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Connectedness between Defi assets and equity markets during COVID-19: A sector analysis

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A B S T R A C T

This paper explores the dynamic connectedness between Defi assets and sector stock markets focused around the COVID-19 pandemic crisis. For that aim, this research applies the TVP-VAR model, and it also computes the optimal weights and hedge ratios for the Defi assets–sector equity portfolios using the DCC-GARCH model. Our main findings reveal that static connectedness is slightly economy- and sector-dependent. Regarding the dynamic connectedness, as expected, the total spillover index changes over time, showing a cruel impact of the global pandemic declaration. Net spillover indices show relevant differences between the Defi assets and certain sectors (net receivers) and sectors such as industrials, materials and information technology (time-varying net transmitters). Finally, the optimal hedge ratios reveal similar levels of coverage in all the periods analyzed, with slight upturns in the cost of such coverage in the crisis period caused by COVID-19.

1. Introduction

DeFi stands for "decentralized finance" and refers to the ecosystem comprised of financial applications that are being developed on top of blockchain and distributed ledger systems (Popescu, 2020). Defi have several applications (Piñeiro-Chousa et al., 2022a) which, together with their benefits in relation to the traditional financial system (Saengchote, 2021), has contributed to their rapid development. In April 2022, the total value locked in Defi systems was approximately 150bn USD, more than twice as much as two years before (Werner et al., 2021).

Inside this ecosystem, according to Yousaf and Yarovaya (2022b), Defi assets are financial services, without any central authority, operating in a peer-to-peer mechanism based on blockchain technology. In Defi assets, customers connect with each other without intermediate party (e.g., bank) involvement in financial services such as borrowing, lending, spot trading, online wallets, and derivatives, among others. There are multiple Defi assets, including LINK-Chainlink, MKR-Maker, and BAT-Basic Attention Token. LINK is a Chainlink token, used as a means of payment to network node operators. MKR is the governance token of the MakerDAO and Maker Protocol, based on the Ethereum blockchain, that allows users to issue and manage the DAI stablecoin. BAT is the native token of the Brave browser; it also works under the Ethereum blockchain and enables users who view advertisements on different websites to receive a small amount of compensation.

On the other hand, it is interesting to note that the impact of the traditional banking sector and financial assets on sectoral returns is beyond doubt and has been widely contrasted throughout the financial literature. However, the impact of new financial assets such as Defi assets on sector portfolio returns is an underexplored topic in the financial literature. Therefore, the contribution of this new line of research is to explore the connectedness between economic sectors and financial services, and new banking assets, such as Defi assets, especially in a context of economic and financial uncertainty such as the recent global pandemic (Umar et al., 2021b). Regardless of the market capitalization of these Defi assets, they are an irreplaceable asset for many investors, in their role as risk-diversifying or hedging assets, as well as for offering very valuable services for a segment of the population that cannot access traditional banking (Cong et al., 2022) and, of course, for their lower costs than traditional financial services (Scharfman, 2022). Thus, investing in these digital asset classes has become increasingly popular among market participants (regulators, policymakers, and portfolio managers) alike due to these reasons.

This study uses the daily data of three Defi assets (LINK-Chainlink, MKR-Maker, BAT-Basic Attention Token) and eleven US equity sectors

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(C.dis-consumer discretionary, Com.S-communication services, C.Stap-consumer staples, Ener-energy, Fina-financials, H.Car-health care, Inds-industrials, Tech-information technology, Matr-materials, R.est-real estate, Util-utilities). We collect data on the Defi assets and equity sectors from the CoinMarketCap.com and S&P Global websites, respectively. We use three sample periods: the full sample period (January 2, 2019, to October 8, 2021), before COVID-19 (January 2, 2019, to December 31, 2019), and during COVID-19 (January 1, 2020, to October 8, 2021).

Therefore, we investigate the static and time-varying return spillovers between Defi assets and US equity sectors during and before COVID-19 pandemic using the TVP-VAR model. We also compute the optimal weights and hedge ratios for the Defi assets sector equity portfolios during and before COVID-19 pandemic using the DCC-GARCH model.

Thus, to our knowledge, this paper is the first to explore the connectedness in terms of return and volatility between three Defi assets and eleven US sector portfolios. For this purpose, the TVP-VAR methodology is applied, unlike most studies that apply the Diebold and Yılmaz (2014) methodology, which is used in terms of robustness. Furthermore, with the same aim, this paper analyzes not only the full sample period but also the pre-COVID-19 period and the pandemic period. Finally, to obtain valuable information for portfolio managers, this paper calculates the optimal weights as well as the hedging ratios for portfolios formed by sector and Defi assets using the DCC-GARCH model.

Main findings showed a somewhat stage- and sector-dependent nature of the static connectedness. Dynamic connectedness reveals a cruel impact of pandemic declaration in terms of the total spillover index changing over time. A close look at the net spillover indices provides insights into the difference between the Defi assets and certain sectors (net receivers) and sectors such as industries, materials, and information technology (time varying net transmitters). Additionally, the optimal hedge ratios show comparable levels of coverage throughout the different periods analyzed, with slight increases in the cost of such coverage during the crisis period caused by COVID-19. These results have important implications for investment decisions made by portfolio managers, so this research seems to shed light on this issue.

The rest of the paper is structured as follows. Section 2 includes the literature review. Section 3 collects the database used in this research. Section 4 shows the time-varying connectedness methodology applied in this study. Section 5 presents the main results achieved in this research, and, finally, Section 6 provides the main conclusions of the analysis conducted in this study.

2. Literature review

Since 2009, the year in which Bitcoin, the first cryptocurrency, was created, a large amount of cryptocurrency research has begun to proliferate due to the interest of investors and academics. In this respect Corbet et al. (2019) conduct a systematic analysis based on the cryptocurrency research published since 2009 up to August 2018, finding that there are numerous gaps in the cryptocurrency related literature. Even though it is a novel technology, there is nowadays a branch of cryptocurrency literature that studies Defi. Among the most relevant studies that address this topic in a general way are Kiong (2020), who provides a guide on how to use all the major Defi platforms, and Chen and Bellavitis (2020), who study the benefits of decentralized finance, identifying existing business models and evaluating potential challenges and limits. Gudgeon et al. (2020) explore how design weaknesses and price fluctuations in Defi protocols could lead to a Defi crisis; inspired by stress-testing as performed by central banks, they develop a stress-testing framework for a stylized Defi lending protocol, focusing attention on the impact of a drying-up of liquidity on protocol solvency and conclude that it is at risk of financial meltdown that it is supposed to be preventing. Related to the previous research, Werner et al. (2021) delineate the Defi ecosystem along the following axes: its primitives, its operational protocol types and its security, and outline the open research challenges in the ecosystem across these security types. Schär (2021) highlights opportunities and potential risks of the Defi ecosystem, proposing a multi-layered framework to analyze the implicit architecture and the various Defi building blocks, including token standards, decentralized exchanges, decentralized debt markets, blockchain derivatives, and on-chain asset management protocols (Corbet et al., 2021).

While there is a large amount of literature on potential connectedness between financial markets, as well as between cryptocurrencies and other financial assets, the analysis of the connectedness between Defi assets and other asset classes has been scarcely explored. Among the former are the studies of Diebold and Yılmaz (2014), who propose several connectedness measures built from pieces of variance decompositions, arguing that they provide natural and insightful measures of connectedness. They also track the daily time-varying connectedness of major US financial institutions' stock return volatilities in recent years, with emphasis on the financial crisis of 2007–2008. Bação et al. (2018) investigate the information transmission among Bitcoin, Litecoin, Ripple, Ethereum and Bitcoin Cash for the period May 1, 2013, until March 14, 2018, using a VAR modeling approach, concluding that there is a strong contemporaneous correlation and that there is not much evidence of lagged effects. The exception appears to be related to the overreaction of Bitcoin returns to contemporaneous shocks. Symitsi and Chalvatzis (2018) employ an asymmetric multivariate VAR-GARCH model to study spillover effects between Bitcoin and energy and technology companies from August 22, 2011, to February 15, 2018, finding unilateral return and volatility spillovers and bidirectional shock influences, demonstrating portfolio management implications of dynamic conditional correlations. Ciaian et al. (2018) examine interdependencies between Bitcoin and altcoin markets in the short and long run using the autoregressive distributed lag (ARDL) model with daily data of 17 virtual currencies (Bitcoin + 16 alternative virtual currencies) and two altcoin price indices for the period 2013–2016. Their empirical findings confirm that Bitcoin and altcoin markets are indeed interdependent. Walther et al. (2019) apply the GARCH-MIDAS framework to forecast the daily, weekly, and monthly volatility of five highly capitalized cryptocurrencies (Bitcoin, Ethereum, Litecoin, Ripple, and Stellar) as well as the cryptocurrency index CRIX during the 2012–2019 period, finding that the global real economic activity outperforms all other economic and financial drivers under investigation. Charfeddine et al. (2020) compare the financial properties of Bitcoin and Ethereum from July 18th, 2010, to October 1st, 2018, and investigate their dynamic relationship with the S&P 500 and gold and crude oil commodities using different time-varying copula approaches and bivariate dynamic conditional correlation GARCH models. They find that the cross-correlation with conventional assets is changing over time and that the relationship between cryptocurrencies and conventional assets is sensitive to external economic and financial shocks. González et al. (2020) examine the connectedness between Bitcoin returns and returns of ten additional cryptocurrencies for several frequencies, i.e., daily, weekly, and monthly, over the period January 2015–March 2020 using a nonlinear autoregressive distributed lag (NARDL) approach, finding important and positive interdependencies among cryptocurrencies and significant long-run relationships among most of them.

