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Connectedness between DeFi, cryptocurrency, stock, and safe-haven assets

Andrea Ugolini [a], Juan C. Reboredo [b,c,*], Walid Mensi [d,e]

[a] Department of Economics, Management and Statistics. University of Milan-Bicocca, Italy
[b] Department of Economics, Universidade de Santiago de Compostela, Spain
[c] ECOBAS Research Centre, Spain
[d] Department of Finance and Accounting, University of Tunis El Manar and IFGT, Tunisia
[e] Department of Economics and Finance, College of Economics and Political Science, Sultan Qaboos University, Muscat, Oman

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ABSTRACT

This paper examines return spillovers within and between different DeFi, cryptocurrency, stock, and safe-haven assets. For the period January 2019 to March 2022, we find that DeFi and cryptocurrency asset markets exhibit strong within-market and between-market return spillovers, that stock and safe-haven markets show weak connectedness, and that safe-haven assets are minor receivers and transmitters of between-market spillover effects. The connectedness between markets is time-varying and reveals structural changes in early 2020. Furthermore, we document that financial conditions shape the dynamics of return spillover effects between markets.

1. Introduction

In recent years, digital asset markets have gained popularity among investors; however, those markets are extremely volatile, with unexpected upturns or downturns that have important size effects on their market capitalization that make them particularly fragile (Taleb, 2021). Along with cryptocurrencies, different kinds of investable crypto assets have been introduced into the market, representing new opportunities for investment in fast-growing technology-backed asset classes. One such asset class gaining prominence – as they are supported by financial services, including lending, borrowing, spot trading, online wallets, and derivatives – is decentralized finance (DeFi) assets, which are traded peer-to-peer on the basis of blockchain technology with no central authority (Gubareva, 2021; Schär, 2021; Yousaf et al., 2022). Such new assets offer new opportunities for investment in terms of both performance and hedging abilities.

In this paper, we assess how DeFi assets are related to other asset classes, such as cryptocurrencies and the usual stocks and safe-haven assets. This information is crucial for investor portfolio and risk management decisions, mainly under extreme market circumstances when hedging and safe-haven features of DeFi assets could be particularly useful for protection against downside risk. Recent events such as the global pandemic (COVID-19) and geopolitical conflict (the Russian-Ukraine military conflict), as well as soaring energy costs, deglobalization, and stronger regulation of cryptocurrencies have increased spillovers among international markets, making hedging difficult and costly (Ha and Nham, 2022; Maitra et al., 2022; Bossman et al., 2023). Therefore, studying

* Corresponding author.
E-mail address: juancarlos.reboredo@usc.es (J.C. Reboredo).

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whether and how DeFi assets are connected with other financial assets in the light of recent events provides valuable information on the potential attractiveness of DeFi assets for hedge or safe haven investment portfolios.

Previous research shows that digital assets are weakly correlated with financial and commodity markets, and the fact that they can be used to hedge against downside stock market movements (see, e.g., Cao and Xie, 2022; Guesmi et al., 2019). Regarding DeFi assets, Yousaf et al. (2022) points to strong connectedness between DeFi and conventional currency markets, mainly in early 2020. Yousaf and Yarovaya (2022a) find no evidence of herding, except for time-varying herding for cryptocurrency and DeFi assets over short investment horizons and for low-volatility days. In contrast, Corbet et al. (2021) show that DeFi asset values fluctuate independently of conventional cryptocurrencies, providing hedging ability for digital investors. Similarly, Yousaf and Yarovaya (2022b) find that DeFi assets are decoupled from traditional asset classes. Piñeiro-Chousa et al. (2022) show that DeFi tokens serve as safe-haven asset against stock market volatility. Cevik et al. (2022) find that DeFis have the property of safe-haven assets for strategic commodity (crude oil and gold) markets. Umar et al. (2022) show an increasing interdependence between DeFi, NFT and financial markets mainly during the pandemic crisis. Finally, in analyzing price explosiveness in DeFi values, Wang et al. (2022) report that DeFi prices are highly correlated with cryptocurrency market uncertainty.

This paper contributes to existing research by studying spillovers within and between DeFí assets (including BAT, Maker, LINK, and SNX), cryptocurrencies (including Bitcoin, Ethereum, Tether, and BNB), conventional stocks (including markets in Japan, US, UK, and Europe), and traditional safe-haven assets (including gold, the USD, and US Treasury bills). We use the block aggregation procedure of Greenwood-Nimo et al. (2015, 2016), based, in turn, on the connectedness approach of Diebold and Yilmaz (2014). For the turbulent 2018–2022 period, marked by the COVID-19 pandemic, the cryptocurrency price crash, and the military conflict in Ukraine, we find that all markets are mainly affected by their own shocks, and that strong spillovers occur within each asset class. We also find strong evidence of spillovers between DeFi and cryptocurrency markets, but weak evidence of spillovers between safe-haven markets and the remaining asset markets. Finally, we document that financial conditions, as given by gold and stock market volatility, illiquidity, cryptocurrency market volatility, term spread, and economic policy uncertainties all play a relevant role in shaping the dynamics of net spillovers for the DeFi, cryptocurrency, stock, and safe-haven asset markets.

