variance of Koop et al. (1996) for H=1, 2...n, given as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e' A_h \Sigma A_h' e_j)} \tag{3}$$

where the variance matrix of the error vector is $\sum$ while, σ_{jj} represents the standard deviation of the error term for the jth equation. e_j is the selection vector, which is valued as 1 or 0. Again, as the sum of the contributions to the forecast error change is not equal to 1, the DY-12 method controls each entry of the variance decomposition matrix by the row sum to benefit fully from the matrix. The standardized H-step forecast error variance decomposition proxied by $\theta_{ij}^{g}(H)$ can be written as:

$$\theta_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(N)} \tag{4}$$

where $\sum_{j=1}^{N} \theta_{ij}^{g}(N)$= 1and $\sum_{j=1}^{N} \theta_{ij}^{g}(N)$=N by construction

2.2. Time-frequency connectedness method

Following the time-frequency domain method of Baruník and Křehlík (2018; hereafter BK-18), we measure the frequency sources of connectedness across the DeFi and cryptocurrency markets. The BK-18 method extends the DY-12 method with considering a frequency response function $\Psi(e^{-ih\omega}) = \sum_{h=0}^{\infty} e^{-ih\omega} \Psi_h$, obtained from a Fourier transform of the moving average coefficients Ψ_h with $i = \sqrt{-1}$. The spectral density of X_t at frequency ω, is defined as:

$$S_X(\omega) = \sum_{h=0}^{\infty} E(X_t X_{t-h}) e^{-ih\omega} = \Psi(e^{-ih\omega}) \Sigma \Psi(e^{ih\omega}) \;, \tag{5}$$

The generalized forecast error variance decompositions (GFEVD) at frequency ω can be defined as:

$$\theta_{ij}(\omega) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{\infty} \left(\Psi(e^{-ih\omega})\Sigma\right)_{ij}^{2}}{\sum_{h=0}^{\infty} \left(\Psi(e^{-ih\omega})\Sigma\Psi(e^{ih\omega})\right)_{ii}}, \tag{6}$$

Eq (6) can be standardized as:

$$\breve{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{h=1}^{n} \theta_{ij}(\omega)} \;, \tag{7}$$

where $\breve{\theta}_{ij}(\omega)$ measures pairwise connectedness from j to i at a given frequency ω. The GFEVD on a frequency band $g = (c, d): c, d \in (-\pi, \pi)$, $c < d$, can be expressed as:

$$\breve{\theta}_{ij}(g) = \int_{c}^{d} \breve{\theta}_{ij}(\omega) g\omega. \tag{8}$$

The total connectedness index within the frequency band g, C^g, is expressed as:

$$C^g = \frac{\sum_{i=1, i \neq j}^{n} \breve{\theta}_{ij}(g)}{\sum_{ij} \breve{\theta}_{ij}(g)} = 1 - \frac{\sum_{i=1}^{n} \breve{\theta}_{ii}(g)}{\sum_{ij} \breve{\theta}_{ij}(g)} \tag{9}$$

The directional connectedness (From) from market i to all other markets j is computed as:

$$C_{i \leftarrow *}^{g} = \sum_{j=1, j \neq i} \breve{\theta}_{ij}(g) \;, \tag{10}$$

The directional connectedness (TO) from all other markets j to market i is defined as:

$$C_{i \rightarrow *}^{g} = \sum_{j=1, i \neq j} \breve{\theta}_{ij}(g) \;, \tag{11}$$

Finally, the net directional connectedness can be computed as:

$$C_{i,net}^{g} = C_{i \rightarrow *}^{g} - C_{i \leftarrow *}^{g}, \tag{12}$$

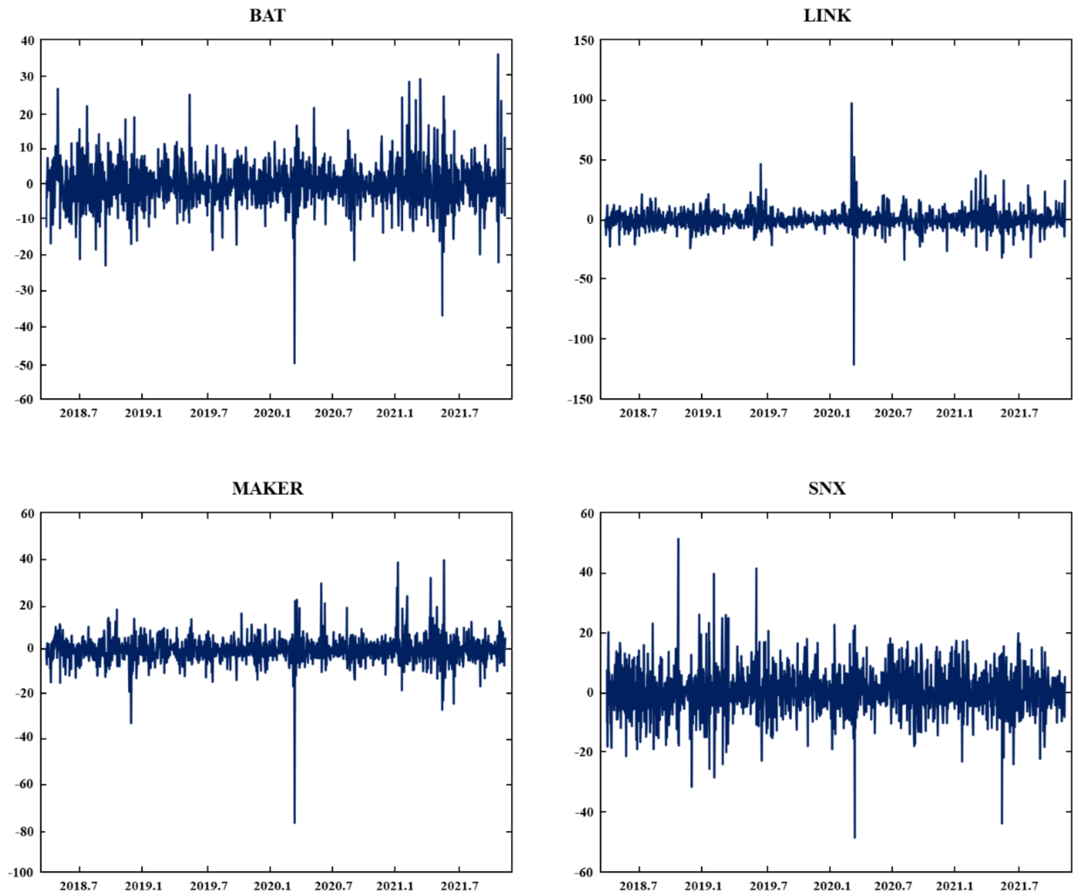
The positive (negative) values of $C_{i,net}^{g}$ determine the net contributor (receiver) of connectedness to (from) all other markets.

3. Data

This paper considers four DeFi assets (BAT, Link, Maker, and SNX) as well as four crypto-currencies (BTC, ETH, LTC, and XRP). The sample period spans since March 14, 2018 to November 20, 2021 and covers the severe repercussions of COVID-19 pandemic. Our dataset is compiled from Bloomberg and Cryptodownload. We calculate daily returns, continuously compounded, by computing the difference in the logarithm percentage of two subsequent prices. Figure 1 displays the evolution of the price returns of DeFi and cryptocurrency markets. We observe a significant fat tails in early 2020 and mid-2021. Similarly, we show volatility clustering in all series, suggesting a nonlinear behavior in all return series.