With regard to the study of the connectedness between Defi assets and other asset classes, Corbet et al. (2021) compare five of the largest conventional cryptocurrencies (Ethereum, Ripple, Bitcoin Cash, Litecoin, Binance) with that of the five largest Defi products (Maker, Loopring, Synthetix, Ren and Link) using supremum augmented Dickey–Fuller bubble tests, Hacker-Hatemi-J causality analysis, and DCC-GARCH and Diebold–Yilmaz return and volatility spillover tests. They conclude that Defi bubbles are mainly self-generated but partly catalyzed by Ethereum and Bitcoin. Yousaf and Yarovaya (2022a) examine the return and volatility spillovers between new non-fungible tokens, NFTs, and Defi assets and other asset classes (oil, gold, Bitcoin, and S&P 500) using the generalized vector autoregressive framework. The results report weak static return and volatility spillovers between NFTs and Defi assets and selected markets, showing that these new digital assets are still relatively decoupled from traditional asset classes and Bitcoin. They also compute the static and dynamic optimal weights, hedge ratios, and hedging effectiveness for the portfolios of NFTs/other asset and Defi asset/other asset and show that investors and portfolio managers should consider adding NFTs and Defi assets in their portfolios of gold, oil, and stock markets to achieve diversification benefits. The same conclusion is found in Corbet et al. (2021) and Piñeiro-Chousa et al. (2022b), that conclude that Defi acts, similar to other crypto assets, as a safe haven so the operational process of portfolio construction needs to consider inclusion of Defi cryptocurrencies to optimize diversification. Yousaf et al. (2022a, 2022b) examine the static and dynamic return connectedness among Chainlink, Maker, Basic Attention Token (BAT), and Synthetix, four renowned Defi assets, and four currencies, i.e., the yuan, yen, euro, and pound sterling, using the TVP-VAR framework. The results of the static analysis show a weak linkage between fiat currency and Defi asset markets. The time-varying analysis show that the spillovers become high between fiat currency and Defi asset markets during the initial phase of the COVID-19. Further, the Defi assets are found to be the net transmitters of the spillovers at the initial phase of the COVID-19. Apart from connectedness analysis, Yousaf and Yarovaya (2022b) explore the herding behavior in Defi assets and provide the evidence of time-varying herding for short time spans in this market.

The impact of the COVID-19 crisis and its effects on financial markets has attracted a great deal of interest among researchers (Ali et al. (2020), Bakas and Triantafyllou (2020), Sharif et al. (2020), Gharib et al. (2021), Umar et al. (2021a), Umar et al. (2022), Yousaf et al. (2022b), Mensi et al. (2022), among others), some of whom have focused on the cryptocurrency market and its relationship with other markets. Corbet et al. (2020) examine the potential contagion effects of the COVID-19 pandemic on gold and cryptocurrencies and consider that cryptocurrencies may play a role similar to that of precious metals during economic crises. Umar and Gubareva (2020), Majdoub et al. (2021) and Umar et al. (2021b) analyze the potential interdependences between foreign exchange and cryptocurrency markets from the perspective of contagion and their possible role as safe havens during periods of economic turbulence, such as the SARS-CoV-2 outbreak. Yousaf and Ali (2020) examine the return and volatility spillover between cryptocurrencies during the pre-COVID-19 period and the COVID-19 period, and they also estimate the optimal weights, hedge ratios, and hedging effectiveness during both sample periods. Yousaf and Yarovaya (2022a) capture the effect of the COVID-19 pandemic on the spillovers between NFTs, Defi assets, and other assets.

As was indicated above, papers that studied the interdependences among cryptocurrencies follow different methodologies, such as the quantile regression approach (Jareño et al., 2020), ARDL models (Ciaian et al., 2018; Nguyen et al., 2019), NARDL models (González et al., 2020 and 2021; Jareño et al., 2020), wavelet-based models (Kumar and Ajaz, 2019; Omane-Adjepong and Alagidede, 2019; Mensi et al., 2019; Sharif et al., 2020), VAR models (Bação et al., 2018), GARCH models (Corbet et al., 2020), VAR-GARCH models (Symitsi and Chalvatzis, 2019; Yousaf and Ali, 2020), the time-varying parameter vector autoregression (TVP-VAR) model (Elsayed et al., 2022; Bouri et al., 2021; Umar et al., 2021b), the bivariate diagonal BEKK model (Katsiampa, 2019; Katsiampa et al., 2019), BEKK-GARCH models (Beneki et al., 2019), BEKK-MGARCH models (Tu and Xue, 2019), the GARCH-MIDAS model (Walther et al., 2019), DCC models (Charfeddine et al., 2020; Kumar and Anandarao, 2019), the Diebold and Yilmaz (2009) approach (Koutmos, 2018) and Diebold and Yılmaz (2012) indices (Ji et al., 2019; Umar et al., 2021b), among others.

3. Data

As previously said, this research studies the static and dynamic connectedness between daily data of three Defi assets (LINK-Chainlink, MKR-Maker, BAT-Basic Attention Token) and eleven US sector stock indices (C.dis-consumer discretionary, Com.S-communication services, C.Stap-consumer staples, Ener-energy, Fina-financials, H.Car-health care, Inds-industrials, Tech-information technology, Matr-materials, R.est-real estate, Util-utilities). We selected the eleven US sectors following the sector classification of "global industry classification standards" (GICS).[1] Further, these eleven sectoral indices are extracted from the S&P 500 based on the GICS. To perform pre and during COVID-19 analysis, we use the data of those highly capitalized Defi assets whose data are available from January 2, 2019.[2]

Specifically, data on Defi assets are collected from the CoinMarketCap site, and daily data for sector stock indices are extracted from the S&P Global website. In addition, for robustness, we use three sample periods: the full sample period (January 2, 2019, to October 8, 2021), before COVID-19 (January 2, 2019, to December 31, 2019), and during COVID-19 (January 1, 2020, to October 8, 2021). We use January 1, 2020 as the starting period of the COVID-19 because of the following reasons. First, following the studies of Yousaf and Ali et al. (2020), Kinateder et al. (2021), Umar et al. (2021a, 2021b, 2021c, 2021d), Rouatbi et al. (2021), Zaremba et al. (2021), Chkili et al. (2021), and Huynh et al. (2021), we selected the cutoff point for the start of the COVID-19 as the January 1, 2020. Second, on January 1, 2020, "WHO had set up the IMST (Incident Management Support Team) across the three levels of the organization: headquarters, regional headquarters and country level, putting the organization on an emergency footing for dealing with the virus outbreak".[3] Third, on January 5, "WHO published the first Disease Outbreak News on the new virus" to the whole world. Finally, in the month of January 2020, the information about the virus was spread around the world due to the cases in China and 18 other countries.[4]

Daily continuous-compounding returns (r_t) are calculated as the natural logarithm between two consecutive days as the formula $r_t = ln(P_t/P_{t-1})$, where P_t and P_{t-1} represent the index prices at business days t and $t-1$, respectively. Table 1 collects the main descriptive statistics and unit-root tests for the daily returns of the three Defi assets and eleven US sector stock indices.

First, the returns of the Defi assets and the sector stock markets show average and median values close to zero during the whole sample and the pre-COVID-19 and COVID-19 subperiods, with a negative sign only for the average value of sector energy and a few other exceptions. The standard deviation is between 1 %–8 %, showing the highest values during the subperiod of the pandemic caused by the SARS-CoV-2 coronavirus, as this was a time of greater uncertainty in the financial markets. All the sector stock returns show negative skewness and excess kurtosis, except the Defi assets during the pre-COVID-19 subperiod. Last, the standard unit root (augmented Dickey–Fuller (ADF, 1979) and Phillips–Perron (PP, 1988)) and stationarity (Kwiatkowski–-Phillips–Schmidt–Shin (KPSS, 1992)) tests confirm that all log-return series are stationary.[5]

Furthermore, if we look at the price series of the sector market indices in Fig. 1, Panel A, we can see how the growing trend, common to

[1] https://www.spglobal.com/spdji/en/documents/methodologies/methodology-gics.pdf

[2] Most of the Defi assets were introduced during the COVID-19 period and the data of few highly capitalized Defi assets were available for the pre-COVID-19 period. Yousaf et al., (2022) also used the MKR, LINK, and BAT as the Defi assets.

[3] https://www.who.int/news/item/27-04-2020-who-timeline—covid-19

[4] https://www.who.int/news/item/27-04-2020-who-timeline—covid-19

[5] These results are available upon request.

Table 1
Summary statistics.

