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Full Length Article

Spillovers between Twitter Uncertainty Indexes and sector indexes: Evidence from the US

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Abstract

The study examines the spillover between Twitter Uncertainty Indexes (TUI) and 10 US sectors. Our methodology is twofold: a time-varying parameter vector autoregression (TVP-VAR) to explore the dynamic connectedness among sectoral returns and a regression, mainly ordinary least squares (OLS) and quantile, to explore the role of TUI in explaining the total connectedness and the net connectedness of each sector. First, our results indicate that industrials and materials are the main net transmitters of shocks, and utilities and energy are the main recipients. Second, TUI increases total connectedness only at higher values of connectedness, suggesting that more diversification benefits are available at low levels of connectedness and TUI. Third, the direction of the TUI's effect on net connectedness changes from one sector to another, indicating that TUI can signal either good or bad news, depending on the sector.

JEL classification: C32; C58; G11; G14; G15

Keywords: Sector indexes; Spillover; Twitter

1. Introduction

Uncertainty indexes (UI) are relatively novel tools used to quantitatively assess uncertainty developments. The utility of an index relies on the data on which it is built, which is important for understanding its capacity and limitations. Nowadays, a wide variety of UI are available, which depend on different sources of information and indicate a certain size and direction of possible risk. They include macroeconomic UI, the economic surprise index, economic policy uncertainty (EPU), cryptocurrency uncertainty index, and volatility index. UI can be divided into several categories based on the data used in constructing them. The first category depends on nowcasts and forecasts by professional forecasters, such as macroeconomic UI (Rossi & Sekhposyan, 2015). The second category relies heavily on official and semiofficial sources of information, such as newspapers and trusted institutional publications; one example is EPU indexes (Al-Thaqeb & Algharabali, 2019). Moreover, volatility indexes, such as the VIX, forecast the expected volatility in the S&P index in the next 30 days.[1] These indexes reflect uncertainty and follow changes in EPU indexes (Shaikh, 2019). Finally, new category has emerged that depends on social media platforms, such as Twitter, which has gained importance because of the data and insight they offer (Bartov et al., 2018; Broadstock & Zhang, 2019; Ganesh & Iyer, 2021).

The literature discusses the ability of some UI, such as EPU indexes, in predicting or transmitting information to other

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[1] Baker developed the US Equity Market Volatility Index (EMV), which tracks the VIX.

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indexes or asset classes (Baker et al., 2016; Gupta et al., 2014; Zhang, 2019; Čižmešija et al., 2017) with little attention to the role of other UI-based social media. Although many papers investigate the impact of Twitter data on asset prices, few studies rely on the newly constructed Twitter Uncertainty Indexes (TUI) by Baker et al. (2021). Given the importance of social media in contemporary life, two TUIs were created using tweets posted on the Twitter social media platform, reflecting the perceptions of economic uncertainty based on the views of social media users.

TUI offers several advantages over other UIs. First, it relies on analyzing the sentiment of tens of millions of tweets, arguably more representative of the mood of the crowd than EPU or investor sentiment indexes (Baker et al., 2021). Second, fintech is mobilizing access to finance and investment; hence, markets are experiencing high investment by social media users (usually individual investors). For example, the cryptocurrency market (1.75 trillion in market cap)[2] has received an influx of investment with unusual investor characteristics (Fujiki, 2020; Saiedi et al., 2021; Shahzad, Hernandez, et al., 2018; Shahzad, Xiu, et al., 2018). The use of social media by a new generation of investors has inspired researchers to further investigate the role of TUI in cryptocurrencies (French, 2021; Karalevicius, 2018; Kraaijeveld & De Smedt, 2020; Shen et al., 2019). Third, TUI reflect the crowd's mood much more rapidly and accurately. Fourth, the large volume of tweets coupled with low data collection costs represents another advantage. Finally, because the behavior of TUI is similar to that of the newspaper-based EPU index by Baker et al. (2016), the perception of economic uncertainty by Twitter users and journalists tends also tends to be similar, which gives TUI an advantage over EPU indexes that are widely used in the literature (Baker et al., 2021).