The paper is organized as follows: Section 2 discusses the methodology and data, Section 3 discusses the results, and Section 4 concludes the paper.

2. Methods and data

2.1. Modelling connectedness

We study return spillover connectedness between four market blocks: DeFi (d), cryptocurrency (c), stock (s), and safe-haven (f) assets, assuming that asset returns in those markets are endogenously determined by a vector autoregressive (VAR) model with p lags:

$$y_t = \mu + \sum_{k=1}^{p} A_k y_{t-k} + \varepsilon_t, \tag{1}$$

where $y_t = (y_{dt}, y_{ct}, y_{st}, y_{ft})'$ is a column vector containing j-four column vectors of returns in the market $j = d, c, s, f$; μ is a column vector of constants; and A is a (4 × 4) coefficient block matrix, where each block A_{jj} accounts for feedback effects between asset returns in market j, and A_{ji} accounts for feedback effects between asset returns in markets j and i, with j, $i = d, c, s, f$. ε_t is a stochastic column vector with zero mean and a (4 × 4) block variance-covariance matrix Σ, with blocks Σ_{jj} accounting for variance-covariance between j-market returns, and Σ_{ji} accounting for covariances between returns in markets j and i. From the moving average (MA) representation of price dynamics as per Eq. (1) we have:

$$y_t = \sum_{w=1}^{\infty} B_w \mu + \sum_{w=1}^{\infty} B_w \varepsilon_{t-w}, \tag{2}$$

with the MA coefficients $B_w = A_1 B_{w-1} + \cdots + A_p B_{w-p}$, $B_w = 0$ for $w < 0$, and B_0 equal to the identity matrix. Return spillovers between asset returns are obtained on the basis of the h-step ahead forecast error variance decomposition (Pesaran and Shin, 1998) as:

$$\theta_{i\leftarrow j}^{h} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' B_w \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' B_w \Sigma B_w' e_i\right)}, \tag{3}$$

where σ_{jj} is the j-diagonal element of Σ, and e_i is a column vector of zeros with 1 for its i^{th} component. Hence, the value of $\theta_{i\leftarrow j}^{h}$ depends on both the feedback effects between asset returns and the variance-covariance matrix. Diebold and Yilmaz (2014) use the information in Eq. (3) to build a connectedness matrix, with $\theta_{i\leftarrow j}^{h}$ components arranged in rows reporting information on the impact of a shock from market j to market i (in rows), or from market i to market j with $\theta_{i\leftarrow j}^{h}$ components arranged in columns. By normalizing $\theta_{i\leftarrow j}^{h}$ in rows to sum 1 ($\widetilde{\theta}_{i\leftarrow j}^{h}$), total spillovers to market i are computed as $\widetilde{\theta}_{i\leftarrow \cdot}^{h} = \sum_{j=1, j\neq i}^{d} \widetilde{\theta}_{i\leftarrow j}^{h}$, and total spillovers from market i to different markets are computed as $\widetilde{\theta}_{\cdot\leftarrow i}^{h} = \sum_{j=1, j\neq i}^{d} \widetilde{\theta}_{j\leftarrow i}^{h}$. Hence, $\widetilde{\theta}_{i\leftarrow i}^{h} + \widetilde{\theta}_{i\leftarrow \cdot}^{h} = 100\%$.

By extending the Diebold-Yilmaz approach as in Greenwood-Nimmo et al. (2015, 2016), we can assess connectedness within and between market blocks, as given by the block form of the connectedness matrix:

$$\begin{bmatrix} \Theta^h_{d\leftarrow d} & \Theta^h_{d\leftarrow c} & \Theta^h_{d\leftarrow s} & \Theta^h_{d\leftarrow f} \\ \Theta^h_{c\leftarrow d} & \Theta^h_{c\leftarrow c} & \Theta^h_{c\leftarrow s} & \Theta^h_{c\leftarrow f} \\ \Theta^h_{s\leftarrow d} & \Theta^h_{s\leftarrow c} & \Theta^h_{s\leftarrow s} & \Theta^h_{s\leftarrow f} \\ \Theta^h_{f\leftarrow d} & \Theta^h_{f\leftarrow c} & \Theta^h_{h\leftarrow s} & \Theta^h_{f\leftarrow f} \end{bmatrix}, \tag{4}$$

where $\Theta^h_{j\leftarrow j}$ and $\Theta^h_{j\leftarrow l}$ include within-block market j spillovers and spillovers from market block l to market block j, respectively. Hence, we can easily obtain total spillovers from different market blocks to market block j and also the reverse spillover effects.

From estimates of parameter matrices of the VAR model, we can obtain the bivariate and block relationship metrics as in Eq. (4), and evaluate statistical significance by Monte Carlo simulation of the VAR model so as to build 95% confidence intervals.