	LINK	MKR	BAT	C_DIS	C_STAP	COM_S	ENER	FINA	H_CAR	INDS	MATR	R_EST	TECH	UTIL
Panel A. Full sample period														
Mean	0.00634	0.00231	0.00244	0.00087	0.00048	0.00095	−0.00001	0.00070	0.00058	0.00064	0.00068	0.00057	0.00128	0.00032
Median	0.00517	0.00179	0.00220	0.00190	0.00056	0.00147	0.00028	0.00130	0.00077	0.00113	0.00115	0.00145	0.00213	0.00107
Maximum	0.48062	0.34059	0.30176	0.08286	0.08075	0.08802	0.15111	0.12425	0.07314	0.12001	0.11003	0.08280	0.11300	0.12320
Minimum	−0.61458	−0.81819	−0.51447	−0.12877	−0.09690	−0.11030	−0.22417	−0.15071	−0.10527	−0.12155	−0.12147	−0.18091	−0.14983	−0.12265
Std. Dev.	0.08078	0.07537	0.06880	0.01504	0.01192	0.01477	0.02637	0.01945	0.01331	0.01701	0.01687	0.01694	0.01806	0.01622
Skewness	−0.52681	−1.27152	−0.54005	−1.30783	−0.37034	−0.76025	−0.96236	−0.71154	−0.47443	−0.71616	−0.77036	−1.82068	−0.75570	−0.17729
Kurtosis	11.43008	25.35933	10.13396	16.88296	20.31631	13.21159	16.41414	17.20218	15.36696	15.82742	14.16556	27.17541	16.04028	20.34998
Jarque-Bera	2099.13[a]	14,727.99[a]	1514.07[a]	5804.40[a]	8736.72[a]	3099.94[a]	5340.96[a]	5925.06[a]	4474.240[a]	4845.11[a]	3694.85[a]	17,383.40[a]	5012.02[a]	8758.37[a]
Panel B. Pre-COVID-19														
Mean	0.00507	0.00004	0.00166	0.00070	0.00080	0.00082	−0.00002	0.00088	0.00062	0.00078	0.00074	0.00076	0.00150	0.00085
Median	−0.00150	0.00125	−0.00100	0.00149	0.00086	0.00149	0.00063	0.00153	0.00122	0.00114	0.00131	0.00149	0.00202	0.00123
Maximum	0.48062	0.24093	0.25783	0.02600	0.01803	0.03667	0.03239	0.02672	0.02187	0.02338	0.03362	0.02300	0.03212	0.02118
Minimum	−0.21636	−0.16293	−0.18847	−0.03189	−0.02730	−0.03112	−0.04206	−0.03624	−0.02930	−0.03040	−0.03310	−0.02412	−0.04153	−0.02175
Std. Dev.	0.07335	0.05437	0.05654	0.00869	0.00667	0.00935	0.01197	0.00952	0.00810	0.00947	0.00952	0.00778	0.01065	0.00693
Skewness	1.61276	0.26234	0.09098	−0.59353	−0.58912	−0.30382	−0.28223	−0.66160	−0.69226	−0.56776	−0.29084	−0.44010	−0.61719	−0.16158
Kurtosis	10.85917	5.10785	5.13020	4.48619	4.48605	4.97404	3.39890	4.84457	4.27626	3.96532	4.07658	3.28351	4.85129	3.53150
Jarque-Bera	727.719[a]	47.5765[a]	46.089[a]	36.4802[a]	36.2658[a]	43.016[a]	4.8172[c]	51.9627[a]	35.752[a]	22.397[a]	15.0985[a]	8.6224[b]	49.9223[a]	4.9015
Panel C. During the COVID-19														
Mean	0.00605	0.00393	0.00316	0.00086	0.00026	0.00091	−0.00014	0.00053	0.00049	0.00048	0.00062	0.00033	0.00113	0.00001
Median	0.00991	0.00228	0.00478	0.00250	0.00043	0.00138	−0.00049	0.00104	0.00057	0.00107	0.00113	0.00134	0.00217	0.00047
Maximum	0.28941	0.34059	0.30176	0.08286	0.08075	0.08802	0.15111	0.12425	0.07314	0.12001	0.11003	0.08280	0.11300	0.12320
Minimum	−0.61458	−0.81819	−0.51447	−0.12877	−0.09690	−0.11030	−0.22417	−0.15071	−0.10527	−0.12155	−0.12147	−0.18091	−0.14983	−0.12265
Std. Dev.	0.08319	0.08494	0.07495	0.01752	0.01400	0.01698	0.03170	0.02320	0.01539	0.01994	0.01975	0.02035	0.02090	0.01955
Skewness	−1.37653	−1.45703	−0.68312	−1.26356	−0.29137	−0.77214	−0.84920	−0.61482	−0.41836	−0.64879	−0.73484	−1.60104	−0.68155	−0.11116
Kurtosis	12.15527	24.21828	10.36115	14.12377	16.53743	11.50088	12.23619	13.18208	13.19258	12.94909	11.62649	20.32266	13.65717	15.05565
Jarque-Bera	1702.29[a]	8543.420[a]	1043.98[a]	2423.57[a]	3419.57[a]	1390.35[a]	1642.57[a]	1959.10[a]	1947.96[a]	1874.94[a]	1426.23[a]	5779.85[a]	2149.94[a]	2707.85[a]

Notes: LINK - Chainlink, MKR - Maker, BAT - Basic Attention Token, C.dis-consumer discretionary, Com.S-communication services, C.Stap-consumer staples, Ener-energy, Fina-financials, H.Car-health care, Inds-industrials, Tech-information technology, Matr-materials, R.est-real estate, Util-utilities. [a, b, c] denotes the 1 %, 5 %, and 10 % level of significance.

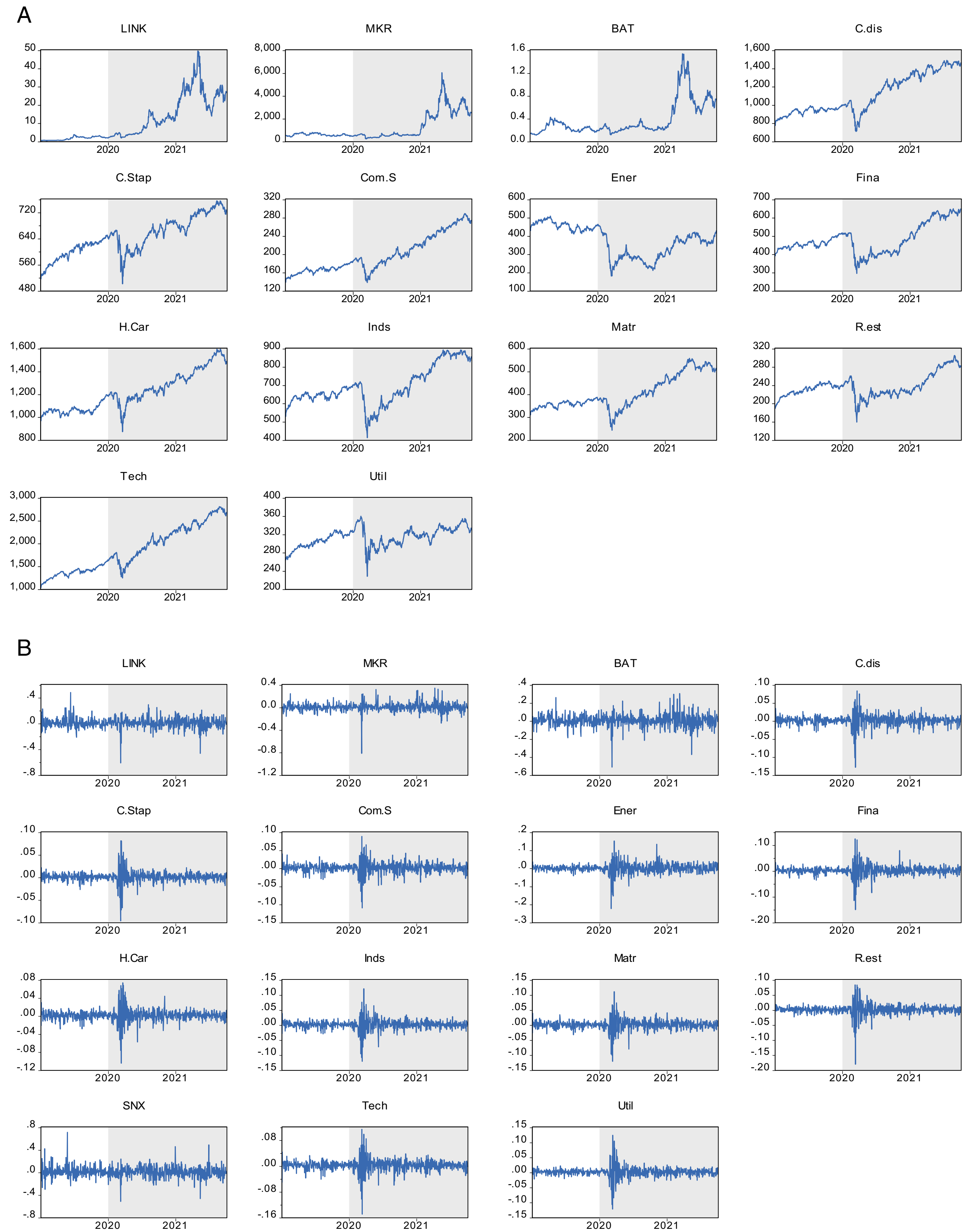

Fig. 1. Panel A: Prices
Panel B: Returns.

Table 2
Unconditional correlations.