Table 1 reports the basic statistics of price return series of all markets. We show that the mean return is positive for all series. The Link asset exhibits the highest mean returns with the SNX, BTC, and ETH mean returns going after. Both LTC and XRP show a weak mean return compared to the remaining assets. Link asset shows the largest swings (see max and min values) among all assets. This asset is the highly volatile market as indicated by the standard deviations. Interestingly, the DeFi assets are more volatile than cryptocurrencies. This result may be understood bearing in mind that the DeFi markets represent new and immature markets compared to cryptocurrencies. We observe that all the return series are asymmetric (see skewness values) and leptokurtic (see kurtosis values). The hypothesis of normal distribution is rejected by the Jarque-Bera test at 1% level of significance. Conversely, the hypothesis of normality of return series is accepted for the 8 markets using ADF and KPSS tests. Finally, the results of Ljung-Box test reveal significant serial autocorrelation for all series, except SNX, BTC, and LTC.

Figure 2 illustrates the unconditional correlation matrix among eight DeFi and cryptocurrency markets. The results show ETH is more correlated to DeFi assets than BTC, LTC, and XRP. BAT is highly correlated with cryptocurrencies where the correlation ranges from 0.58 for XRP to 0.67 for ETH. The correlation among DeFi assets is moderate and varies between 0.32 for SNX-Link pair to 0.55 for BAT-Maker pair. The highest correlation is observed between BTC and ETH. This observation is in line with the previous results of Moratis (2021).



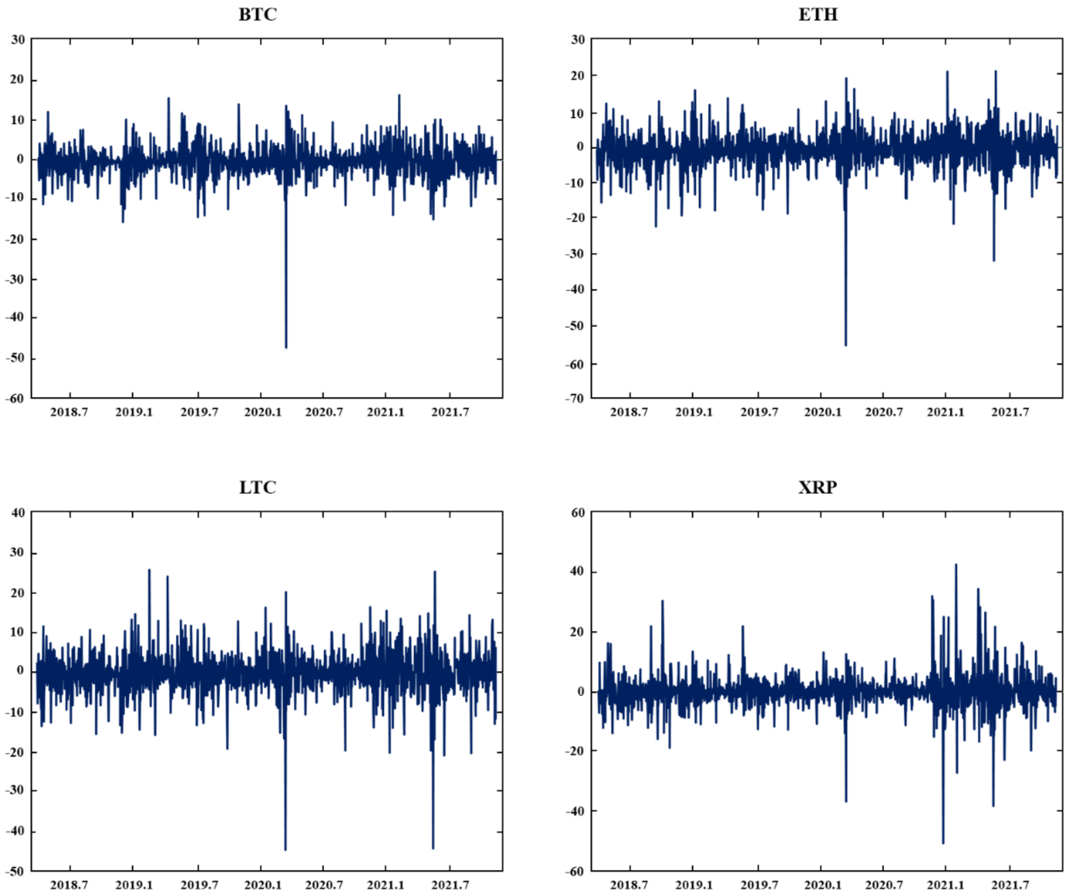


Figure 1. Dynamics of sample returns

Table 1. Preliminary statistics for sample returns

	BAT	Link	Maker	SNX	BTC	ETH	LTC	XRP
Mean(%)	0.1197	0.4676	0.1058	0.2160	0.1473	0.1464	0.0256	0.0345
Max	37.36	100.9	42.27	54.33	17.77	23.40	26.69	44.95
Min	-51.5	-124.6	-81.82	-51.54	-49.39	-57.56	-45.74	-53.89
Std. Dev.	6.3333	8.7815	6.2237	8.3568	3.9979	5.2977	5.4875	6.163
Skew.	-0.0869	-0.4958	-1.0576	0.0854	-1.3639	-1.2038	-0.7593	0.1265
Kurt.	9.9380	48.51	30.70	7.3661	21.99	15.81	11.77	15.05
J.-B.	2705.***	1.1643e+005***	43370. ***	1072.***	20691.***	9551. ***	4453. ***	9577. ***
Q(20)	46.99***	66.04***	48.79***	39.49	36.69	59.16***	38.33	17.60
ADF	-22.24	-20.68	-21.23	-23.11	-21.02	-20.53	-21.51	-21.39
KPSS	0.1078	0.1177	0.1661	0.2717	0.3085	0.7312	0.2809	0.1867

Note: This table presents the sample statistics of the returns. For the autocorrelation of the returns series we use the Ljung-Box test (Q(20)). We present the results of the ADF unit root test of Dickey-Fuller (1979) and KPSS stationary test of Kwiatkowski et al. (1992). *** indicates significance at the 1% level.