2.2. Data

The dataset consists of prices for four asset classes: (a) DeFi assets (including BAT, Maker, LINK, and SNX); (b) cryptocurrency assets (including Bitcoin, Ethereum, Tether, and BNB); (c) stocks (represented by the Nikkei 225 for Japan, Euro Stoxx 50 for Europe, FTSE 100 for the UK, and S&P 500 for the USA); and (d) safe-haven assets (including gold, a trade-weighted index for the USD, and 3-month US Treasury bills). Data were sourced from Bloomberg for daily periods from 1 January 2018 (with the starting date delimited by data availability) to 18 March 2022. The sample period includes several key economic and political events such as the Bitcoin price crash (with a price fall of 65% in February 2018), the COVID-19 pandemic with its different variants and waves, the global fall in oil demand, and the military conflict in Ukraine.

Table 1 summarizes the main statistical features of the data. Average daily price returns are near zero; DeFi and safe-haven assets exhibit the highest and lowest volatilities, respectively; asset returns are asymmetric and leptokurtic; normality is rejected; and all return series are stationary at the 1% level.

3. Empirical evidence

3.1. Connectedness estimates

We computed return spillovers as per Eq. (3) from the estimated VAR model in Eq. (1) with 1 lag, selected according to the Bayesian information criterion (BIC). The evidence in Table 2 shows that all markets are mainly influenced by their own shocks. For example, 31% of total shocks for BAT come from their own shocks, while BAT contributes 9.3%, 10.3%, and 8% to the forecasting variance for Maker, LINK, and SNX, respectively. It also contributes 33.5% to the forecasting variance for cryptocurrency, 9.1% to stocks, and under

Table 1
Descriptive statistics.

	Mean	Std. dev.	Max	Min	Skewness	Kurtosis	JB	ADF	PP	KPSS
DeFi assets										
BAT	0.001	0.073	0.303	-0.595	-0.486	9.472	1868.408*	-9.557***	-35.237***	0.064
Maker	0.001	0.073	0.442	-0.881	-1.338	27.767	27,071.808*	-9.840***	-36.994***	0.094
LINK	0.003	0.078	0.479	-0.662	-0.520	11.129	2929.634*	-9.877***	-33.327***	0.105
SNX	0.002	0.096	0.543	-0.515	0.265	6.778	634.815*	-8.058***	-35.623***	0.251
Crypto assets										
Bitcoin	0.002	0.045	0.203	-0.465	-1.045	15.473	6977.370*	-9.128***	-33.431***	0.175
Ethereum	0.001	0.060	0.354	-0.551	-0.829	12.761	4276.465*	-9.238***	-34.273***	0.450*
Tether	0.000	0.004	0.053	-0.053	0.311	49.598	94,743.029*	-13.026***	-61.450***	0.007
BNB	0.004	0.064	0.529	-0.543	-0.193	14.959	6245.657*	-8.700***	-32.404***	0.165
Stocks										
Nikkei 225	0.000	0.012	0.077	-0.063	-0.089	7.534	898.057*	-9.348***	-32.446***	0.055
S&P 500	0.000	0.013	0.090	-0.128	-0.984	20.862	14,087.699*	-8.935***	-39.974***	0.071
FTSE 100	0.000	0.012	0.087	-0.115	-1.181	18.651	10,930.191*	-9.188***	-33.628***	0.071
Euro Stoxx 50	0.000	0.013	0.088	-0.132	-1.155	18.867	11,215.886*	-9.273***	-33.715***	0.045
Safe-haven assets										
Gold	0.000	0.010	0.058	-0.051	-0.305	8.705	1436.229*	-10.453***	-32.848***	0.086
USDX	0.000	0.004	0.020	-0.015	0.265	4.973	182.079*	-10.958***	-30.563***	0.137**
T-Bill	0.000	0.003	0.012	-0.015	-0.086	6.364	495.038*	-9.286***	-33.449***	0.628

Notes: This table presents summary statistics for the analyzed DeFi, cryptocurrency, stock, and safe-haven assets. JB denotes the Jarque-Bera statistic, with the asterisk denoting rejection of the null of normality at the 5% level. ADF, PP, and KPSS denote the augmented Dickey-Fuller test, Phillips-Perron unit root test, and the one-sided Kwiatkowski-Phillips-Schmidt-Shin stationarity test, respectively, with an asterisk indicating rejection of the null hypothesis.

Table 2
Connectedness matrix between variables.