	LINK	MKR	BAT	C_DIS	C_STAP	COM_S	ENER	FINA	H_CAR	INDS	MATR	R_EST	TECH	UTIL
Panel A. Full sample period														
LINK	1.000													
MKR	0.558	1.000												
BAT	0.584	0.543	1.000											
C_DIS	0.234	0.288	0.298	1.000										
C_STAP	0.221	0.271	0.260	0.710	1.000									
COM_S	0.235	0.268	0.272	0.864	0.728	1.000								
ENER	0.195	0.238	0.230	0.596	0.520	0.568	1.000							
FINA	0.212	0.261	0.254	0.742	0.714	0.705	0.819	1.000						
H_CAR	0.203	0.240	0.222	0.753	0.809	0.760	0.569	0.731	1.000					
INDS	0.227	0.268	0.278	0.785	0.748	0.719	0.792	0.921	0.768	1.000				
MATR	0.258	0.284	0.302	0.771	0.740	0.709	0.762	0.883	0.761	0.915	1.000			
R_EST	0.204	0.229	0.235	0.714	0.781	0.675	0.578	0.750	0.756	0.771	0.744	1.000		
TECH	0.225	0.273	0.286	0.899	0.741	0.882	0.562	0.717	0.808	0.758	0.754	0.704	1.000	
UTIL	0.206	0.225	0.214	0.599	0.819	0.596	0.464	0.661	0.731	0.681	0.674	0.833	0.608	1.000
Panel B. Pre-COVID-19														
LINK	1.000													
MKR	0.296	1.000												
BAT	0.284	0.436	1.000											
C_DIS	−0.039	−0.029	0.014	1.000										
C_STAP	−0.027	−0.013	0.023	0.564	1.000									
COM_S	−0.005	0.007	0.068	0.770	0.474	1.000								
ENER	0.013	0.013	0.078	0.575	0.290	0.501	1.000							
FINA	0.004	−0.020	0.048	0.737	0.462	0.596	0.657	1.000						
H_CAR	−0.012	−0.069	−0.002	0.612	0.535	0.587	0.460	0.576	1.000					
INDS	0.001	−0.019	0.069	0.778	0.494	0.602	0.681	0.820	0.582	1.000				
MATR	−0.014	−0.042	0.049	0.676	0.500	0.489	0.583	0.739	0.552	0.810	1.000			
R_EST	0.029	0.017	0.076	0.324	0.521	0.306	0.058	0.148	0.408	0.243	0.227	1.000		
TECH	−0.007	0.003	0.064	0.855	0.507	0.755	0.582	0.715	0.644	0.770	0.673	0.303	1.000	
UTIL	0.006	0.006	0.019	0.131	0.549	0.171	−0.039	0.055	0.323	0.065	0.074	0.600	0.119	1.000
Panel C. During the COVID-19														
LINK	1.000													
MKR	0.656	1.000												
BAT	0.703	0.571	1.000											
C_DIS	0.314	0.350	0.359	1.000										
C_STAP	0.283	0.327	0.312	0.729	1.000									
COM_S	0.303	0.325	0.321	0.878	0.764	1.000								
ENER	0.243	0.274	0.261	0.599	0.543	0.578	1.000							
FINA	0.266	0.308	0.295	0.744	0.741	0.721	0.833	1.000						
H_CAR	0.265	0.306	0.272	0.771	0.847	0.784	0.583	0.751	1.000					
INDS	0.294	0.323	0.325	0.785	0.779	0.735	0.805	0.934	0.792	1.000				
MATR	0.338	0.346	0.356	0.782	0.770	0.739	0.782	0.900	0.789	0.927	1.000			
R_EST	0.250	0.266	0.271	0.761	0.810	0.724	0.620	0.804	0.802	0.829	0.801	1.000		
TECH	0.300	0.330	0.337	0.906	0.774	0.903	0.562	0.719	0.829	0.754	0.763	0.757	1.000	
UTIL	0.257	0.264	0.254	0.650	0.847	0.647	0.502	0.713	0.780	0.743	0.735	0.851	0.664	1.000

Notes: LINK - Chainlink, MKR - Maker, BAT - Basic Attention Token, C.dis-consumer discretionary, Com.S-communication services, C.Stap-consumer staples, Ener-energy, Fina-financials, H.Car-health care, Inds-industrials, Tech-information technology, Matr-materials, R.est-real estate, Util-utilities.

all of them, was cut short by the declaration of a global pandemic, which led to an abrupt fall in all sectors without exception. However, we also can observe how the prices of the sector market indices recovered, returning to current levels, following the previous upward trend. The impact of COVID-19 also can be seen in the representation of the Defi assets and sector stock market returns (Fig. 1, Panel B), which show high volatility around the pandemic declaration by the World Health Organization (WHO).

The aforementioned drop in sector index prices is not as evident in the Defi assets included in this study. Moreover, unconditional correlations (Table 2) are high and of positive sign between Defi assets and sector stock market returns in all periods, except in the pre-COVID-19 subperiod, where we find some negative correlations between Defi assets and some sectors.

4. Methodology

We utilize the TVP-VAR framework to investigate the connectedness between Defi and US sectoral equity markets, this framework was introduced by Koop and Korobilis (2014) combined with the connectedness approach of Diebold and Yılmaz (2012, 2014). We use the TVP-VAR framework because it is useful in estimating the total connectedness, pairwise connectedness, connectedness from system to each market, connectedness from each market to system, and net connectedness. The main advantage of this approach is that it allows the variances to vary over time via a Kalman filter estimation that relies on decay factors. Thus, the TVP-VAR approach overcomes the burden of an arbitrarily chosen rolling window size, which leads to very erratic or flattened parameters, and loss of valuable observations (Antonakakis and Gabauer, 2017; Gabauer and Gupta, 2018; Korobilis and Yılmaz, 2018).

According to the Bayesian information criterion (BIC), we employ a TVP-VAR (1), which can be written as follows:

$$Y_t = \Phi_t Y_{t-1} + u_t; u_t \backslash \Omega_{t-1} \backsim N(0, S_t) \tag{1}$$

$$\Phi_t = \Phi_{t-1} + v_t; v_t \backslash \Omega_{t-1} \backsim N(0, R_t) \tag{2}$$

where Y_t is a $(N \times 1)$ vector and Ω_{t-1} is the set of information available at $t-1$. Y_{t-1} denotes a $(Np \times 1)$ lagged vector of the dependent variables.

Table 3
Static spillovers during the full sample period.

	LINK	MKR	BAT	C.dis	Com.S	C. Stap	Ener	Fina	H.Car	Inds	Tech	Matr	R.est	Util	FROM others
LINK	51.26	13.38	14.2	2.03	2.1	2.01	1.57	1.96	1.8	2.15	2.03	2.62	1.32	1.58	48.74
MKR	12.99	49.36	12.6	2.83	2.52	2.1	2.2	2.29	2.15	2.52	2.57	2.79	1.56	1.52	50.64
BAT	13.6	12.09	47.62	3.11	2.77	1.86	2.33	2.1	1.82	2.91	2.95	3.31	2.04	1.48	52.38
C.dis	1.16	1.56	1.6	18.47	11.83	4.7	5.88	5.61	7.87	8.57	13.27	8.55	7.52	3.4	81.53
Com.S	1.15	1.4	1.49	12.17	19.02	6.25	5.1	6.5	8.88	7.34	13.23	7.09	6.36	4.03	80.98
C.Stap	1.31	1.49	1.29	5.06	6.82	21.79	2.72	9.85	9.88	7.44	7.02	6.92	7.06	11.35	78.21
Ener	1.23	1.49	1.46	7.41	6.31	3.19	23.91	11.01	5.77	12.04	6.35	11.47	5.68	2.67	76.09
Fina	1.15	1.33	1.2	5.65	6.59	8.67	8.49	19.26	7.19	11.78	7.09	10.05	5.8	5.74	80.74
H.Car	0.96	1.17	1.08	7.9	8.63	8.62	4.5	6.92	18.69	8.7	9.9	8.74	7.42	6.77	81.31
Inds	1.01	1.19	1.4	7.86	6.57	6	8.52	10.61	8.04	16.9	7.42	12.69	6.43	5.36	83.1
Tech	1.11	1.35	1.5	12.66	12.28	6.13	4.96	6.6	9.47	7.82	17.55	7.99	6.86	3.71	82.45
Matr	1.22	1.45	1.67	8.05	6.51	5.8	8.35	9.41	8.22	12.98	7.76	17.32	6.41	4.86	82.68
R.est	1.08	1.16	1.24	8.44	6.91	6.77	4.98	6.1	8.33	7.66	7.87	7.56	22.11	9.8	77.89
Util	1.17	1.2	1.13	4.13	4.93	13.05	2.56	7.16	8.81	7.4	4.74	6.6	11.37	25.75	74.25
TO others	39.16	40.26	41.85	87.31	84.78	75.14	62.16	86.12	88.23	99.3	92.19	96.39	75.83	62.26	1030.99
Inc. own	90.42	89.62	89.47	105.79	103.8	96.93	86.07	105.38	106.92	116.21	109.74	113.71	97.94	88.01	TCI
NET	−9.58	−10.38	−10.53	5.79	3.8	−1.07	−13.93	5.38	6.92	16.21	9.74	13.71	−2.06	−11.99	73.64

Notes: LINK - Chainlink, MKR - Maker, BAT - Basic Attention Token, C.dis-consumer discretionary, Com.S-communication services, C.Stap-consumer staples, Ener-energy, Fina-financials, H.Car-health care, Inds-industrials, Tech-information technology, Matr-materials, R.est-real estate, Util-utilities.

Table 4
Static spillovers during the pre-COVID-19 subperiod.

	LINK	MKR	BAT	C.dis	Com.S	C.Stap	Ener	Fina	H.Car	Inds	Tech	Matr	R.est	Util	FROM others
LINK	83.13	7.45	6.43	0.35	0.19	0.72	0.12	0.6	0.37	0.24	0.08	0.1	0.18	0.06	16.87
MKR	7.61	77.04	13.63	0.13	0.06	0.04	0.19	0.26	0.37	0.11	0.15	0.26	0.08	0.07	22.96
BAT	6	13.25	75.35	0.29	0.66	0.12	1.41	0.14	0.08	0.91	0.66	0.64	0.39	0.09	24.65
C.dis	1.64	1.13	0.89	25.5	12.93	1.56	10.11	2.44	6.06	9	14.01	9.67	4.31	0.73	74.5
Com.S	1.32	0.71	1.05	15.02	29.52	1.61	7.49	3.25	8.45	7.36	14.96	5.89	2.88	0.51	70.48
C.Stap	2.05	1.3	1.62	1.79	2.54	38.73	0.78	19.34	8.72	3.53	4.32	1.79	2.14	11.35	61.27
Ener	2.59	1.02	0.97	12.62	8.2	0.55	31	2.53	5.54	12.18	9.32	12.32	0.76	0.42	69
Fina	1.67	1.72	1.15	3.18	4.4	18.56	2.58	35.9	7.16	7.7	8.73	3.63	1.19	2.43	64.1
H.Car	1.25	0.67	1.01	6.91	8.43	6.27	5.15	5.64	29.43	9.24	10.96	8.32	3.79	2.93	70.57
Inds	1.39	0.72	1.33	9.21	6.58	2.32	10.14	5.81	8.39	26.48	9.31	15.47	1.22	1.64	73.52
Tech	1.69	1.01	0.94	13.83	12.55	2.62	7.61	5.72	9.25	8.77	24.75	8.21	2.66	0.39	75.25
Matr	1.29	1.12	1.38	10.66	5.71	1.51	11.09	3.46	8.05	16.45	9.21	27.97	1.71	0.38	72.03
R.est	3.27	2.02	0.9	8.49	4.92	2.93	1.22	2.05	6.43	2.27	5.47	3.14	49.67	7.21	50.33
Util	2.17	1.89	1.39	1.45	1.23	16.66	0.79	4.95	5.83	3.16	1.01	0.78	7.94	50.75	49.25
TO others	33.94	34.01	32.69	83.92	68.41	55.47	58.68	56.17	74.71	80.92	88.19	70.21	29.25	28.21	794.79
Inc. own	117.07	111.04	108.04	109.42	97.93	94.2	89.67	92.07	104.14	107.41	112.94	98.18	78.92	78.95	TCI
NET	17.07	11.04	8.04	9.42	−2.07	−5.8	−10.33	−7.93	4.14	7.41	12.94	−1.82	−21.08	−21.05	56.77

Notes: LINK - Chainlink, MKR - Maker, BAT - Basic Attention Token, C.dis-consumer discretionary, Com.S-communication services, C.Stap-consumer staples, Ener-energy, Fina-financials, H.Car-health care, Inds-industrials, Tech-information technology, Matr-materials, R.est-real estate, Util-utilities.