Twitter is popular, especially in the United States, where, as of January 2022, it had more than 76.9 million users.[3] The United States ranks first, with Japan (58.95 million) and India (23.6 million) ranked second and third, respectively. Because of the popularity of Twitter in the US, it is important to investigate the role of TUI in US markets. A careful review of the literature reveals that existing studies have used Twitter data to predict returns on equity markets (Azar & Lo, 2016; Bartov et al., 2018; Leitch & Sherif, 2017) and Bitcoin and other cryptocurrency markets. Shen et al. (2019) find that the number of tweets related to Bitcoin drives the next day's trading volume and realized volatility of Bitcoin, and Öztürk and Bilgiç (2021) conclude that tweets can be used to predict Bitcoin returns. Wu et al. (2021) demonstrate significant causality from TUI to Bitcoin, Ethereum, and Ripple, mainly in times of greater uncertainty, such as the Covid-19 pandemic. The strong causality between TUI and cryptocurrency is supported by Aharon et al. (2022). Twitter data has also been used to predict stock market movement (Behrendt & Schmidt, 2018; Nisar & Yeung, 2018). Huang and Liu (2021) investigate the impact of TUI on stock returns in G7 markets and find that the impact is asymmetric: it is greater for EPU increases than EPU decreases.

During the pandemic, spillovers and connectedness among financial markets have been hot topics, in view of their importance to various aspects of risk. During periods of crisis and turbulence, the size and direction of spillovers are critical for improving investment decisions and reducing risk. Among studies on connectedness, sectoral connectedness is of particular importance given the presence of several investors that trade in national markets. Although most studies focus on overall trends between stock markets, they do not give any insights into dynamic connections between different sectors of an economy, and sectoral connectedness is examined by few researchers. Among them, Baruník et al. (2016) focus on asymmetries in volatility spillovers using seven sectors and find an increase in connectedness during the global financial crisis. Mensi et al. (2021) investigate volatility connectedness among ten US sectors, finding that it is reinforced during economic and geopolitical events. Costa et al. (2022) examine sectoral connectedness among eleven US sectors before and during the Covid-19 pandemic, using Diebold and Yilmaz (2009, 2012, 2014) methodology; they find that total connectedness increased during the pandemic, with relevant changes in the intensity and direction of pairwise connections.

This study aims, first, to examine the level of connectedness between US sectors before and during Covid in order to see how the pandemic affects the nature of connectedness across different sectors. Our central hypothesis is that economic uncertainty affects connectedness. To test this hypothesis, we extend previous studies that address sectoral connectedness by exploring the role of economic uncertainty in the connectedness before and during the pandemic. Specifically, we consider total connectedness among US sectors and net connectedness in each sector with two new measures of uncertainty: Twitter-based economic uncertainty (TEU) and Twitter-based market uncertainty (TMU).

We contribute to the existing literature in several ways. First, although Costa et al. (2022) examine sectoral connectedness among US sectors before and during the pandemic using the Diebold and Yilmaz methodology, our study uses a time-varying parameter vector autoregressive (TVP-VAR) connectedness approach (Antonakakis et al., 2020), which is considered an improvement on the standard rolling-windows approach of Diebold and Yilmaz. Second, this study adds to work on the role of economic uncertainty in financial connectedness. Although most studies use EPU as a proxy for uncertainty, our study uses Twitter Uncertainty Indexes (TEU and TMU), which focus on sentiment that generates uncertainty, which is most likely to affect the stock market. An advantage of this index is the dominance of Twitter users in the US, thus allowing us to capture investor sentiment at a broader level. Whereas the EPU index is constructed based on the count of words related to uncertainty in leading newspapers, resulting in the use of monthly data in some cases, TUI

[2] https://coinmarketcap.com, accessed March 5, 2021.

[3] https://www.statista.com/statistics/242606/number-of-active-twitter-users-in-selected-countries/.

are daily indexes that can better assess consumer uncertainty in the short term. More specifically, TEU and TMU are constructed based on the tweets of users, which is more accurate than newspapers for reflecting uncertainty. Moreover, the EPU index is often regarded as a macro-level measure (Aharon et al., 2022). Given Twitter's popularity, it is becoming a new kind of newspaper that contains up-to-date details about any topic, thus serving as a good platform for measuring mood and sentiment. This paper explores whether crowd sentiment can drive total connectedness among US sectors and net connectedness in individual sectors. Third, following previous studies, we consider the impact of uncertainty on connectedness using regressions and at different quantiles (Arouri et al., 2016; Azimli, 2020; Naeem et al., 2021; Youssef et al., 2021). To the best of our knowledge, this is the first study to examine the effects of these two new TUI measures (i.e., TEU and TMU) on the time-varying connectedness of sectoral return spillovers in the US using two methodologies. The first is our use of the TVP-VAR approach of Antonakakis and Gabauer (2017), which avoids the problems involved in choosing the optimal size of a rolling window and the loss of observations during estimation. The second is our use of regression analysis, both ordinary least squares (OLS) and quantile.