	BAT	Maker	LINK	SNX	Bitcoin	Ethereum	Tether	BNB	S&P 500	FTSE 100	Euro Stoxx 50	Nikkei 225	Gold	USDX	T-Bill
BAT	31.06 [29.64, 31.50]	9.36 [8.79, 9.78]	9.91 [9.38, 10.40]	5.75 [5.40, 6.28]	11.82 [11.25, 12.15]	14.03 [13.25, 14.26]	0.54 [0.18, 1.72]	11.07 [10.40, 11.46]	1.95 [1.88, 2.84]	1.48 [1.38, 2.90]	2.10 [1.94, 3.48]	0.50 [0.47, 1.56]	0.10 [0.09, 0.70]	0.24 [0.21, 1.17]	0.10 [0.07, 1.10]
Maker	9.32 [8.68, 10.72]	30.06 [27.16, 30.55]	9.07 [8.26, 9.72]	5.80 [5.34, 6.64]	11.51 [10.40, 11.96]	15.84 [14.57, 16.31]	1.15 [0.51, 3.33]	10.05 [9.14, 10.63]	1.90 [1.65, 2.86]	1.57 [1.24, 3.88]	2.35 [1.86, 4.66]	0.24 [0.12, 1.38]	0.35 [0.17, 1.11]	0.70 [0.32, 1.58]	0.10 [0.02, 0.97]
Link	10.30 [9.70, 10.99]	9.66 [8.89, 10.17]	32.00 [29.60, 32.43]	7.05 [6.39, 7.60]	10.91 [10.19, 11.56]	14.33 [13.27, 14.75]	0.53 [0.08, 1.75]	9.71 [9.01, 10.06]	1.42 [1.30, 2.81]	1.44 [1.20, 3.25]	2.06 [1.69, 4.16]	0.11 [0.10, 0.83]	0.11 [0.04, 0.80]	0.36 [0.19, 1.72]	0.02 [0.01, 0.90]
SNX	8.05 [7.61, 9.04]	8.50 [8.01, 9.16]	9.33 [8.89, 10.47]	42.66 [39.25, 43.14]	8.69 [8.16, 9.15]	11.81 [11.22, 12.37]	0.59 [0.04, 2.23]	6.92 [6.41, 7.60]	0.65 [0.57, 1.55]	0.61 [0.47, 1.58]	1.18 [0.95, 2.08]	0.05 [0.03, 0.84]	0.39 [0.33, 1.56]	0.55 [0.52, 2.03]	0.04 [0.02, 1.10]
Bitcoin	10.55 [9.94, 10.83]	10.54 [9.87, 10.65]	9.52 [9.11, 10.36]	5.66 [5.32, 6.09]	27.74 [26.35, 28.03]	18.43 [17.50, 18.61]	0.34 [0.05, 1.56]	12.09 [11.44, 12.55]	1.21 [1.16, 2.02]	1.19 [1.04, 2.86]	1.67 [1.45, 3.44]	0.12 [0.10, 0.63]	0.36 [0.32, 0.78]	0.53 [0.41, 1.27]	0.05 [0.03, 0.79]
Ethereum	11.05 [10.64, 11.89]	12.85 [12.17, 13.01]	10.97 [10.51, 11.52]	6.81 [6.45, 7.07]	16.30 [15.46, 16.67]	24.79 [23.61, 25.00]	0.50 [0.13, 1.46]	11.71 [11.12, 11.97]	1.29 [1.20, 2.14]	1.15 [1.03, 2.61]	1.64 [1.41, 2.87]	0.21 [0.17, 0.96]	0.26 [0.23, 0.77]	0.43 [0.31, 1.35]	0.03 [0.03, 0.97]
Tether	1.01 [0.38, 2.00]	2.94 [0.56, 4.10]	0.70 [0.13, 2.09]	0.77 [0.03, 3.34]	0.30 [0.06, 2.21]	0.66 [0.30, 2.77]	81.55 [72.22, 87.76]	0.74 [0.47, 2.12]	3.44 [1.68, 6.21]	2.30 [1.48, 4.76]	1.88 [1.29, 4.25]	1.33 [0.33, 3.03]	0.07 [0.02, 2.03]	0.44 [0.05, 3.30]	1.86 [1.22, 6.43]