Table 5
Static spillovers during the COVID-19 subperiod.

	LINK	MKR	BAT	C.dis	Com.S	C.Stap	Ener	Fina	H.Car	Inds	Tech	Matr	R.est	Util	FROM others
LINK	41.67	16.89	17.56	1.16	1.6	2.64	2.55	1.27	1.17	2.09	2.8	3.9	2.23	2.47	58.33
MKR	16.64	41.33	12.58	0.58	2.99	3.03	2.98	3.01	2.88	1.5	4.41	3.29	2.32	2.45	58.67
BAT	16.74	11.69	38.05	0.41	5.04	2.39	2.73	4.65	4.16	0.74	5.58	2.55	2.68	2.59	61.95
C.dis	1.34	0.89	0.9	27.77	3.5	8.65	3.26	4.05	3.99	19.54	2.53	13.52	6.23	3.82	72.23
Com.S	1.46	2.21	3.19	2.49	21.12	5.21	3.13	13.71	15.63	1.62	15.75	2.57	6.08	5.82	78.88
C.Stap	2.15	2.19	1.71	6.6	3.61	20.2	5	3.34	4.69	9.85	6.57	11.1	11.03	11.97	79.8
Ener	2.05	2.4	1.96	2.62	3.03	6.65	27.37	8.65	3.16	10.24	4.97	12.9	8.68	5.31	72.63
Fina	1.37	2.15	2.95	2.77	13.89	4.5	6.71	21	15.12	1.78	11.05	3.83	6.54	6.32	79
H.Car	1.17	2.05	2.72	2.74	16.11	5.13	2.89	15.08	21.9	1.03	14.14	1.94	6.22	6.89	78.1
Inds	1.49	1.26	0.89	15.61	1.78	10.27	8.31	2.34	1.68	21.96	2.05	17.42	8.92	6.01	78.04
Tech	1.98	2.66	3.24	1.64	14.58	7.12	4.37	10.66	13.13	1.85	19.3	4.32	8.41	6.73	80.7
Matr	2.17	1.96	1.56	10.17	2.41	10.34	9.06	4.14	2.48	15.75	4.12	19.4	9.2	7.24	80.6
R.est	1.83	1.83	2.03	4.04	5.14	10.6	6.31	6.01	6.12	7.6	8.17	9.16	19.25	11.91	80.75
Util	1.62	1.64	2.08	3.53	7.08	11.48	3.91	7.73	8.91	5.46	7.7	7.01	11.99	19.84	80.16
TO others	52.03	49.82	53.38	54.36	80.77	88.04	61.21	84.64	83.11	79.05	89.84	93.52	90.54	79.54	1039.85
Inc. own	93.7	91.15	91.43	82.13	101.8	108.2	88.58	105.64	105.01	101.01	109.14	112.91	109.79	99.38	TCI
NET	−6.3	−8.85	−8.57	−17.87	1.89	8.24	−11.42	5.64	5.01	1.01	9.14	12.91	9.79	−0.62	74.28

Notes: LINK - Chainlink, MKR - Maker, BAT - Basic Attention Token, C.dis-consumer discretionary, Com.S-communication services, C.Stap-consumer staples, Ener-energy, Fina-financials, H.Car-health care, Inds-industrials, Tech-information technology, Matr-materials, R.est-real estate, Util-utilities.

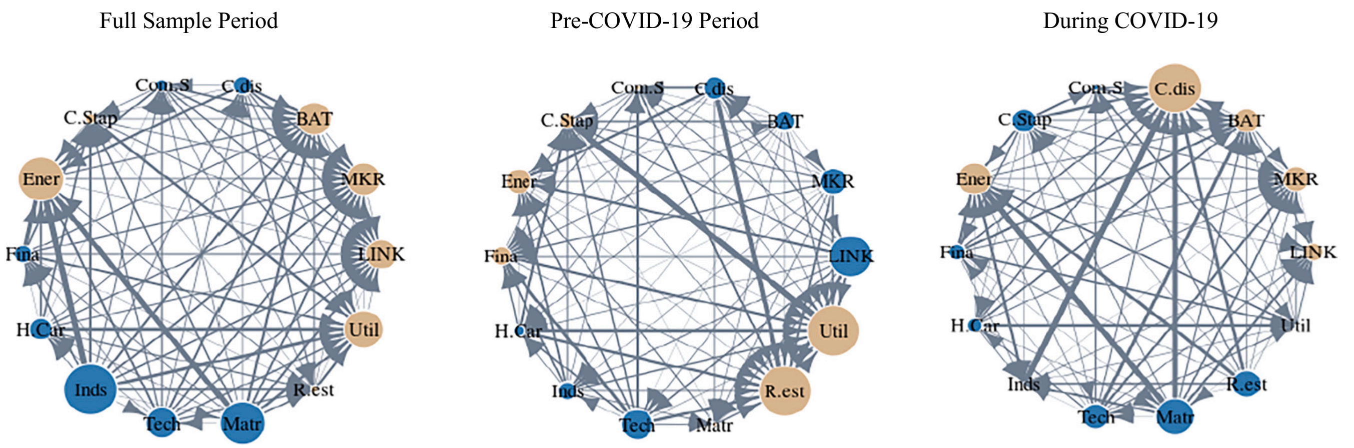

Fig. 2. Network diagram of Net pairwise spillovers
[Blue (yellow) nodes illustrate net transmitter (receiver) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. Size of nodes represent weighted average net total directional connectedness.] (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

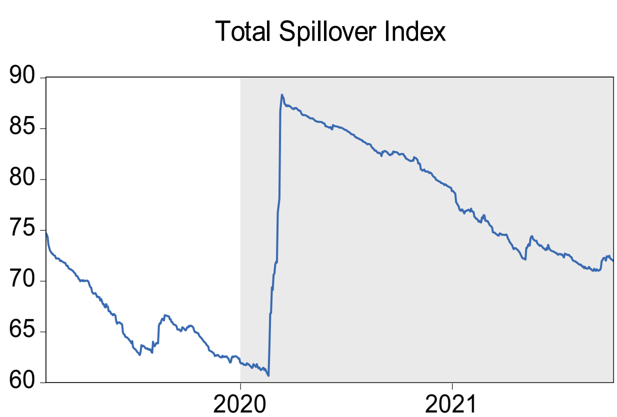

Fig. 3. Total spillovers index.

Φ_t is an $(N \times Np)$ matrix of coefficients, which is supposed to be time-varying. u_t and v_t are two $(N \times 1)$ vectors of the error terms. S_t and R_t are $(N \times N)$ and $(Np \times Np)$ time-varying variance-covariance matrices of the error terms u_t and v_t, respectively. After estimating the TVP-VAR parameters, in the next step, we need to transform the TVP-VAR to its vector moving average TVP-VMA. The time-varying parameters of the vectors VMA are fundamental to the connectedness index introduced by Diebold and Yılmaz (2012) through the generalized impulse response function (GIRF) and the generalized forecast error variance decomposition (GFEVD) introduced by Koop et al. (1996) and Pesaran and Shin (1998). Therefore, we transform Eq. (1) as follows:

$$Y_t = \Phi_t Y_{t-1} + u_t = A_t u_t \tag{3}$$

where $A_t = \begin{pmatrix} A_{1,t} & A_{2,t}, & \dots & A_{p,t} \end{pmatrix}'$ is an $(N \times N)$ matrix of parameters verifying $A_{i,t} = \sum_{k=1}^{p} \Phi_{1,t} A_{i-k,t}$ *if* $i \neq 0$, and I_N otherwise. Thus, the generalized impulse response function (GIRF) defines the responses of all variables following a shock in variable *i*.

The pairwise directional connectedness from *j* to *i* is presented by the GFEVD, $\Psi^g_{j,\ t}(J)$.In fact, it represents the influence variable *j* has on variable *i* in terms of its forecast error variance share, which may be defined as follows:

$$\Pi^g_{j,t}(J) = \frac{\sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}} \tag{4}$$

where $\Pi^g_{j,\ t}(J)$ denotes the variance share one variable has on others. $\Psi^g_{j,t}(J) = S^{-\frac{1}{2}}_{jj,t} A_{J,t} S_t u_{j,t}$, $\sum_{j=1}^{N} \Pi^N_{j,t}(J) = 1$ and $\sum_{i,j=1}^{N} \Pi^N_{j,t}(J) = N$.