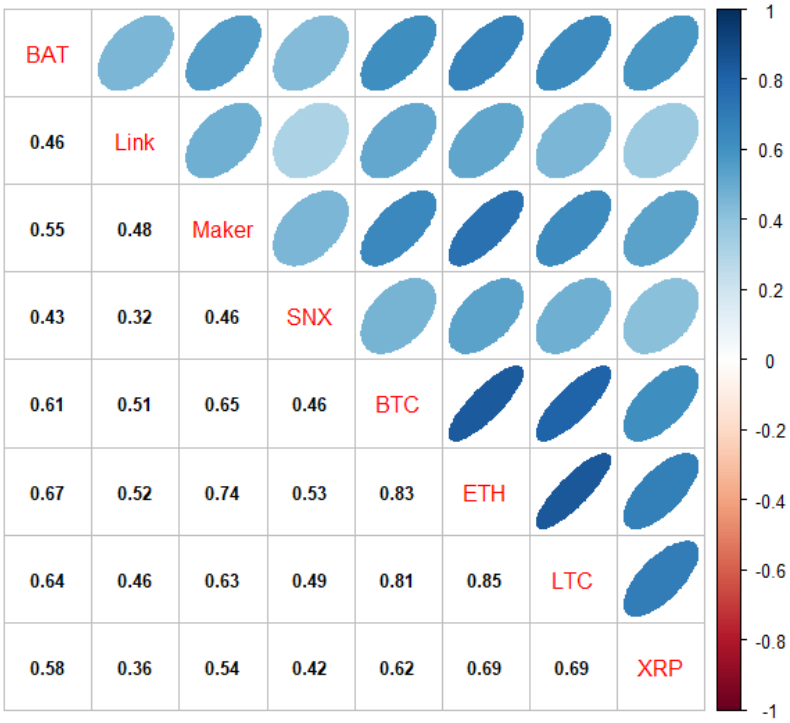


Figure 2. Heat map of the correlation

Notes: The colored disc depicts the strength of the correlation. The color represents the sign of the pairwise correlation (blue = positive and red = negative).

4. Empirical Results

4.1. Connectedness among DeFi and cryptocurrency assets

We use the spillover index approach of DY-12 and the frequency connectedness spillover index of BK-18 to study connectedness within the system composed of four DeFi assets (BAT, Link, Maker, and SNX) and four crypto-currencies (BTC, ETH, LTC, and XRP). Table 2 presents the connectedness estimates for the two employed approaches.

As shown in Table 2, Panel A, the strongest net contributor to the system is ETH with the net connectedness estimate of 25.02%. It is a rather expected result as usually ETH is the cryptocurrency, in which the DeFi asset tokens are predominantly quoted. A similar conclusion, in respect to non-fungible tokens (NFTs) stating that cryptocurrency pricing behaviors might be of some benefit in understanding NFT pricing patterns has been obtained in early literature (Dowling, 2022). Considering the four quadrants Panel A, DeFi-DeFi, DeFi-Crypto; Crypto-DeFi, and Crypto-Crypto, we observe that the connectedness among DeFi assets is the lowest. The DeFi-Crypto, and Crypto-DeFi represent a more pronounced connectedness estimates, while the crypto currency are most strongly connected within their sub-system quadrant. Our results reveal that, for the entire studied time interval, LINK (-20.3%), SNX (-19.85%), BAT (-4.22%), and Maker (-1.70%) play role of net shock recipients of shocks in the network. It is worth highlighting the net recipient role of DeFi assets in contrast to the cryptocurrencies, while vis-à-vis the conventional currencies the DeFi assets predominantly play role of the net transmitters as reported in the early literature (Yousaf et al., 2022).

Table 2. DY and BK connectedness estimate results among DeFi assets and cryptocurrency assets

Panel A : Connectedness Metrics following Diebold and Yilmaz (2012)										
	BAT	Link	Maker	SNX	BTC	ETH	LTC	XRP	FROM	
BAT	30.63	6.3	9.25	5.66	11.49	13.64	12.5	10.54	69.4	
Link	8.72	41.03	9.49	4.1	11.09	11.28	8.79	5.49	59	
Maker	8.95	6.68	29.29	6.06	12.37	16.24	11.87	8.53	70.7	
SNX	7.83	4.05	8.69	41.58	8.83	11.87	9.94	7.2	58.4	
BTC	9.31	6.49	10.56	5.28	24.99	17.36	16.36	9.64	75	
ETH	10.03	6.02	12.43	6.39	15.61	22.6	16.15	10.76	77.4	
LTC	9.88	5.07	9.77	5.8	15.92	17.49	24.31	11.75	75.7	
XRP	10.44	4.05	8.82	5.27	11.73	14.53	14.83	30.34	69.7	
TO	65.2	38.7	69	38.6	87	102.4	90.5	63.9	555.2	
ALL	95.8	79.7	98.3	80.1	112	125	114.8	94.2	69.40%	
NET	-4.22	-20.3	-1.69	-19.85	12.04	25.02	14.76	-5.76		
Panel B: Connectedness Metrics following Baruník and Křehlík (2018)										
	BAT	Link	Maker	SNX	BTC	ETH	LTC	XRP	FROM ABS	FROM WTH
Panel B1: Short-term horizon (1 day to 5 days)										
BAT	25.98	5.28	7.84	4.84	9.9	11.74	10.72	8.98	7.41	8.71
Link	7.58	34.33	8.19	3.62	9.81	9.82	7.74	4.82	6.45	7.58
Maker	7.65	5.69	24.6	5.13	10.56	13.75	10.15	7.29	7.53	8.85
SNX	6.82	3.52	7.5	35.25	7.68	10.28	8.58	6.21	6.32	7.43
BTC	7.91	5.54	9.07	4.55	21.08	14.89	13.87	8.28	8.02	9.42
ETH	8.6	5.08	10.47	5.48	13.3	19.14	13.7	9.22	8.23	9.67
LTC	8.33	4.34	8.23	4.95	13.43	14.87	20.35	9.99	8.02	9.42
XRP	8.7	3.54	7.44	4.49	10.01	12.37	12.75	24.94	7.41	8.71
TO_ABS	6.95	4.12	7.34	4.13	9.34	10.97	9.69	6.85	59.39	
TO_WTH	8.16	4.85	8.63	4.86	10.97	12.89	11.39	8.05		69.79
NET	-0.46	-2.33	-0.19	-2.19	1.32	2.74	1.67	-0.56	0.63	
	BAT	Link	Maker	SNX	BTC	ETH	LTC	XRP	FROM ABS	FROM WTH

Panel B2: Intermediate-term horizon (5 days to 22 days)										
BAT	3.43	0.75	1.04	0.61	1.18	1.4	1.32	1.16	0.93	8.46
Link	0.85	4.95	0.96	0.36	0.95	1.08	0.78	0.5	0.68	6.21
Maker	0.96	0.73	3.47	0.69	1.34	1.84	1.27	0.92	0.97	8.78
SNX	0.75	0.39	0.88	4.68	0.85	1.18	1.01	0.74	0.73	6.58
BTC	1.04	0.7	1.11	0.54	2.89	1.83	1.84	1.01	1.01	9.14
ETH	1.06	0.69	1.45	0.68	1.7	2.56	1.81	1.14	1.07	9.68
LTC	1.15	0.54	1.14	0.63	1.84	1.94	2.93	1.31	1.07	9.68
XRP	1.29	0.38	1.02	0.57	1.28	1.6	1.54	3.98	0.96	8.7
TO_ABS	0.89	0.52	0.95	0.51	1.14	1.36	1.2	0.84	7.41	
TO_WTH	8.04	4.75	8.62	4.61	10.37	12.32	10.86	7.67		67.24
NET	-0.04	-0.16	-0.02	-0.22	0.13	0.29	0.13	-0.12		
	BAT	Link	Maker	SNX	BTC	ETH	LTC	XRP	FROM ABS	FROM WTH
Panel B3: Long-term horizon (22 days to inf. days)										
BAT	1.21	0.27	0.37	0.21	0.41	0.49	0.46	0.41	0.33	8.44
Link	0.3	1.75	0.34	0.12	0.33	0.38	0.27	0.17	0.24	6.14
Maker	0.34	0.26	1.23	0.24	0.47	0.65	0.45	0.32	0.34	8.78
SNX	0.26	0.14	0.31	1.65	0.3	0.41	0.35	0.26	0.25	6.54
BTC	0.37	0.25	0.39	0.19	1.02	0.64	0.65	0.35	0.35	9.12
ETH	0.37	0.24	0.51	0.24	0.6	0.9	0.64	0.4	0.38	9.68
LTC	0.41	0.19	0.4	0.22	0.65	0.68	1.04	0.46	0.38	9.7
XRP	0.46	0.13	0.36	0.2	0.45	0.56	0.54	1.42	0.34	8.69
TO_ABS	0.31	0.18	0.33	0.18	0.4	0.48	0.42	0.3	2.6	
TO_WTH	8.04	4.74	8.62	4.6	10.33	12.29	10.82	7.64		67.08
NET	-0.02	-0.06	-0.01	-0.07	0.05	0.1	0.04	-0.04		