BNB	10.87 [9.98, 11.29]	10.04 [9.10, 10.34]	9.26 [8.55, 9.83]	4.89 [4.41, 5.50]	13.42 [12.41, 14.59]	14.53 [13.29, 14.80]	0.41 [0.24, 1.99]	30.62 [27.31, 30.54]	1.48 [1.33, 2.83]	1.38 [1.27, 3.61]	1.78 [1.60, 3.77]	0.29 [0.17, 1.62]	0.41 [0.31, 1.07]	0.54 [0.25, 1.70]	0.09 [0.02, 1.54]
S&P 500	2.83 [2.36, 5.01]	3.10 [2.14, 4.85]	2.22 [1.63, 4.64]	0.83 [0.51, 3.15]	2.42 [1.64, 4.04]	2.68 [2.14, 4.97]	3.29 [1.28, 5.89]	2.17 [1.63, 4.02]	36.63 [31.46, 38.99]	15.27 [12.87, 16.51]	17.43 [14.68, 18.52]	5.69 [4.75, 6.81]	0.52 [0.03, 1.67]	1.08 [0.64, 2.60]	3.83 [3.04, 4.51]
FTSE 100	1.76 [1.58, 2.75]	1.25 [1.07, 2.09]	1.62 [1.35, 3.25]	0.68 [0.41, 1.80]	1.55 [1.29, 1.97]	1.85 [1.45, 2.81]	1.40 [0.69, 2.35]	1.37 [1.27, 2.06]	13.46 [12.75, 14.35]	35.98 [33.98, 36.78]	27.61 [26.13, 28.32]	6.41 [6.02, 7.28]	0.24 [0.04, 0.98]	0.53 [0.23, 2.17]	4.29 [4.00, 4.98]
Euro Stoxx 50	2.40 [2.14, 3.87]	1.90 [1.51, 2.51]	2.09 [1.73, 3.55]	1.10 [0.77, 2.49]	2.12 [1.66, 2.88]	2.42 [1.92, 3.48]	1.20 [0.57, 2.42]	1.86 [1.63, 2.79]	14.40 [13.62, 15.55]	25.75 [23.98, 26.43]	34.07 [31.79, 34.96]	5.56 [5.19, 6.17]	0.25 [0.01, 1.05]	0.86 [0.55, 1.85]	4.03 [3.73, 4.91]
Nikkei 225	2.11 [1.25, 5.00]	1.81 [1.16, 5.51]	1.47 [0.72, 4.86]	0.90 [0.10, 3.09]	1.98 [0.56, 4.44]	1.72 [0.82, 4.70]	0.49 [0.14, 1.45]	1.15 [0.49, 3.55]	16.60 [11.52, 17.79]	11.67 [8.90, 13.18]	15.09 [12.49, 17.83]	40.90 [31.33, 47.82]	0.24 [0.05, 1.24]	0.71 [0.18, 3.17]	3.15 [1.92, 4.41]
Gold	0.37 [0.22, 1.91]	0.89 [0.45, 3.08]	0.50 [0.11, 2.13]	0.86 [0.57, 3.19]	1.41 [0.98, 5.09]	1.07 [0.71, 2.75]	0.51 [0.04, 1.78]	1.35 [0.76, 3.67]	0.49 [0.10, 4.20]	0.38 [0.07, 1.71]	0.76 [0.02, 2.60]	0.22 [0.10, 3.61]	74.22 [62.74, 76.23]	8.93 [7.64, 10.68]	8.04 [6.53, 11.77]
USDX	1.31 [0.67, 3.75]	2.47 [1.22, 6.14]	0.93 [0.55, 3.42]	1.39 [0.90, 3.36]	2.29 [1.43, 5.06]	2.15 [1.37, 5.02]	0.47 [0.07, 2.77]	2.04 [1.28, 6.30]	4.68 [1.93, 6.58]	2.44 [0.76, 3.47]	3.86 [1.61, 5.39]	0.93 [0.22, 2.85]	8.66 [6.56, 10.34]	64.92 [50.41, 71.66]	1.48 [1.22, 5.24]
T-Bill	0.24 [0.17, 2.11]	0.25 [0.12, 3.43]	0.05 [0.03, 1.39]	0.07 [0.03, 1.56]	0.12 [0.10, 2.44]	0.15 [0.08, 2.61]	2.10 [0.91, 6.67]	0.07 [0.05, 1.40]	6.99 [6.11, 8.89]	7.85 [6.85, 8.54]	7.69 [6.76, 8.66]	3.11 [2.74, 4.26]	5.78 [4.97, 7.60]	1.25 [0.94, 3.25]	64.27 [54.82, 63.81]