The remainder of this study is organized as follows. Section 2 describes the data and methodology. The empirical results and analysis are presented in Section 3, while Section 4 concludes this study.

2. Data and methods

2.1. Data

The data used in this study is extracted from the Reuters database and includes the prices of S&P 500 sectoral indexes from January 5, 2015,[4] until January 29, 2022 (the last date available). This period is divided into two subperiods: before the Covid pandemic (January 5, 2015–December 30, 2019) and during the pandemic (December 31, 2019–January 29, 2022). Following Costa et al. (2022), we used December 31, 2019, as the start of the pandemic, because that is the day that it was spotted in Wuhan, China, as reported by the World Health Organization (WHO).

Ten US sectoral indexes are covered in this study: energy (SPNY), technology (SPLRCT), utilities (SPLRCU), financial (SPSY), health care (SPXHC), consumer staples (SPLRCS), industrials (SPLRCI), materials (SPLRCM), real estate (SPLRCR), and consumer discretionary (SPLRCD). One sector, mainly telecom services, was excluded given its monotonic trends. TUI are measured using the TEU and TMU indexes introduced by Baker et al. (2016). Whereas TEU reflects uncertainty in the economy in general, TMU focuses on uncertainty in equity markets.

[4] We start the dataset at the beginning of 2015 for two main reasons: (1) before that period the volume of tweets was small, and (2) in 2015, the Twitter "favorite" function was renamed "like," leading to a change in user behavior.

We transform the raw price data into log returns, measured as ln (P_t/P_{t-1}). Table 1 reports the descriptive statistics on the log returns of the indexes examined. All indexes, except SPNY (energy), experienced positive returns over the period. Technology had the highest average return (0.08%), followed by consumer discretionary (0.06%) and financials (0.04%). The energy sector is the riskiest, as measured by the standard deviation, followed by financials and technology, whereas consumer staples had the lowest risk. All sectoral indexes were skewed to the left as indicated by negative skewness, characterized by excess kurtosis. Thus, all sectors have a leptokurtic distribution with fat tails. Moreover, the results indicate that the series are nonnormally distributed and stationary at the 1 percent significance level, according to Jarque–Bera and Elliot–Rothenberg–Stock (ERS) tests. Furthermore, the findings indicate the presence of autocorrelation in the squared series, implying that the time-varying variance–covariance structure using TVP-VAR is appropriate.

The resulting series, along with the UI, are depicted in Fig. 1. As shown, all the stock market indexes examined had sudden and extreme fluctuations near the onset of the Covid-19 pandemic.

2.2. Methodology

2.2.1. TVP-VAR

To achieve the first objective (measuring the dynamic connectedness), we use the TVP-VAR methodology of Antonakakis and Gabauer (2017), which extends the connectedness approach of Diebold and Yilmaz (2009, 2012, 2014).

This model offers several advantages over the rolling-windows-based VAR approach of Diebold and Yilmaz, as follows: (1) no sensitivity to outliers; (2) no arbitrary window size selection, which might cause fattened parameter estimations; (3) no loss of observations because it is based on a Kalman filter procedure to determine the variance–covariance matrix; and (4) the ability to analyze low-frequency datasets (Antonakakis et al., 2020).

The TVP-VAR model is outlined in the following sets of equations. Let z_t be a (N × 1) dimensional vector consisting of N number of sectors. The TVP-VAR model can be constructed as follows:

$$z_t = B_t z_{t-1} + u_t; \qquad u_t \sim N(0, S_t) \tag{1}$$

$$B_t = B_{t-1} + v_t; \qquad v_t \sim N(0, R_t) \tag{2}$$

where z_{t-1} is the lagged vector of the dependent variable. B_t is a time-varying $(N \times N)$ dimensional coefficient matrix. u_t and v_t are two different error terms defined by the vectors $(N \times 1)$ and $(N^2 \times 1)$, respectively. S_t and R_t are $(N \times N)$ and $(N^2 \times N^2)$ matrixes that show the time-varying variance–covariance matrixes of the error terms u_t and v_t, respectively.$_2$

Then, we perform generalized forecast error-variance decompositions (GFEVD) by transforming TVP-VAR into a TVP-VMA using the Wold representation theorem:

Table 1
Descriptive statistics.