Note: The "FROM" column presents the total connectedness got by the asset i from the entire network. The "TO" row presents the total connectedness emitted by the asset i to the entire network. The "NET" row shows the net each market connectedness.

Our results lead to few implications. First, the considered cryptocurrencies do not seem to be good predictors of BAT and maker. Second, the low connectivity of DeFi markets with the cryptocurrency markets with the average asset-to-asset connectedness across the DeFi-Crypto and Crypto-DeFi quadrants of 9.29%, suggests that the role of DeFi assets in adequate hedging against cryptocurrency market risks should be further addressed in future research.

In Panels B1, B2, and B3, we conclude that the frequency connectedness analysis following the methodology by BK-18 corroborates in general line with the findings from the DY-12 total connectedness index application. For instance, we find that the four considered DeFi assets are the net receivers of innovations from the system in short, medium and long-term analysis, whereas the three cryptocurrencies, namely BTC, ETH, and LTC, are the net shock transmitters into the network. We also highlight another relevant finding. We comparing the sum of the elements in the upper-left quadrant representing connectedness solely within the DeFi assets among themselves with the sum of the elements in the lower-right quadrant representing connectedness solely within the cryptocurrencies among themselves, for the short-, middle-, and long-term. We observe that DeFi assets are connected among themselves much weaker, than the cryptocurrencies with the other cryptocurrencies, implying that the inherent diversification potential of the DeFi assets is superior to that of the cryptocurrencies, revealing a much stronger connectedness among themselves.

Figure 3 provides the total spillover between DeFi and cryptocurrency assets according to both, the DY-12 spillover index and BK-18 time-frequency index methodologies. As shown in Panel A, the DY-12 total spillover varies considerably along the time, thus suggesting that investors may find appropriate to periodically reevaluate and rebalance their investment portfolios. We observe sharp increases in the connectedness metrics across the DeFi and cryptocurrency assets around March 2020, which coincides with the swift advancement of the pandemic. In graphic terms, it is worth comparing the COVID-19 impact on the total spillover to the "rectangular" unit impulse signal function ( ), representing the systemic pandemic-triggered impact, which is superposed with the otherwise "normal" specific trend in the analyzed herein DeFi-cryptocurrencies network, defined mostly by idiosyncratic drivers of the considered DeFi and cryptocurrency markets.

There is also an increase in the spillovers of total returns in the second semester of 2021, highlighting the influence of a widespread optimism in cryptocurrency market at those times. Wrapping up, it is clean that the overall spillover changes its behavior as a results of the COVID-19-caused meltdown in financial markets by the end of the first quarter of 2020 and reveals its sensitivity to remarkable upward trends in the predominant crypto-currency assets.

Panel B of Figure 3 presents total short-, intermediate-, and long-term spillovers in accordance with the BK 18 frequency index model. The short-term spillover is almost identic to the DY-12 total spillover, while intermediate- and long-term spillovers are notoriously weaker, and whose trends differ considerably from the behavior of the short-term spillover, hence, evidencing remarkable deficiencies of the DY-12 spillover index approach. This conclusion corroborates the findings reported by Umar et al. (2022), who studying NFTs and major asset class interrelations by means of the wavelet based technique demonstrate serious shortcomings of the DY-12 spillover index methodology.