Notes: The table reports results on spillovers among the DeFi, cryptocurrency, stock, and safe-haven assets indicated in the first row and first column using a forecast horizon of $h = 10$ trading days for the (normalized) spillover metric in Eq. (3). Reported for the market in each row is the forecast error variance that is explained by the markets indicated in the columns, with values adding 100%. Reported for the market in each column is the contribution of the variance of that market to the markets indicated in the rows. 95% confidence intervals reported in squared brackets are computed using 10,000 Monte Carlo simulations of the reduced-form VAR model.

2% to safe-haven assets. Two-way spillovers for the other asset classes also reveal that own shocks are more relevant than shocks from other assets. Table 3 confirms that markets are largely affected by their own shocks, e.g., stock and safe-haven markets. In contrast, DeFi markets show a lower own influence, receiving a greater impact from other markets (mainly from cryptocurrency) and contributing most shocks (29.6%) to the cryptocurrency market. Overall, DeFi and the cryptocurrency markets are closely interconnected, and also relatively disconnected from both stock markets, as reported by Yousaf and Yarovaya (2022b), and safe-haven markets; the latter, in turn, show weak connectedness, as would be expected from their safe-haven nature, a result that is consistent with Cevik et al. (2022).

Fig. 1 plots connectedness and the size and direction of spillovers within and between DeFi, cryptocurrency, stock and safe-haven asset markets. DeFi, cryptocurrency, and stock markets are net contributors of spillovers, whereas safe-haven assets are a net receiver of spillovers. A stronger bidirectional spillover is observed between DeFi and cryptocurrency markets, reflecting greater integration between those markets – consistent with the evidence reported by Yousaf et al. (2022) but at odds with that reported by Corbet et al. (2021). Safe-haven assets receive spillovers from all markets, transmitting some risk to stock markets and negligible risk to the DeFi and cryptocurrency markets. Stock markets show bidirectional connectedness with all markets. Within DeFi assets, BAT, Maker, and LINK are net contributor of spillovers, whereas SNX is a net receiver. In the cryptocurrency market, the connectedness network shows significant bidirectional linkages between Bitcoin and Ethereum, consistent with the findings of Beneki et al. (2019). BNB is connected with both Bitcoin and Ethereum, while Tether, interestingly, is disconnected from the three remaining cryptocurrencies, pointing to potential implications for hedging against downward cryptocurrency price movements. For stock markets, there is high connectedness, with the Japanese stock market a net receiver of spillovers from other stock markets. In contrast, safe-haven assets are weakly connected, suggesting possible diversification effects between gold, Treasury bills, and the USD index. Overall, equity investors may consider DeFi assets, cryptocurrencies, gold, Treasury bills, and the USD index to hedge their positions against stock price downward movements.

3.2. Spillover dynamics and financial conditions

We explore whether spillovers change over the sample period by estimating those spillovers for a daily rolling window of 220 trading days, which allows feedback effects and variance-covariance matrix to swing over the sample period, and thus connectedness values as per Eq (4). The graphical evidence in Fig. 2 shows that spillovers rose during the first COVID-19 wave (March-April 2020) and from early 2021: (a) spillovers from DeFi assets to cryptocurrencies and vice versa exhibited the same patterns, ranging from 22% in December 2020 to above 35% in March 2022, the latter reflecting the military conflict in Ukraine; (b) spillovers between safe-haven assets and DeFi and cryptocurrency assets were smoother than those between DeFi assets and stock markets; (c) between January 2020 and January 2021, spillovers between stocks and cryptocurrency and DeFi assets increased, and decreased for safe-haven assets, underlying the importance of adding safe-haven assets to equity-DeFi or equity-cryptocurrency portfolios; and finally, (d) spillovers from safe-haven assets to the other markets were lower than those from DeFi assets, cryptocurrencies, and stocks to safe-haven assets.

We examine whether time-varying net spillovers are shaped by financial market conditions. Particularly, we consider: (a) uncertainty as given by volatility in the gold and stock markets (CBOE gold and VIX indices); (b) illiquidity in the interbank market as given by the TED spread (3-month LIBOR based on the USD minus the 3-month Treasury yield); (c) Treasury spread (US government 10-year yield minus US government 3-month yield); (d) cryptocurrency market volatility (see Wang et al., 2022) as given by the VCRIX index (Royalton VCRIX Crypto Index; see Kim et al., 2021); and (e) the Economic Policy Uncertainty (EPU) index.

Table 4 reports estimated impacts of six control variables on net spillovers for each of the four asset classes. Gold volatility has a negative and significant impact on net spillovers of DeFi, cryptocurrency, and stock markets, implying that an increase in gold uncertainty reduces net spillovers in those markets. In contrast, effects are positive for safe-haven assets. VIX has no impact on net spillovers of cryptocurrency and safe-haven assets, but does positively influence net spillovers in DeFi markets. Likewise, the impact of VIX on net spillovers in the stock markets is negative, implying that a rise in VIX reduces net spillovers in stock markets. As for the illiquidity impact, TED positively affects net spillovers in all markets, with the exception of safe-haven assets where the sign is

Table 3
Connectedness matrix for DeFi, cryptocurrency, stock, and safe-haven asset markets.

	DeFi	Crypto	Stocks	Safe-haven
DeFi	59.47	34.88	4.90	0.77
	(55.25, 62.14)	(32.02, 37.82)	(4.21, 10.16)	(0.50, 3.68)
Crypto	29.61	63.53	5.59	1.27
	(26.78, 32.48)	(57.99, 68.16)	(4.17, 11.90)	(0.79, 5.50)
Stocks	7.02	7.42	80.63	4.93
	(5.11, 14.60)	(4.79, 13.46)	(70.36, 86.82)	(3.60, 8.39)
Safe-haven	3.11	4.58	13.13	79.18
	(1.67, 11.82)	(2.59, 15.18)	(9.08, 20.26)	(65.27, 86.86)

Notes. This table presents evidence of market connectedness among DeFi, cryptocurrency, stock, and safe-haven markets using a forecast horizon of $h = 10$ trading days and the block aggregation procedure of Greenwood-Nimmo et al. (2015). Reported for the market in each row is the fraction of the forecast error variance that is explained by the markets indicated in the columns, with values adding 100%. Reported for the market in each column is the contribution to each market indicated in the rows. 95% confidence intervals reported in round brackets are computed using 10,000 Monte Carlo simulations of the reduced-form VAR model.