Based on the GFEVD, we can construct the total connectedness index (TCI), which represents the interconnectedness of the network. More explicitly, this approach shows how a shock on one variable spills over to other variables and is formulated by:

$$H^g_t(J) = \frac{\sum_{i,j=1, i\neq j}^{N} \Pi^g_{ij,t}(J)}{N} \times 100 \tag{5}$$

We also can compute the directional connectedness that a variable *i* receives from variables *j*, called the *total directional connectedness from others*, expressed by:

$$H^g_{i\leftarrow j,t}(J) = \frac{\sum_{i,j=1, i\neq j}^{N} \Pi^g_{ij,t}(J)}{\sum_{j=1}^{N} \Pi^N_{ij,t}(J)} \times 100 \tag{6}$$

Equally, we calculate the directional connectedness that a variable *i* transmits its one shock to all other variables, named the *total directional connectedness to others* and expressed by:

$$H^g_{i\to j,t}(J) = \frac{\sum_{i,j=1, i\neq j}^{N} \Pi^g_{ji,t}(J)}{\sum_{j=1}^{N} \Pi^N_{ji,t}(J)} \times 100 \tag{7}$$

Finally, the net total directional connectedness is expressed as follows:

$$H^g_{i,t}(J) = H^g_{i\to j,t}(J) - H^g_{i\leftarrow j,t}(J) \tag{8}$$

If $H^g_{i,\ t}(J) > 0$, then the variable *i* influences the network more than being influenced by it. If $H^g_{i,\ t}(J) < 0$, it means that variable *i* is driven by the network.

Finally, we estimate optimal weights and hedge ratios following Kroner and Ng (1998), Kroner and Sultan (1993), and Ku et al. (2007). We use the DCC-GARCH model to estimate dynamic covariances and variances to compute optimal weights and hedge ratios for the Defi

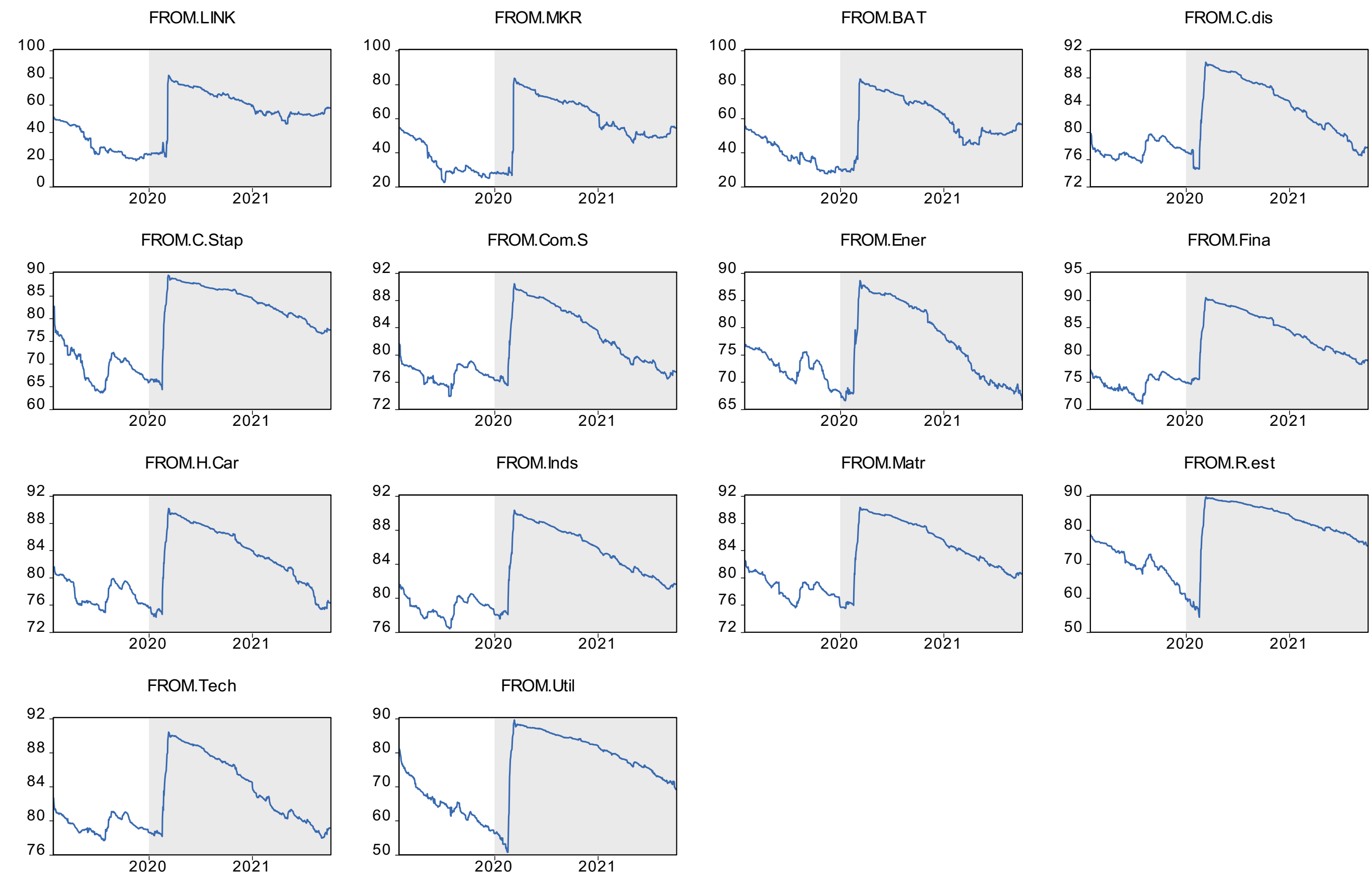

Fig. 4. Spillover from each market to system.

assets–equity sectors pairs.

5. Results

5.1. Static connectedness during the whole sample and the pre-COVID and COVID-19 subperiods

The static connectedness measures for the Defi assets (LINK-Chainlink, MKR-Maker, BAT-Basic Attention Token) and the US sector stock market returns (C.dis-consumer discretionary, Com.S-communication services, C.Stap-consumer staples, Ener-energy, Fina-financials, H.Car-health care, Inds-industrials, Tech-information technology, Matr-materials, R.est-real estate, Util-utilities) are collected in Table 3 (whole sample period), Table 4 (pre-COVID-19 subperiod) and Table 5 (COVID-19 subperiod).

Our estimates show high values of the total connectedness index (TCI) in all the periods. In concrete terms, the TCI is 73.64 % in the whole sample period (Table 3), 56.77 % during the pre-COVID-19 subperiod (Table 4) and 74.28 % during the COVID-19 subperiod (Table 5). As expected, the connectedness level is higher during periods of economic turbulence, as recent studies have shown (Yousaf and Ali, 2020; González et al., 2021; Umar et al., 2021b, among others).

In addition, the static pairwise connectedness measures between Defi assets and sector stock market returns are shown by the off-diagonal figures. Thus, regarding the whole sample period, first, industrials, materials, and information technology show the highest directional return connectedness TO the system. On the other hand, Defi assets exhibit the lowest values of the connectedness TO the system. Second, similar results are observed for the directional return connectedness FROM the system, generally showing smaller differences between values among the assets and indices analyzed. Finally, as far as the NET directional return connectedness measure is concerned, some sector stock returns, such as industrials, materials and information technology, may appear as leading net transmitters in the system analyzed in this paper and, on the contrary, energy, utilities and the Defi assets may seem like relevant net receivers of shocks from the system. We check the robustness of the results using the Diebold and Yılmaz (2012) approach; see the results in Table A1 (Appendix).[6]

Regarding the directional static connectedness between Defi assets and sector stock market returns TO/FROM the system during the pre-COVID-19 subperiod, a priori, the results we observe are similar to those found for the entire period, with the industrials, materials and information technology sectors showing the highest levels of connectedness (TO/FROM). However, as far as the NET connectedness measure is concerned, we do find some differences, since, although the industrials and information technology sectors continue to show net transmitter profiles, the Defi assets also offer this transmitter profile during this pre-COVID period, with values even higher than those shown by the aforementioned sectors. On the other hand, the real estate, utilities and energy sectors continue to be those that show the clearest net receiver profiles.

Finally, as far as the connectedness measures during the COVID-19 subperiod are concerned, the results we found are slightly different from previous periods, with the highest levels of connectedness found in the materials, real estate, information technology, and consumer staples sectors. In the estimated measures of the connectedness FROM, we discover very few differences between the values found for the different

[6] We apply robustness checks using the Diebold and Yılmaz (2012) approach on all subsamples but report only full sample results for the robustness check due to space constraints.

Fig. 5. Spillover from system to each market.

sectors, mainly in those with higher values, such as real estate, information technology, materials and utilities, among others. In both measures (connectedness TO/FROM), Defi assets show the smallest values. Finally, regarding the net connectedness values, the results are again similar to the full sample period, as we find positive values (net transmitters) in sectors such as materials, real estate and information technology, as well as negative values (net receivers) in all Defi assets, as well as in sectors such as consumer discretionary and energy.

Moreover, Fig. 2 illustrates the network diagram of the system to investigate the net pairwise connectedness between various pairs of Defi assets and sector stock indices. Thus, following Umar and Gubareva (2020) and Umar et al. (2021a, 2021b, 2021c), among others, the direction of the arrowhead shows the net receiver (edge of the arrow) and net transmitter (base of the arrow) variable for each pair. In concrete, blue (yellow) nodes illustrate the net transmitter (receiver) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. The size of the nodes represents the weighted average net total directional connectedness. In short, these results confirm the previous evidence shown in Tables 3–5. Thus, Defi assets and the energy sector may appear as net receivers of shocks for the whole sample period and the pandemic subperiod. However, the Defi assets would be net transmitters of shocks for the pre-COVID-19 subperiod, which could have implications for portfolio management. Finally, sectors such as industrials, materials and information technology would appear, to a greater or lesser extent, as net transmitters for all the periods.

5.2. Dynamic connectedness during the whole sample and the pre-COVID and COVID-19 subperiods

According to Gabauer and Gupta (2018), Umar and Gubareva (2020), Umar et al. (2021b) and Bouri et al. (2021), among many others, the dynamic total connectedness of the Defi assets and the US sector indices explored in this research is expected to vary over time (Fig. 3).