	Mean	Min	Max	SD	Skew	Kurt	JB	ERS	Q(10)	Q2(10)
TEU-USA	0.000502	−2.033568	2.908126	0.494416	0.501***	3.375***	915.336***	−12.146***	347.972***	357.529***
TMU-US	0.000756	−2.116890	2.264277	0.469323	0.371***	2.271***	421.310***	−20.724***	246.029***	218.410***
SPNY	−0.000107	−0.224172	0.151108	0.019687	−1.541***	27.202***	55335.455***	−8.412***	67.938***	570.402***
SPLRCT	0.000830	−0.149833	0.113002	0.014437	−1.080***	21.272***	33754.670***	−8.895***	168.865***	898.419***
SPLRCU	0.000232	−0.122653	0.123204	0.012498	−0.241***	27.305***	55062.765***	−10.334***	131.149***	1374.990***
SPSY	0.000427	−0.150707	0.124251	0.014914	−0.931***	23.639***	41514.542***	−8.748***	148.636***	1141.307***
SPXHC	0.000387	−0.105274	0.073138	0.011190	−0.873***	15.902***	18895.478***	−13.427***	114.807***	1007.280***
SPLRCS	0.000282	−0.096900	0.080747	0.009589	−0.699***	23.642***	41413.556***	−18.581***	123.993***	1395.713***
SPLRCI	0.000365	−0.121550	0.120008	0.012995	−0.589***	22.394***	37130.920***	−19.141***	100.775***	1121.841***
SPLRCM	0.000354	−0.121470	0.110034	0.013426	−0.696***	17.285***	22203.343***	−18.797***	95.293***	1014.178***
SPLRCR	0.000289	−0.180910	0.082802	0.013020	−3.117***	44.433***	148640.244***	−13.129***	116.519***	501.986***
SPLRCD	0.000590	−0.128772	0.082862	0.012194	−1.602***	21.288***	34217.685***	−5.445***	81.802***	712.418***

Notes: This table reports the descriptive statistics of the stock market returns considered. JB is the Jarque–Bera normality test statistics. ERP denotes the Elliot–Rothenberg–Stock unit-root test. Q(10) and Q2(10) are the Ljung–Box tests for 20th-order serial correlations for returns and squared returns, respectively. ***, **, and * indicate the statistical significance, respectively, at 1%, 5%, and 10%.

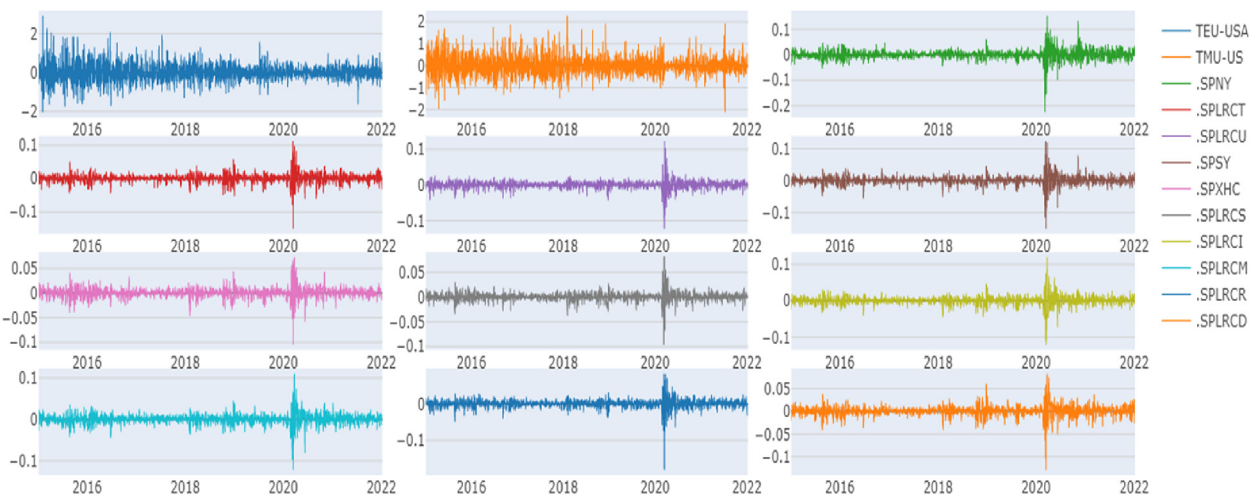


Fig. 1. Daily returns.