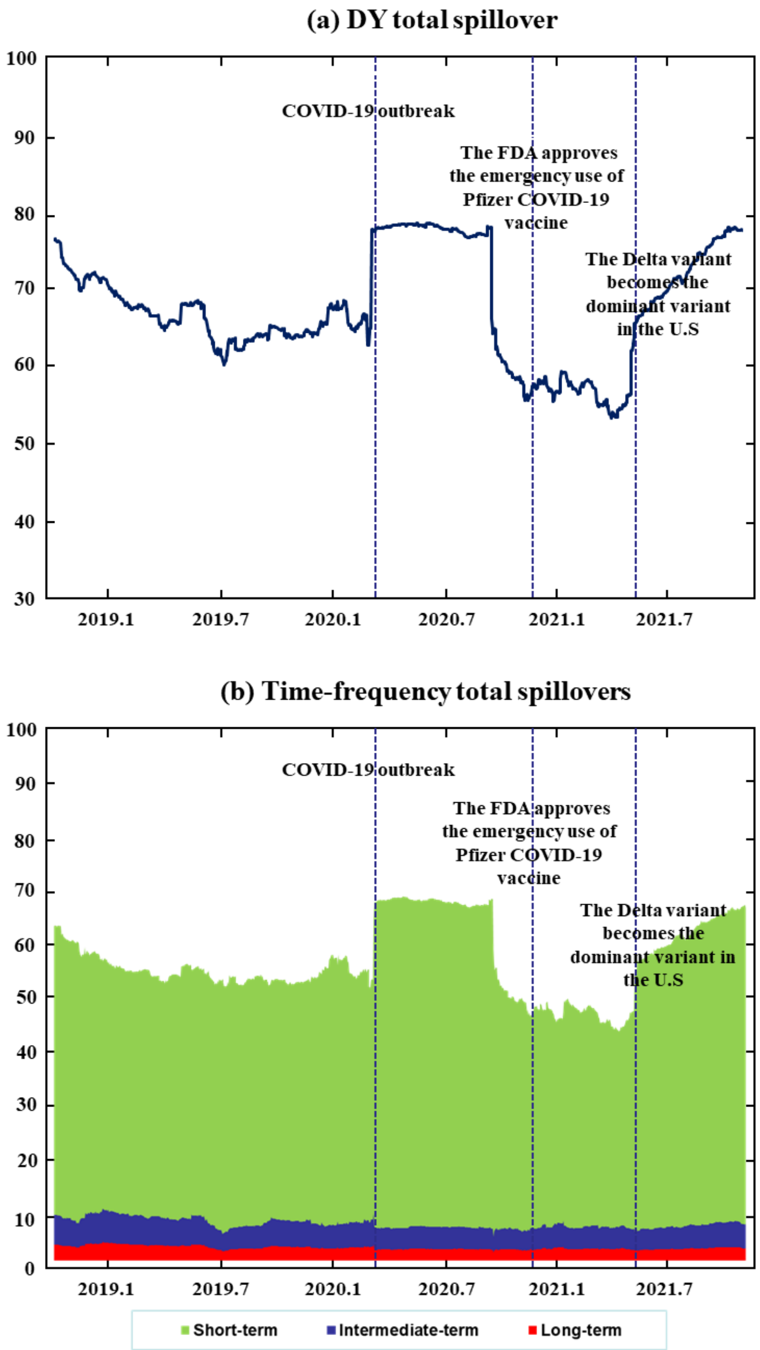
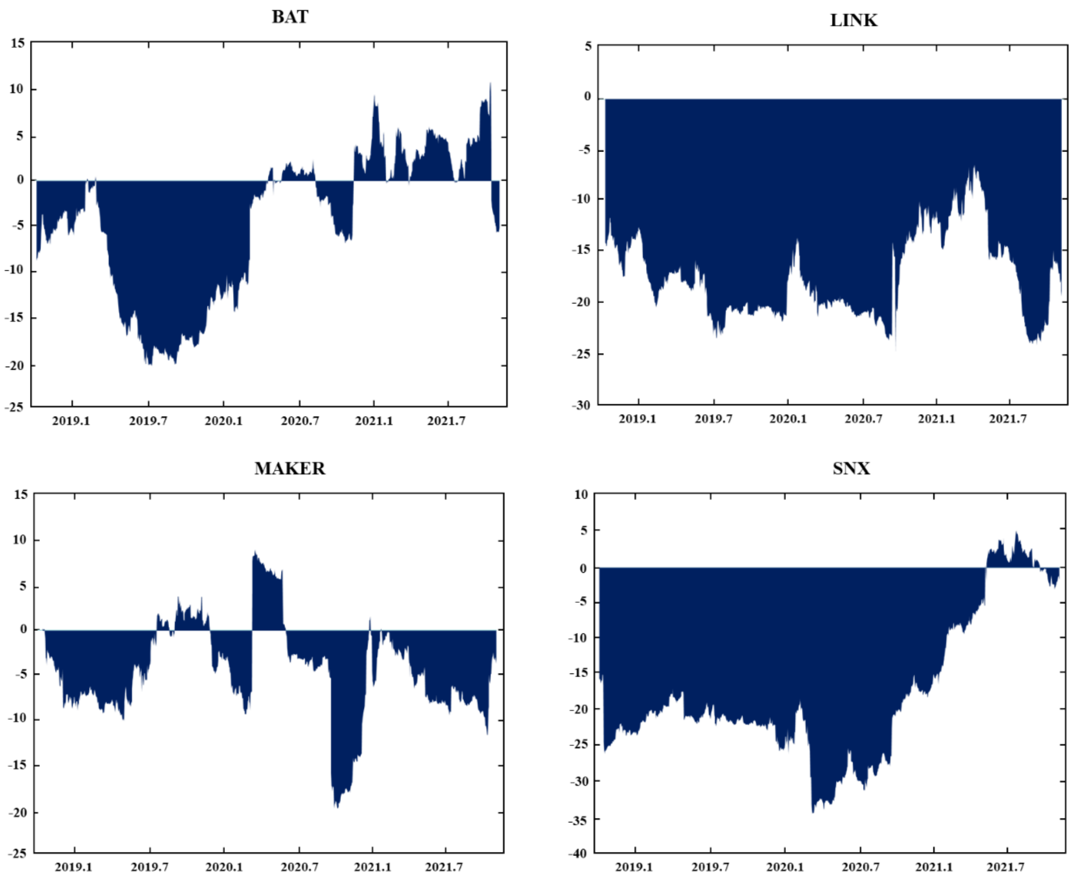


Figure 3. Dynamics of time-frequency total spillovers: (a) DY total spillover; (b) BK total spillover

4.2. Net connectedness

Figure 4 presents the net spillover metrics from each of the considered DeFi and cryptocurrency markets to the entire network according to DY-12 spillover index approach.

There is an abrupt hike in the total spillovers from the BAT, Maker, and BTC markets to the system by the end of March 2020, matching the escalation of the virulent disease, while, on the contrary, for ETH and LTC, we observe a drastic drop in the net connectedness with the system at the same occasion. We also note that, interestingly enough that the profile of the net spillover for ETH, as per Figure 4, is but inverted profile of the DY-12 total spillover metrics and the BK-18 short-term total spillover results; see Figure 3, Panels A and B, respectively. This phenomenon deserves to be further explored in future research in order to uncover the mechanisms at play. However, it seems plausible to argue that ETH does play a distinctive role in the system as it is widely used for quoting DeFi tokens´ prices.