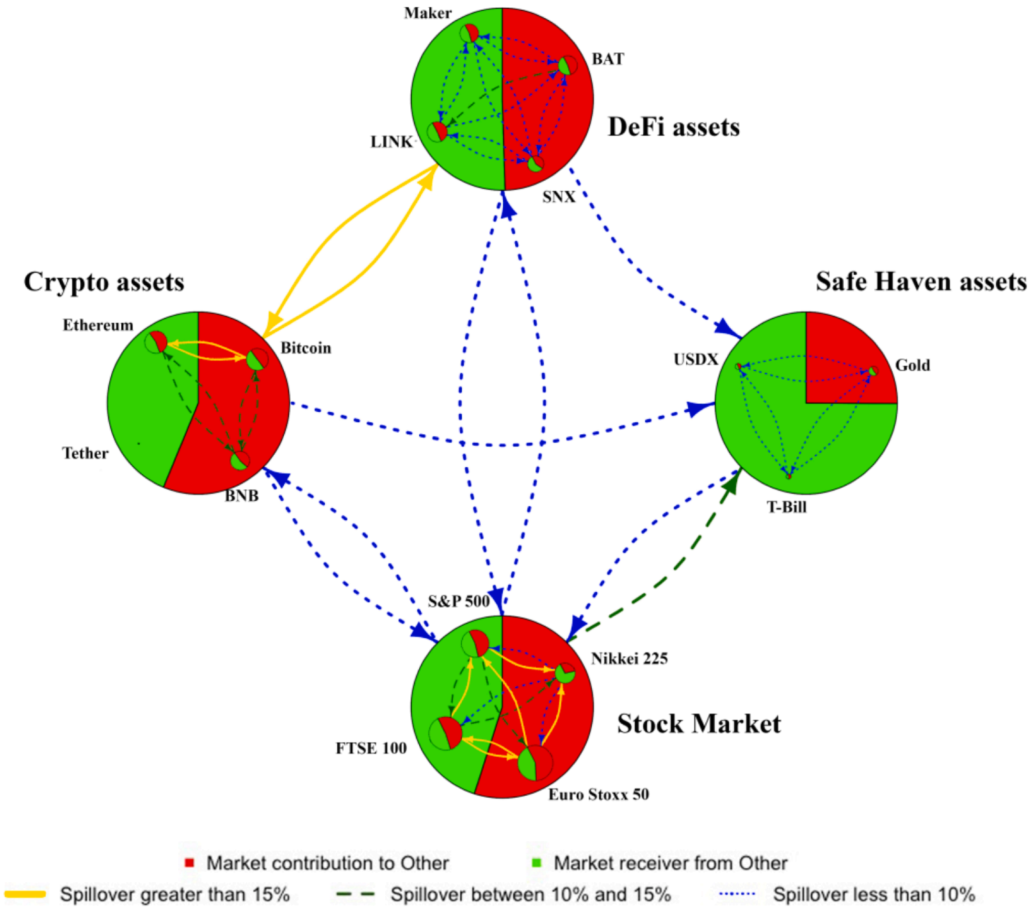

Fig. 1. Connectedness within and between DeFi, cryptocurrency, stock, and safe-haven asset markets.

negative. The Treasury spread impacts negatively on spillovers for both the DeFi and safe-haven asset markets, and positively for cryptocurrency and stock markets. The VCRIX contributes positively to net spillovers of DeFi, stock, and cryptocurrency markets, and negatively to net spillovers of safe-haven asset markets. Finally, a rise in EPU reduces spillovers in all markets, except for safe-haven assets. Overall, those results highlight the relevance of financial market conditions in shaping spillovers across markets, a finding that is consistent with Reboredo et al. (2021) for commodity markets.

4. Conclusions

This study examines spillovers between four market blocks, namely DeFi (BAT, Maker, LINK, and SNX), cryptocurrencies (Bitcoin, Ethereum, Tether, and BNB), stock markets (Japan, US, UK, and Europe), and safe-haven assets (gold, USD index, and US Treasury bills) using the Diebold and Yilmaz (2014) spillover index and the Greenwood-Nimmo et al. (2015, 2016) methodology. Additionally investigated is the impact of certain financial conditions on the size of spillovers, including implied gold volatility, equity market uncertainty (VIX), TED spread, Treasury spread, the Royalton VCRIX Crypto Index, and the EPU index.

Our results reveal that all markets are mainly affected by their own shocks. Of all the asset classes, DeFi assets and cryptocurrencies exhibit the highest spillovers, while the safe-haven assets are those least connected with other assets. Spillovers among markets are dynamic and reach their highest level between early 2020 and early 2021. Finally, the gold volatility index, VIX, TED, Treasury spread, Royalton VCRIX Crypto Index, and EPU index all impact on net spillover size within each asset class. These findings are helpful for investors and portfolio managers and have implications for the design of policies.

CRediT authorship contribution statement

Andrea Ugolini: Methodology, Software, Data curation, Writing – original draft, Writing – review & editing. **Juan C. Reboredo:** Conceptualization, Methodology, Writing – original draft, Formal analysis, Writing – review & editing, Funding acquisition. **Walid Mensi:** Conceptualization, Writing – original draft, Writing – review & editing.