As expected, the dynamic total connectedness changes over time. Specifically, the total spillover index shows a decreasing trend in the pre-COVID-19 subperiod, with a dramatic increase coinciding with the beginning of the pandemic period, which was declared on March 11, 2020, by the WHO. This significant increase is followed by a phase of a slightly decreasing trend but maintaining levels of connectedness higher than those reached throughout the prepandemic subperiod. Therefore, the terrible impact of the pandemic on the Defi assets and sector stock indices studied is clearly shown in this research, with even greater evidence than in recent studies, as in Umar et al. (2021b). Moreover, this time-varying total connectedness measure coincides with Antonakakis et al. (2020) and Umar et al. (2021b), among others, remarking on high interdependence levels during periods of economic turmoil.

As suggested in previous studies, the dynamic total connectedness is broken into two measures: the connectedness TO the system (Fig. 4) and the connectedness FROM the system (Fig. 5). The main feature of all the graphs is that the connectedness FROM the system decreases in the pre-COVID-19 subperiod, experiencing spectacular growth with the onset of the pandemic caused by the SARS-CoV-2 coronavirus. The level of connectedness decreases subtly during the following waves of the pandemic, although it always remains above the connectedness observed in the prepandemic period. Although the effect is less pronounced, we observe the same behavior in the measure of connectedness TO the system and, moreover, for all the Defi assets analyzed, as well as for all the sector indices studied. Therefore, these results are in line with the previous evidence reached in the preceding sections.

Regarding the NET spillover index (difference between

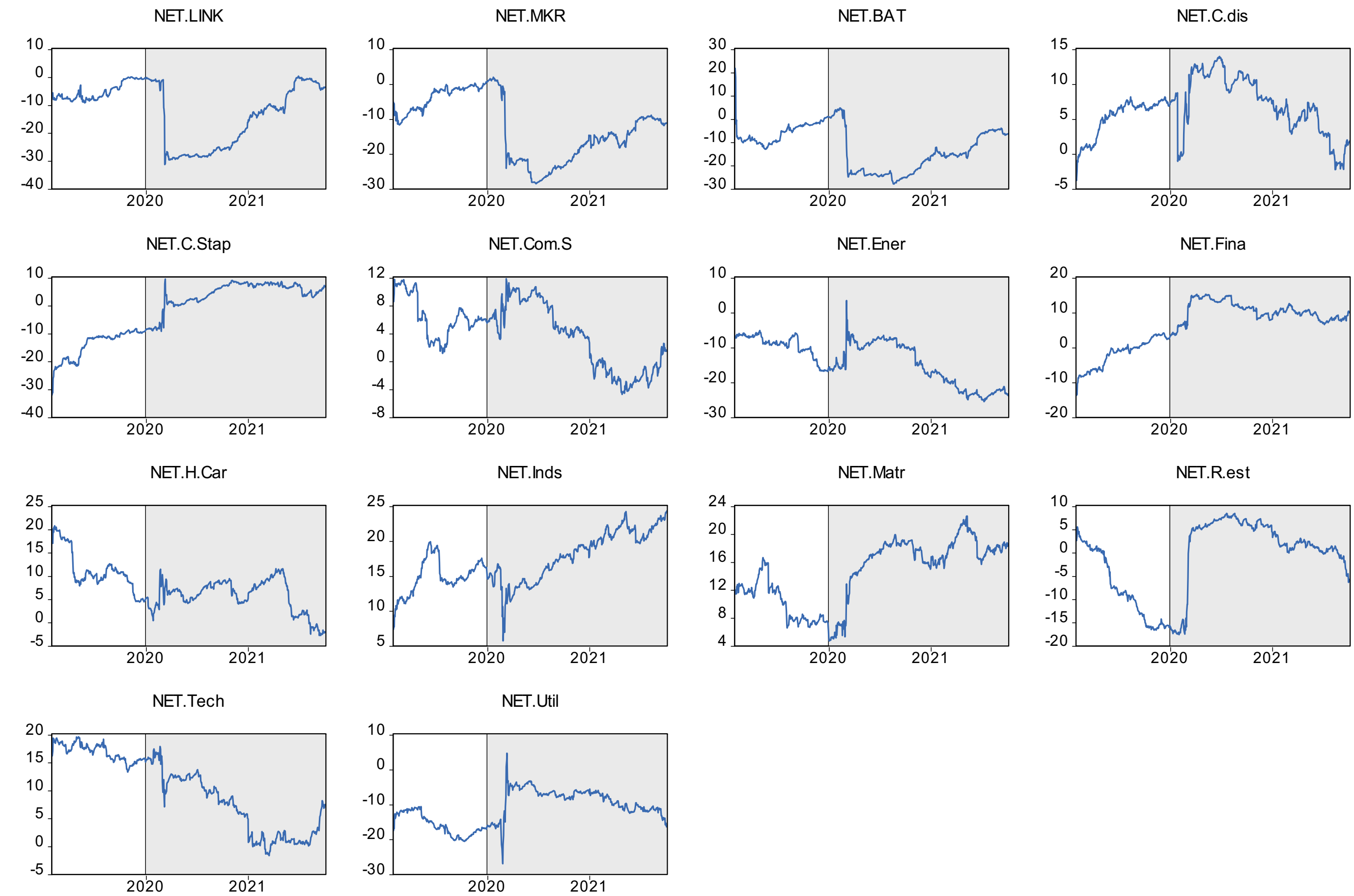

Fig. 6. Net spillover index.

connectedness TO and connectedness FROM), Fig. 6 collects the net dynamic total connectedness of the Defi assets and the US sector stock returns. First, we observe that the Defi assets show high net dynamic connectedness levels during the prepandemic subperiod, experiencing a dramatic drop with the advent of the COVID-19 pandemic. Subsequently, net connectedness levels recover in all three Defi assets. These results are consistent with the previous analysis, as Defi assets show net transmitter positions during the prepandemic period, which change to clearly net receiver positions with the arrival of the SARS-CoV-2 pandemic.

Regarding the positions observed by the sector indices, these show significant differences between them and throughout the sample period analyzed (prepandemic and pandemic subperiods). These differences clearly show that the impact of the pandemic has been different depending on the sector analyzed, as there are sectors that have been more shaken by the worldwide stoppage caused by the COVID-19 pandemic, as well as the confinement of the population. Moreover, to a greater or lesser extent, the impact of the onset of the pandemic is observed in all sectors, although the effect is different from one sector to another. Only the industrial, materials, information technology and health care sectors show positive values of the net spillover index throughout the sample period, with net transmitter profiles. It is worth noting that the information technology and health care sectors show positive but decreasing net connectedness over the entire period analyzed. Finally, it is interesting to note that the sectors that have shown the greatest impact of the onset of the pandemic on the levels of net spillover are real estate, utilities, consumer discretionary and industrials.

In line with previous studies, these results confirm that the inclusion of Defi assets as well as sector stock indices could act as hedging, diversification or safe-haven assets depending on the specific economic stage in which they are included in investment portfolios. Therefore, an analysis of the implications for portfolio management may be necessary.

5.3. *Portfolio implications*

In this section, we explore several portfolio implications about the role of Defi assets–sector stock portfolios by computing their static and dynamic optimal weights, hedge ratios, and hedging effectiveness. We hypothesize that investors and portfolio managers should consider adding Defi assets and certain sector stock indices in their portfolios to obtain diversification gains (Chemkha et al., 2021).

According to Chemkha et al. (2021), optimal portfolio weights and hedge ratios provide a general understanding of how hedges are constructed to minimize risk. Specifically, we calculate optimal hedge ratios by comparing portfolios including Defi assets and sector stock indices. Furthermore, Table 6 shows these optimal portfolio weights and hedge ratios for the whole sample period and for two subperiods: pre-COVID-19 and COVID-19. During the full sample period, the optimal weight for the C.dis-LINK pair is 0.981, indicating that, for $1 portfolio, investor should allocate 98.1 cents in the C.dis (consumer discretionary) equity sector whereas remaining 1.9 cents in the LINK Defi asset. During the full sample period, the optimal hedge ratio for C.dis-LINK pair 0.025, showing that $1 long position in C.dis (consumer discretionary) equity sector can be hedged for 2.5 cents with a short position in LINK Defi asset.

In general, we find that the optimal weights are higher during the pre-COVID-19 period compared to the after COVID-19 period for almost all pairs of equity sector-Defi asset, indicating that investors should decrease their investment in equity stocks (and increase investment in

Table 6
Portfolio implications.

	Optimal Portfolio Weights			Optimal Hedge Ratios		
	Full Sample Period	Pre-COVID-19	During COVID-19	Full Sample Period	Pre-COVID-19	During COVID-19
C.dis-LINK	0.981	0.990	0.977	0.025	0.015	0.030
C.dis-MKR	0.978	0.988	0.973	0.028	0.019	0.033
C.dis-BAT	0.975	0.991	0.968	0.042	0.028	0.049
Com.S-LINK	0.984	0.989	0.981	0.024	0.016	0.029
Com.S-MKR	0.980	0.988	0.975	0.025	0.018	0.028
Com.S-BAT	0.978	0.990	0.972	0.039	0.030	0.045
C.Stap-LINK	0.989	0.993	0.987	0.018	0.012	0.021
C.Stap-MKR	0.987	0.992	0.983	0.020	0.015	0.023
C.Stap-BAT	0.980	0.995	0.968	0.028	0.020	0.032
Ener-LINK	0.922	0.971	0.898	0.040	0.021	0.050
Ener-MKR	0.920	0.972	0.891	0.041	0.024	0.051
Ener-BAT	0.913	0.974	0.884	0.058	0.034	0.071
Fina-LINK	0.964	0.984	0.955	0.026	0.016	0.032
Fina-MKR	0.962	0.982	0.952	0.028	0.017	0.034
Fina-BAT	0.957	0.986	0.944	0.039	0.024	0.047
H.Car-LINK	0.987	0.991	0.984	0.019	0.014	0.022
H.Car-MKR	0.987	0.993	0.983	0.022	0.016	0.025
H.Car-BAT	0.985	0.991	0.982	0.026	0.018	0.030
Inds-LINK	0.969	0.985	0.960	0.030	0.020	0.035
Inds-MKR	0.974	0.986	0.966	0.028	0.019	0.032
Inds-BAT	0.968	0.990	0.957	0.044	0.031	0.050
Tech-LINK	0.973	0.984	0.967	0.030	0.019	0.035
Tech-MKR	0.966	0.979	0.959	0.032	0.022	0.037
Tech-BAT	0.961	0.982	0.950	0.049	0.035	0.057
Matr-LINK	0.974	0.989	0.965	0.037	0.025	0.044
Matr-MKR	0.974	0.988	0.965	0.035	0.025	0.041
Matr-BAT	0.969	0.990	0.961	0.050	0.035	0.058
R.est-LINK	0.977	0.992	0.969	0.021	0.013	0.025
R.est-MKR	0.974	0.990	0.966	0.019	0.012	0.023
R.est-BAT	0.971	0.993	0.961	0.032	0.020	0.039
Util-LINK	0.975	0.996	0.966	0.025	0.015	0.030
Util-MKR	0.975	0.993	0.966	0.024	0.015	0.029
Util-BAT	0.971	0.994	0.960	0.029	0.017	0.036