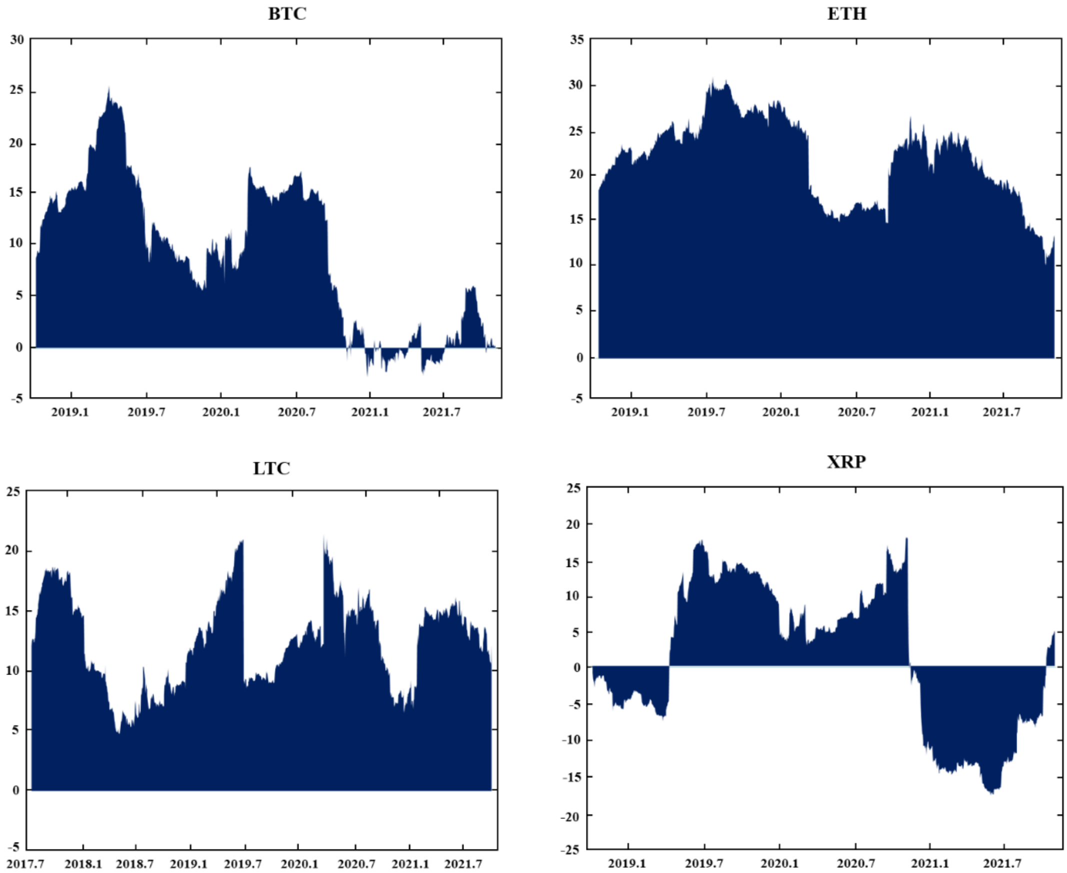
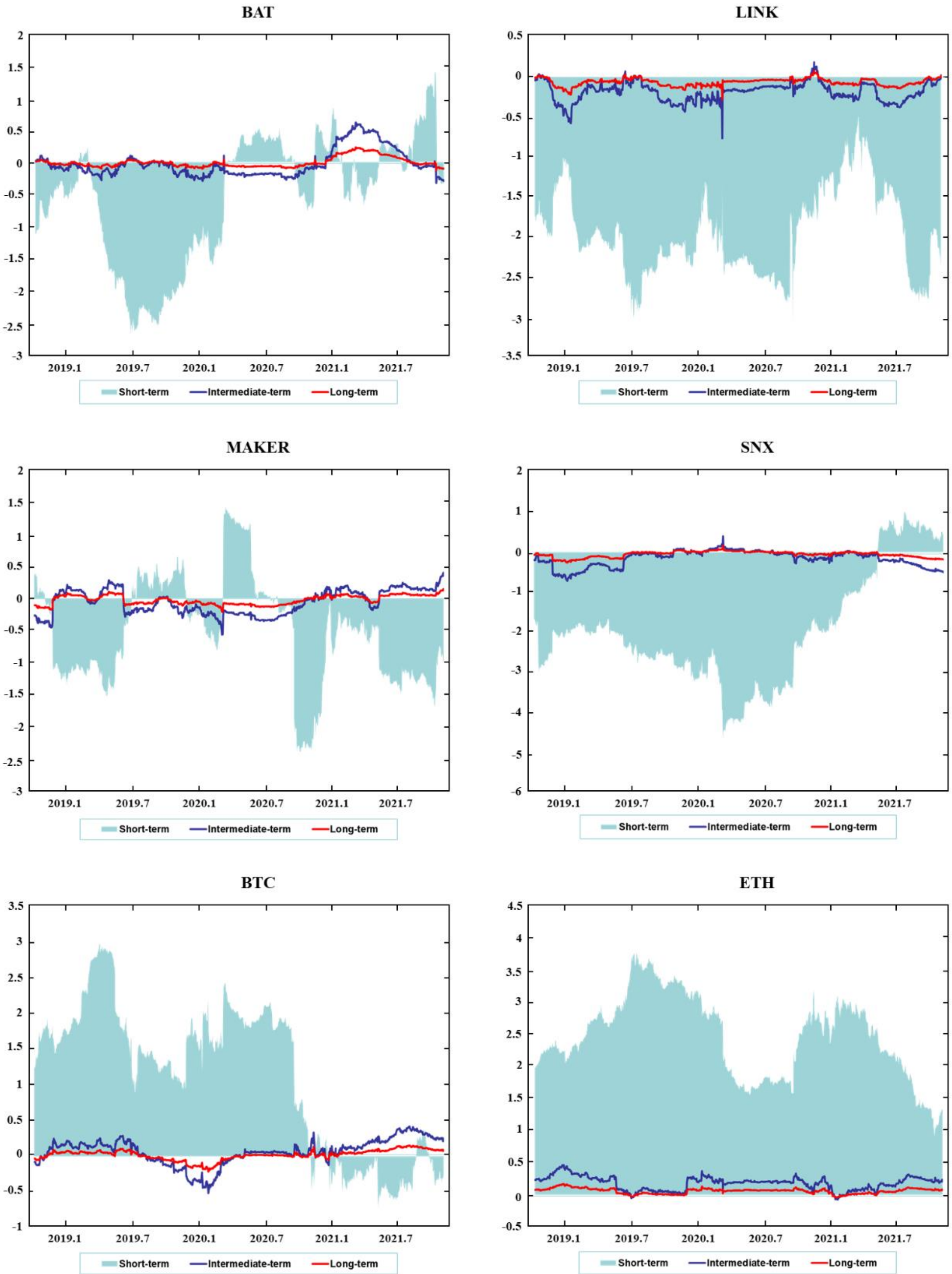


Figure 4. Net directional connectedness of DY method

Figure 5 presents the net spillover time paths from each of the considered DeFi and cryptocurrency markets to the entire network according to the BK-18 time-frequency approach. We observe that the short-terms spillovers are similar to those under the DY 12 spillover index approach, while intermediate- and long-term not so. It is important to highlight that for the DeFi assets, differently from the cryptocurrencies, the onset of the Covid-19 makes their intermediate- and long term spillovers invert their trends vis-à-vis the short term, behaving thus since then in an opposite mode.



BAT
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
2019.1
2019.7
2020.1
2020.7
2021.1
2021.7
Short-term
Intermediate-term
Long-term
LINK
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
2019.1
2019.7
2020.1
2020.7
2021.1
2021.7
Short-term
Intermediate-term
Long-term
MAKER
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
2019.1
2019.7
2020.1
2020.7
2021.1
2021.7
Short-term
Intermediate-term
Long-term
SNX
2
1
0
-1
-2
-3
-4
-5
-6
2019.1
2019.7
2020.1
2020.7
2021.1
2021.7
Short-term
Intermediate-term
Long-term
BTC
3.5
3
2.5
2
1.5
1
0.5
0
-0.5
-1
2019.1
2019.7
2020.1
2020.7
2021.1
2021.7
Short-term
Intermediate-term
Long-term
ETH
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
-0.5
2019.1
2019.7
2020.1
2020.7
2021.1
2021.7
Short-term
Intermediate-term
Long-term

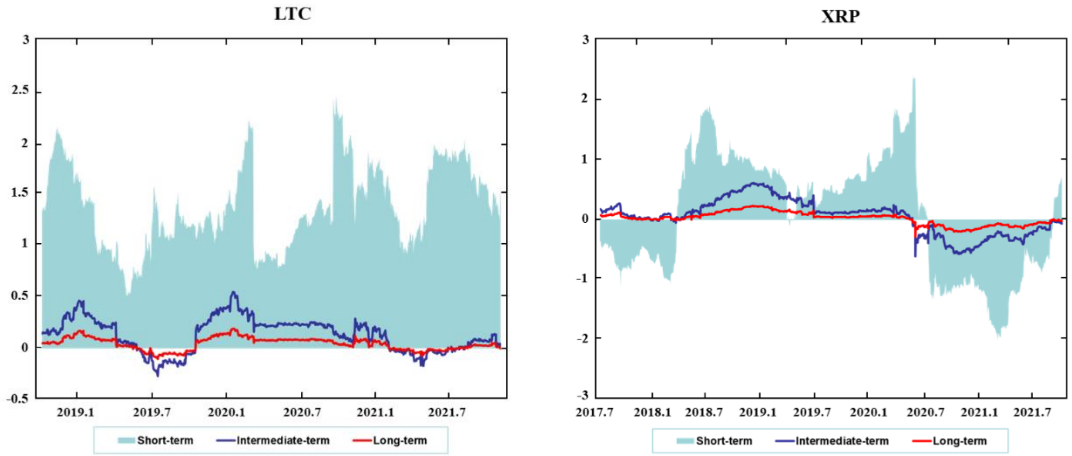
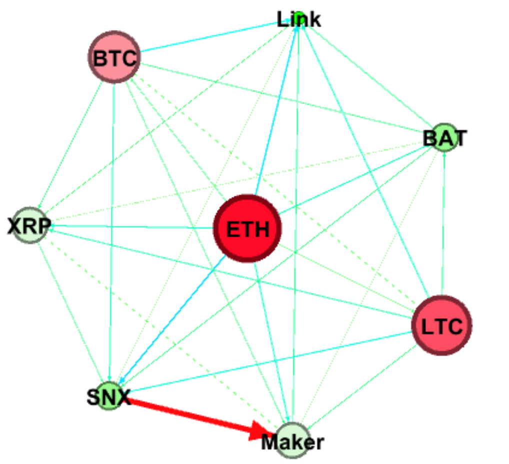