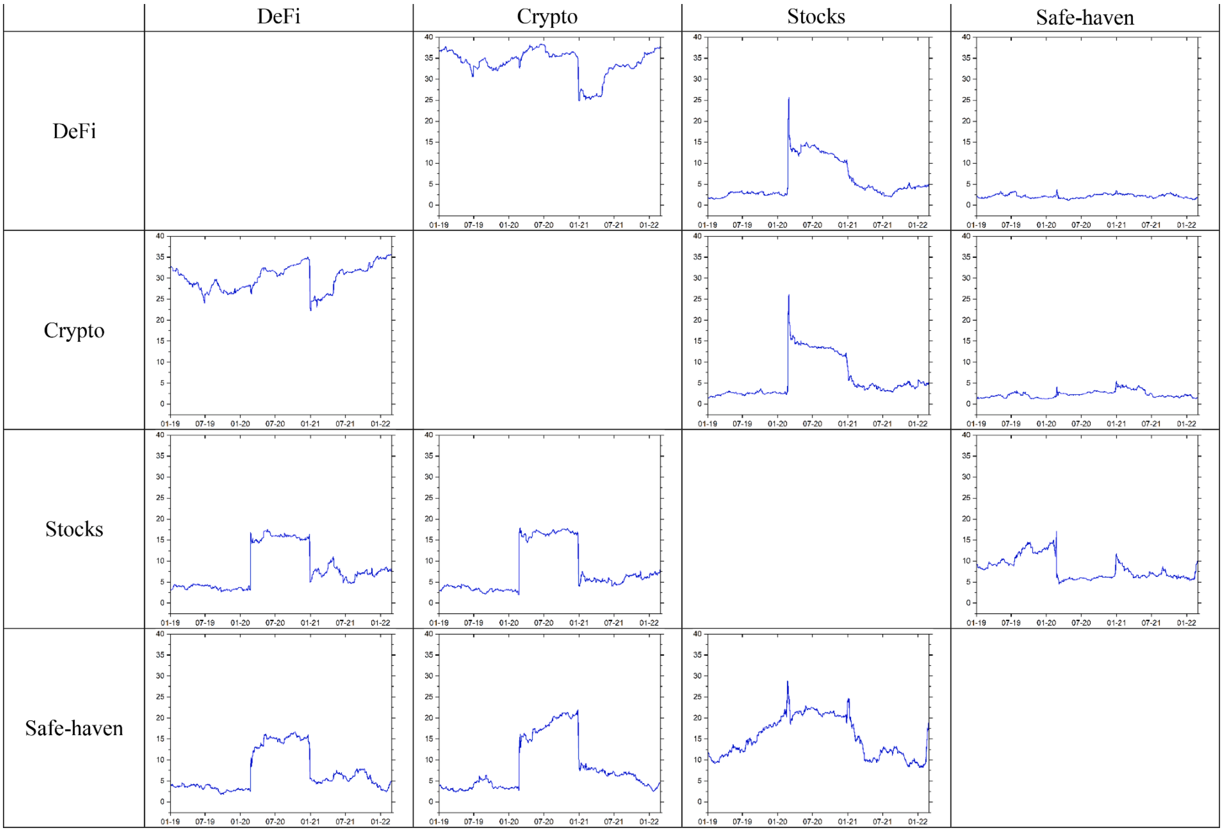

Fig. 2. Connectedness dynamics for DeFi, cryptocurrency, stock, and safe-haven asset markets.

Table 4
Financial market conditions and net spillovers in the DeFi, cryptocurrency, stock, and safe-haven asset markets.

	DeFi	Crypto	Stocks	Safe-haven
β_0	4.553***	-8.059***	4.245***	-0.739
	(0.615)	(0.691)	(0.502)	(1.353)
Gold Vol	-0.495***	-0.628***	-0.415***	1.538***
	(0.054)	(0.06)	(0.044)	(0.118)
VIX	0.114***	0.051	-0.138***	-0.027
	(0.921)	(1.035)	(0.752)	(2.025)
TED	14.101***	10.084***	1.294*	-25.479***
	(0.921)	(1.035)	(0.752)	(2.025)
TS	-4.248***	3.809***	2.840***	-2.400***
	(0.244)	(0.275)	(0.199)	(0.538)
VCRIX	0.003***	0.008***	0.003***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
EPU	-0.027***	-0.031***	-0.012***	0.069***
	(0.002)	(0.002)	(0.001)	(0.004)
Adj. R^2	0.647	0.622	0.656	0.694

Notes. This table presents evidence on the effects of financial market conditions as given by the volatility of gold, stocks, cryptocurrencies, illiquidity, Treasury spread, and economic policy uncertainty on net spillovers in the DeFi, cryptocurrency, stocks, and safe-haven asset markets. T-statistics are reported in round brackets. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Declaration of Competing Interest

There is no conflict of interest among authors.

Data availability

Data will be made available on request.

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