$$z_t=\sum\nolimits_{i=1}^{p}B_{it}\,z_{t-i}\;+\;u_t=\sum\nolimits_{i=0}^{\infty}A_{jt}\,u_{t-j} \tag{3}$$

Next, based on GFEVD, we calculate four connectedness measures as follows. Note that $\varphi^{g}_{ij,t}(H)$ is the impact of a shock in variable j on variable i. The first is *total directional connectedness TO others*, or the impact of a shock in one variable i to other indexes, j, which is expressed in the following equation:

$$TO_{jt}:\ C^{g}_{i\to j,t}(H)=\sum\nolimits_{i=1,i\neq j}^{N}\varphi^{g}_{ij,t}(H) \tag{4}$$

The second is *the total directional connectedness FROM others,* the impact that i receives from j, which is expressed as follows:

$$FROM_{jt}:\ C^{g}_{i\leftarrow j,t}(H)=\sum\nolimits_{i=1,i\neq j}^{N}\varphi^{g}_{ji,t}(H) \tag{5}$$

Third, we calculate the *net total directional connectedness* as the difference between the total directional connectedness TO others and the total directional connectedness FROM others. The value determines whether a variable is driving other variables (positive values) or driven by other variables (negative values).

$$NET:TO_{jt}-FROM_{jt}:=\sum\nolimits_{i=1,i\neq j}^{N}\varphi^{g}_{ij,t}(H)-\sum\nolimits_{i=1,i\neq j}^{N}\varphi^{g}_{ji,t}(H) \tag{6}$$

Finally, we calculate the total connectedness index (TCI) or the average impact of one variable on all others, which indicates the interconnectedness of the network and hence the market risk

$$TCI_t=N^{-1}\sum\nolimits_{j=1}^{N}TO_{jt}=N^{-1}\sum\nolimits_{j=1}^{N}FROM_{jt} \tag{7}$$

The main limitation in the calculation of TCI is that it ranges within [0, (N−1)/N] and not within [0,1]. Thus, to improve its interpretation, TCI is slightly adjusted (Chatziantoniou & Gabauer, 2021) to range between 0 and 1.

2.2.2. Regression

After obtaining the TCI, we further extend prior studies focused on sectoral connectedness (Chatziantoniou et al., 2021; Costa et al., 2022; Ekinci & Gençyürek, 2021) by using the quantile and OLS approach to examine the effect of investor sentiment, proxied by TEU and TMU, on the TCI. Several studies argue that the relationship between financial markets, especially stock markets, is affected by uncertainty indexes (Badshah et al., 2019; Fang et al., 2017, 2019; Li et al., 2015; Li & Peng, 2017; Matkovskyy et al., 2020). Therefore, TUI, by gauging crowd sentiment, might drive the connectedness between the stock returns.

After calculating the different time-varying spillover indexes based on the TVP-VAR model, we examined whether TUI drives this connectedness between stock market returns using a regression following Arouri et al. (2016), Azimli (2020), Naeem et al. (2021), and Youssef et al. (2021). To this end, we constructed the following equation:

$$Y_t = \theta_0 + \theta_1 TUI_t + \varepsilon_t \tag{8}$$

where Y_t represents total connectedness or net connectedness measures, and TUI is the uncertainty index developed by Baker et al. (2016), measured by TEU or TMU in period *t*. We use OLS regression and quantile regression (QR) by Koenker and Bassett (1978) to quantify the impact of TUI on connectedness. QR has several advantages, such as its robustness to outliers and heteroskedasticity and its ability to address nonlinearity and asymmetric effects (Koenker & Hallock, 2001).