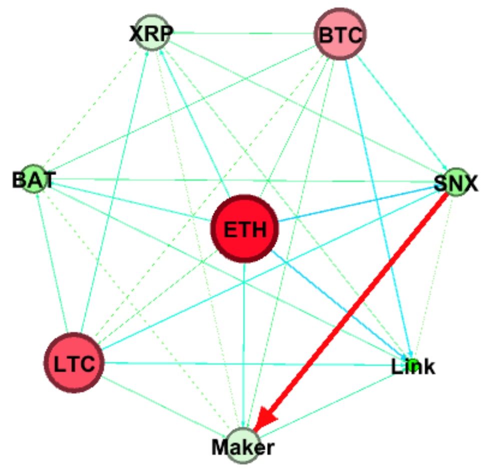
Figure 5. Net directional connectedness for different time horizons (short-term, intermediate-term and long-term).

4.3. Connectedness network analysis

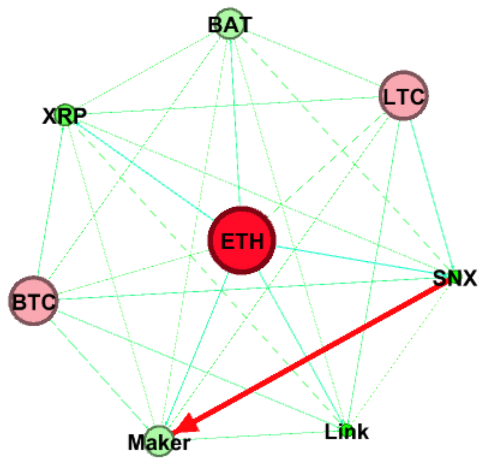
Figure 6 presents the network graphs for the net connectedness at different horizons. The graphs show the strength of the net connectedness within the system over the full sample period. The net connectedness is measured using the DY-12 spillover index and BK-18 time-frequency spillover methodologies. The node size represents the amplitude of each variable contribution to the network connectivity. The node tonality reveals the type of connectedness. The reddish gamma indicates that the analyzed variable contributes to other variables in the network. The greenish tonalities mean that the other variables contribute to the investigated variable. The tonality and the style of the linking arrows indicate the magnitude of the analyzed connectedness linkage. The reddish tonalities and bold lines indicate solid spillovers. The greenish and blue tonalities of the arrow lines represent intermediary and low spillovers, respectively.

Panel A: DY connectedness network **Panel B: Short-term connectedness network**





Panel C: Intermediate-term connectedness network **Panel D: Long-term connectedness network**



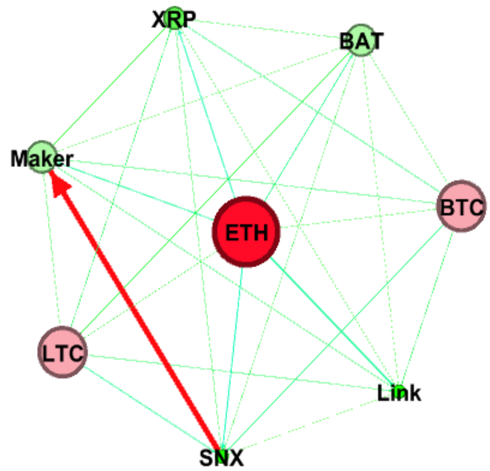


Figure 6. Net connectedness network at different horizons

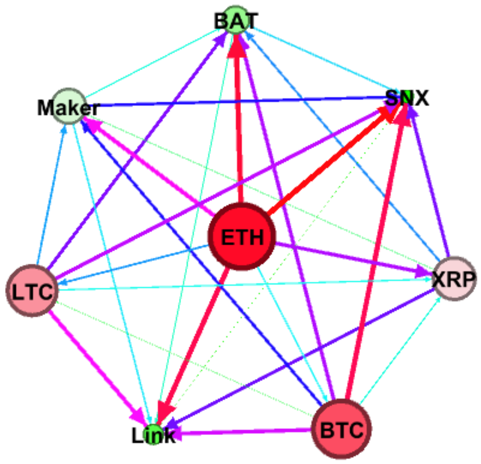
Notes: The plots present the Diebold and Yilmaz (2012) system connectedness charts and Baruník and Křehlík (2018) frequency system connectedness charts; short run corresponds to 1 to 5 days, mid-term corresponds to 5 to 22 days, and long-run regards the above 22 day intervals.

All the graphs in Figure 6 corroborate our finding, obtained in the previous sections that the strongest influencer of the system is ETH, the fact that we ascribe to the ETH-based quotation of the DeFi assets. To the less extent, the two other net transmitters of the influence to the system are BTC and LTC, while the most influence DeFi asset is Maker.

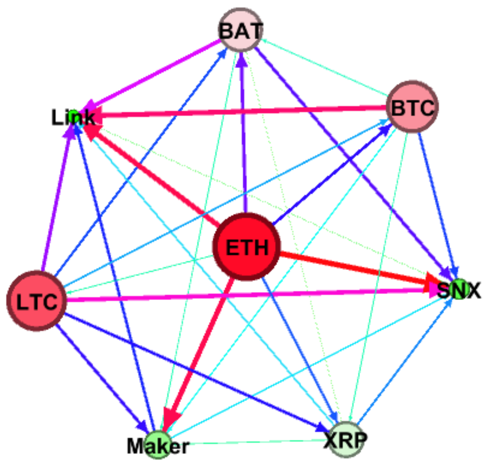
Figure 7 presents the network graphs for the net connectedness at different horizons in accordance with the BK-18 time-frequency spillover model. Although the exact mechanisms at play and pair-wise channels of influence vary as a function of analyzed time horizon and exhibit certain differences for the before-COVID-19 and during-COVID-19 time intervals, the main message is the very same that we have obtained from the analysis of Table 2. The four considered cryptocurrencies are predominantly the transmitters of innovations to the system, in general and to the DeFi assets in particular, while the four analyzed DeFi assets by large play a role of the recipients, mainly receiving shocks form the system and, in particular, from the cryptocurrency markets.