Notes: LINK - Chainlink, MKR - Maker, BAT - Basic Attention Token, C.dis-consumer discretionary, Com.S-communication services, C.Stap-consumer staples, Ener-energy, Fina-financials, H.Car-health care, Inds-industrials, Tech-information technology, Matr-materials, R.est-real estate, Util-utilities.

Defi assets) during the COVID-19 period compared to the pre-COVID-19 period. Further, we observe that the optimal hedge ratios for Defi assets and sector stock indices show similar values for the whole sample period and subperiods, and these values are quite low. In addition, the optimal hedge ratios increased slightly during the COVID-19 subperiod, in line with López Cabrera and Schulz (2016) and Chemkha et al. (2021), among others. Furthermore, all the ratios show positive values, indicating that reverse positions are necessary to hedge against the risk of each asset. For example, to reduce the risk, a long position of $1 in, for example, consumer discretionary can be hedged with 2.5-, 1.5- and 3-cent short positions in the Defi asset LINK-Chainlink for the whole sample period and pre-COVID and COVID-19 subperiods, respectively. According to López Cabrera and Schulz (2016) and Chemkha et al. (2021), the lower the hedge ratio is, the less expensive the hedge. Therefore, in line with previous literature such as Akhtaruzzaman et al. (2021), asset coverage was cheaper for the whole sample period and before the SARS-CoV-2 coronavirus pandemic than during the COVID-19 subperiod due to the rise of uncertainty during periods of economic turbulence.

6. Conclusions

This research explores the static and dynamic spillover between three Defi assets (LINK-Chainlink, MKR-Maker, BAT-Basic Attention Token) and the US sector indices (C.dis-consumer discretionary, Com.S-communication services, C.Stap-consumer staples, Ener-energy, Fina-financials, H.Car-health care, Inds-industrials, Tech-information technology, Matr-materials, R.est-real estate, Util-utilities) between January 2, 2019, and October 8, 2021. To that end, this study applies the TVP-VAR model. In addition, for robustness, this analysis splits the whole sample period into two subperiods: pre-COVID-19 and COVID-19. Moreover, this research computes the optimal weights and hedge ratios for the Defi assets–sector stock portfolios using the DCC-GARCH model.

First, our results confirm high levels of the total connectedness index (TCI) in all periods. Second, regarding the static pairwise connectedness measures between Defi assets and sector stock market returns, in general, the industrials, materials, and information technology sectors may show the highest directional return connectedness, and Defi assets would reveal the lowest spillover indices. Third, in line with previous literature, the dynamic total connectedness varies over time, experiencing a dramatic rise coinciding with the onset of the pandemic subperiod. Fourth, all the connectedness FROM/TO measures decrease in the pre-COVID-19 subperiod, suffering a dramatic increase at the beginning of the coronavirus pandemic but decreasing during the subsequent waves of the pandemic. Fifth, the NET spillover indices for the Defi assets and the US sector stock returns reveal that the Defi assets show high net dynamic connectedness levels during the prepandemic subperiod (net transmitters), experiencing a dramatic drop with the advent of the COVID-19 pandemic (net receivers) but recovering later. Regarding the US sector indices, the net spillover indices are economic stage- and sector-dependent. Regardless, only the industrials, materials, information technology and health care sectors may reveal net transmitter profiles.

Finally, as far as investment portfolio implications are concerned, the optimal hedge ratios for Defi assets and sector stock indices may show comparable values for the whole sample period and subperiods. In addition, the optimal hedge ratios increased slightly during the COVID-19 subperiod, so asset coverage was cheaper for the whole sample period and before the COVID-19 pandemic than during the pandemic subperiod. Thus, the variety of risks associated with the SARS-CoV-2 coronavirus crisis would have negatively impacted the level of economic development all over the world due to the increasing volatility, among other collateral effects. Moreover, this variety of risks may have increased hedging costs for international investors.

Some limitations of the paper refer to the small sample period, since the main objective of the paper is to analyze the connectedness between DeFi assets and sector asset market returns during the COVID-19 pandemic period. Therefore, an interesting extension of the work would be to enlarge the sample forward and backward, so that more sample sub-periods can be compared. Another limitation of the paper could refer to the different market capitalization shown by the sector equity portfolios and the selected DeFi assets. Despite the recent growth of the latter, the difference between them is still significant, so the connectedness explored in this study could be further analyzed in future research. Finally, while our study reveals some interesting and useful insights about the dynamic interdependence of sector equity portfolios in the US (the world's biggest and most influential stock market), it ignores these interdependencies across other leading European and Asian stock markets. Therefore, future studies could focus on comparing the results revealed in the US stock market during the COVID-19 pandemic crisis to those found in other international stock markets.

These results are relevant for portfolio managers, governments and regulators to reduce losses in periods of economic turbulence. Therefore, some extensions of this research could consist of applying time-frequency domain techniques to manage financial risks for different time horizons. Another extension could be to explore potential diversification benefits in hedging strategies that consist of including digital assets in portfolios containing commodities instead of sector stock indices.

CRediT authorship contribution statement

Imran Yousaf: Conceptualization, Data curation, Methodology, Software, Supervision.

Francisco Jareño: Visualization, Investigation, Writing- Original draft preparation, Validation, Writing- Reviewing and Editing, Funding acquisition, Formal analysis.

Marta Tolentino: Investigation, Validation, Writing- Reviewing and Editing, Funding acquisition, Formal analysis.

Data availability

Data will be made available on request.

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Appendix A. Robustness check

Table A1

Static spillovers during the full sample period using Diebold and Yılmaz (2012) Approach.

	LINK	MKR	BAT	C.dis	Com.S	C.Stap	Ener	Fina	H.Car	Inds	Tech	Matr	R.est	Util	FROM others
LINK	42.17	12.69	14.12	3.24	3.35	2.62	2.88	2.55	2.36	2.89	2.87	3.36	2.16	2.73	57.83
MKR	12.68	45.05	11.56	3.17	3.12	2.62	2.58	3.05	2.74	2.95	2.58	2.71	2.26	2.94	54.95
BAT	13.66	11.09	43.81	3.56	3.16	2.59	2.87	2.71	2.45	2.95	3.09	3.33	2.55	2.18	56.19
C.dis	1.7	1.86	2.2	18.06	11.67	7	4.27	7.23	7.52	8.57	12.87	7.66	5.69	3.7	81.94
Com.S	2.02	1.76	2.31	12.45	20.12	7.42	4.06	6.56	7.95	6.91	13.13	6.31	5.12	3.87	79.88
C.Stap	1.55	1.72	2.08	7.62	7.24	20.53	3.5	6.14	9.32	7.34	7.77	7.71	8.27	9.21	79.47
Ener	2.07	2.08	1.9	5.75	5.26	4.09	26.04	13.58	4.7	12.08	5.61	10.23	3.78	2.82	73.96
Fina	1.84	2.02	1.95	7.39	6.22	5.62	9.89	18.5	5.8	13.84	6.37	11.79	4.9	3.86	81.5
H.Car	1.66	1.82	1.69	8.36	8.23	9.53	3.64	6.11	21.36	7.44	9.77	7.78	6.54	6.08	78.64
Inds	1.54	1.42	1.75	8.37	6.3	6.41	8.45	12.81	6.43	17.01	7.46	12.72	5.47	3.87	82.99
Tech	1.73	1.94	2.4	13.08	12.41	7.1	4.06	6.31	9.01	7.84	18.38	7.16	5.48	3.11	81.62
Matr	1.8	1.84	1.87	7.86	6.26	7.27	7.32	11.36	7	13.35	7.18	17.94	5.06	3.9	82.06
R.est	1.9	1.77	2.24	6.92	6.02	9.72	3.52	5.47	7.17	6.83	6.75	5.8	24.54	11.35	75.46
Util	1.81	1.95	1.86	5.04	4.9	12.32	3.04	4.9	7.59	5.64	4.55	5.07	12.86	28.46	71.54
TO others	45.95	43.96	47.93	92.8	84.15	84.32	60.07	88.76	80.04	98.64	90	91.63	70.14	59.63	1038.02
Inc. own	88.12	89.02	91.73	110.86	104.27	104.85	86.11	107.26	101.4	115.65	108.38	109.57	94.68	88.09	TCI
NET	−11.88	−10.98	−8.27	10.86	4.27	4.85	−13.89	7.26	1.4	15.65	8.38	9.57	−5.32	−11.91	74.14

Notes: LINK - Chainlink, MKR - Maker, BAT - Basic Attention Token, C.dis-consumer discretionary, Com.S-communication services, C.Stap-consumer staples, Ener-energy, Fina-financials, H.Car-health care, Inds-industrials, Tech-information technology, Matr-materials, R.est-real estate, Util-utilities.

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