3. Empirical results and discussion

3.1. Sectoral connectedness

3.1.1. Static analysis

Table 2 demonstrates the average dynamic connectedness measures, generated by the TVP-VAR model for the periods before and during Covid, from which several points emerge. First, the results indicate that the TCI is 71.75 percent and 76.59 percent in the periods before and during COVID, respectively, which measures the average influence of all variables on the forecast error variance in one variable over time. In other words, more than 70 percent of a shock in one index spills over to all others, indicating that US sectors are dependent on one another. This result highlights the low risk diversification provided by US sectors.

Second, TCI is higher in the period during Covid than prior period, suggesting an increase in systemic risk and spillover during turbulent periods, consistent with the finding that during the pandemic dependence increased between sectors (Costa et al., 2022) and stock markets (Cepoi, 2020; Zhang et al., 2020).

Third, the results show some changes in the transmission power of some sectors. In the period before the pandemic, the main transmitters of shocks were SPLRCI (Industrials) and SPLRCD (consumer discretionary). During the pandemic, the transmission from SPLRCI increased from 95.5 percent to 100.96 percent, whereas transmission from SPLRCD decreased from 95.04 percent to 68.08 percent. Before the pandemic, the sectors with the least transmission were SPLRCU (utilities) and SPNY (energy). During the pandemic, the transmission from SPLRCU increased from 31.42 percent to 63.2 percent. This demonstrates that the role of sectors in contributing to market interconnectedness is affected by the pandemic.

Fourth, industrials as a sector received the most from the system in before and during the pandemic, with 79.25 percent and 81.26 percent, respectively. However, the sectors that received the least from the system were utilities, with 51.49 percent before the pandemic, confirming Costa et al. (2022), and energy, with 70.63 percent during the pandemic.

Fifth, the last column reports the net total directional connectedness measures or the difference between how much of a shock in one asset spills over to all others and how much of a shock in all others spills over to that asset. The results show that industrials are the main net transmitter of shocks in both periods, with 16.25 percent and 19.7 percent, respectively, consistent with Costa et al. (2022). This is in line with the intuition that industrials is a major pillar of US economic development, contributing the most to the country's gross domestic product, which makes it one of the most influential sectors.

Utilities are the main recipients of shocks before the pandemic (−20.07%), and energy has the least net connectedness during the pandemic (−17.35%). This finding contradicts Costa et al. (2022), who find that utilities are the net recipients during Covid (−39.2%). These divergent findings could be contributed to the different time frames employed for the pandemic. Whereas the end point for the data used by Costa et al. (2022) was December 31, 2022, our data was extended to the end of January 2022. Sixth, the role of sectors, mainly technology, utilities, consumer staples, real estate, and consumer discretionary, underwent some radical changes. Technology was a net transmitter before the pandemic (6.64%), but a net recipient during Covid (−6.48%), consistent with Costa et al. (2022). The utility sector increased its net connectedness, from −20.07 percent to −10.15 percent, the highest jump among all sectors. Consumer staples was a net recipient before the pandemic (−0.19%) and a net transmitter during it (1.73%), consistent with Costa et al. (2022), but its effect is negligible. Real estate changed from being a net recipient (−8.67%) to a net transmitter (3.36%), and consumer discretionary changed from being a net transmitter (12.13%) to a net recipient (−7.17%). Although our results before the pandemic are consistent with those of Costa et al. (2022), they differ during the pandemic. Finally, the financial sector increased its net connectedness, consistent with Costa et al. (2022) and Akhtaruzzaman et al. (2021), which highlight the increased role of the financial sector in the transmission of contagion during the pandemic.

Sectors are generally considered either defensive or aggressive. Whereas defensive sectors are known for their inelastic demand, low beta, low volatility, stable earnings, and lower vulnerability to economic cycles, aggressive sectors are characterized by their elastic demand, high beta, high volatility

Table 2
Average connectedness table.