Panel A: Pre-COVID 19

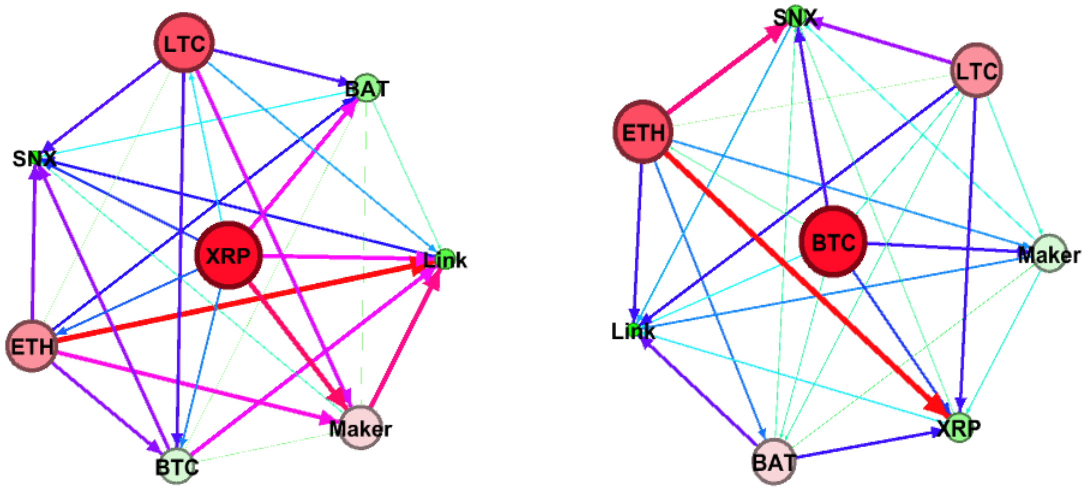
Short-term horizon



Panel B: COVID-19 pandemic



Intermediate-term horizon



Long-term horizon

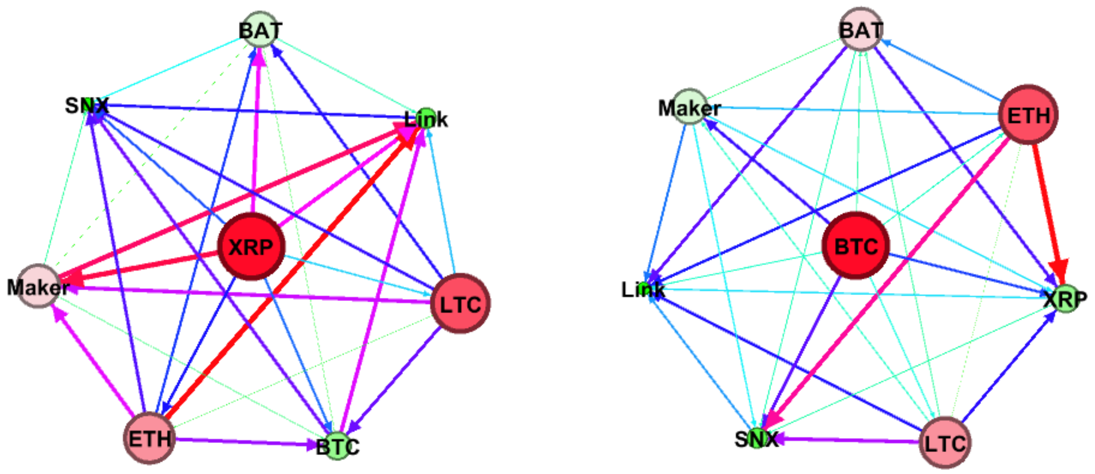


Figure 7. Net connectedness network during pre-COVID 19 and COVID-19 pandemic

5. Conclusion

We have presented the study of the dynamic time-frequency connectedness between the DeFi assets (BAT, Link, Maker, and SNX) and cryptocurrencies (BTC, ETH, LTC, and XRP). Due to the COVID-19 pandemic, a vast body of research focused on documenting empirical evidence on the connectedness among different financial markets appeared. Our work follows this strand by analyzing separately the total static and net dynamic spillover metrics across the

DeFi and cryptocurrency assets. Vis-à-vis an incipient and barely sufficient coverage of DeFi assets in published academic researches, with rare exceptions (Karim et al., 2022; Yousaf et al., 2022), of our work helps to fill the currently existing void, relative to the investigation of separate class of crypto instruments, denominated as DeFi. We use both the Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) approaches, which provide robustness to our findings.

In what concerns the static connectedness, our findings demonstrate weak linkages between DeFi and cryptocurrency assets, implying that DeFi investments are unlikely to represent adequate hedge opportunities to withstand market risk of cryptocurrencies downturns. It is as well found that among cryptocurrencies, the major consistent transmitter of innovations to the system and to DeFi assets is ETH, followed by BTC and LTC that, however, exercise a lesser influence if compared to ETH. This result is consistent across the methodologies used as well as holds for both the before-COVID-19 and during-COVID-19 pandemic time intervals.

Regarding our dynamic spillover analyses, we show that the total spillover in the system as well as the net individual spillover metrics vary along the time, with sharp increases (BAT, Maker, and BTC) or abrupt decreases (ETH and LTC) in connectedness in the first quarter of 2020, during the drastic advancement of the COVID-19 virulent disease. In addition, we show that DeFi assets act preponderantly as net shock receivers throughout the entire sample period comprising both pre-COVID-19 and COVID-19 pandemic periods, although the connectedness of BAT and Maker with the network remains rather weak. This may attract investors in search of diversifying their portfolios of cryptocurrencies to consider certain DeFi assets, such as BAT and Maker. Still, ETH plays a strong net-emitter role along the whole sample period. This outcome may indicate that a need of a certain caution while entering the DeFi market is advisable.

We also report that, interestingly enough, the profile of the net spillover for ETH is but inverted profile of the DY-12 total spillover metrics and the short-term BK-18 total spillover results. This phenomenon deserves to be further explored in future research in order to uncover the mechanisms at play. However, we argue a possible explanation is that ETH does play a distinctive role in the system as it is widely used for quoting DeFi token prices.

Our outcomes convey remarkably useful messages to market players during, especially in times of transversal meltdowns of financial markets and considerable downturns in economic activities, e.g., coronavirus health crisis and/or other systemic risk events of different nature. Cryptocurrency investors may find useful our findings on return spillovers across DeFi and the cryptocurrency assets, allowing to engineer cross-asset and/or cross-currency hedge strategy setups.

Bearing in mind that the transmission and reception dynamics vary along the time for all the considered market segments, policymakers and investors may find useful our spillover analysis results to, respectively, enhance regulatory decisions and improve investment allocation.

For future studies, we suggest that further research in the DeFi assets be carried on as these crypto-instruments are becoming each time increasingly more integrated into the global investment universe, comprising both the traditional financial and crypto assets. It is worth noting that crypto instruments, in general, and DeFi assets, in particular, have become already too much important to disregard and ignore, as nowadays any relevant trouble in the crypto-universe will considerably impact the real world economic activity as well as stability of the global conventional financial system. In this manner, the cross-crypto-instruments studies similar to this research could help improving financial health of both, the real world economy and the crypto-economy of the virtual reality domain.

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