	SPNY	SPLRCT	SPLRCU	SPSY	SPXHC	SPLRCS	SPLRCI	SPLRCM	SPLRCR	SPLRCD	From others
Before Covid (January 5, 2015–December 30, 2019)											
SPNY	31.8	8.07	1.04	10.89	6.87	4.14	12.11	13.42	2.6	9.05	68.2
SPLRCT	5.93	23.06	1.42	9.95	10.61	6.48	12.52	10.43	4.17	15.42	76.94
SPLRCU	1.61	2.83	48.51	1.8	3.94	15.06	2.72	2.23	18.62	2.68	51.49
SPSY	8.23	10.41	0.8	23.71	9.44	5.34	14.88	12.33	2.93	11.94	76.29
SPXHC	5.55	11.78	2.05	10.22	26.11	7.69	11.06	9.27	5.04	11.24	73.89
SPLRCS	3.74	7.82	8.94	6.47	8.72	28.95	8.2	7.13	10.94	9.08	71.05
SPLRCI	8.14	11.46	1.21	13.12	9.15	6.07	20.75	13.94	3.56	12.6	79.25
SPLRCM	9.73	10.43	1.13	11.94	8.39	5.81	15.26	22.72	3.4	11.19	77.28
SPLRCR	2.73	6.17	13.55	4.05	6.98	13.25	5.63	4.97	35.34	7.34	64.66
SPLRCD	6.33	14.62	1.28	10.97	9.67	7	13.12	10.7	4.73	21.59	78.41
TO others	52	83.58	31.42	79.41	73.77	70.86	95.5	84.42	55.99	90.54	717.47
Inc. own	83.8	106.64	79.93	103.11	99.87	99.81	116.25	107.13	91.33	112.13	TCI
NET	−16.2	6.64	−20.07	3.11	−0.13	−0.19	16.25	7.13	−8.67	12.13	71.75
During Covid (December 31, 2019–January 5, 2022)											
SPNY	29.37	3.55	3.08	17.37	4.3	4.44	14.51	13.2	5.33	4.84	70.63
SPLRCT	3.27	25.38	4.85	6.05	10.63	8.45	8.43	7.07	9.25	16.62	74.62
SPLRCU	2.88	5.02	26.65	7.05	9.75	14.05	8.73	7.38	13.74	4.74	73.35
SPSY	12.39	5.13	5.66	20.94	6.18	6.96	16.18	13.08	7.63	5.83	79.06
SPXHC	3.71	9.82	8.85	6.97	23.24	11.33	9.08	9.35	9.79	7.85	76.76
SPLRCS	3.77	7.69	11.96	7.6	10.91	22.34	9.96	8.79	10.59	6.38	77.66
SPLRCI	9.4	6.4	6.36	14.5	7.28	8.31	18.74	13.56	8.54	6.92	81.26
SPLRCM	9.12	5.81	6.1	12.72	8.41	8.14	14.73	20.18	7.43	7.37	79.82
SPLRCR	4.35	8.23	11.65	8.15	9.12	10.48	10.07	7.91	22.5	7.53	77.5
SPLRCD	4.37	16.48	4.69	6.97	8.61	7.23	9.27	9.08	8.55	24.75	75.25
TO others	53.27	68.14	63.2	87.36	75.19	79.39	100.96	89.43	80.86	68.08	765.9
Inc. own	82.65	93.52	89.85	108.3	98.43	101.73	119.7	109.62	103.36	92.83	TCI
NET	−17.35	−6.48	−10.15	8.3	−1.57	1.73	19.7	9.62	3.36	−7.17	76.59

especially during a turbulent period, and more vulnerability to macroeconomic fluctuations. Defensive sectors include necessary goods and services, such as utilities (water, gas, electricity), consumer staples (food, beverage), and health care (hospitals, pharmaceuticals), whereas aggressive sectors include consumer discretionary (automobile, leisure, luxury goods), industrials (machinery, transportation), materials (metals, chemicals, papers), and finance (banks, insurance). Our results show that before the pandemic, defensive sectors, mainly utilities (−201.7%), consumer staples (−0.19%), and health care (−0.13%), were net recipients, with negative values for net connectedness, and aggressive sectors, namely industrials (16.25%), consumer discretionary (12.13%), materials (7.13%), technology (6.64%), and financials (3.11%), were net transmitters. The role of energy as a net recipient is not surprising, given that it became a basic input in industrial production and transportation and, thereby, demand inelastic (−16.2%). Aggressive sectors generate higher returns than defensive stocks during an economic expansion or in normal times. However, during turbulent periods, the story is different, as the performance may decline more in aggressive sectors than in defensive ones. The evidence shows that three primarily defensive sectors (utilities, energy, and health care) remained net shock recipients during the full sample period, and three aggressive sectors (financials, industrials, and materials) remained net shock transmitters. Defensive stocks such as utilities are considered necessities that are not expected to be affected by the pandemic. However, the financial sector's role as a net transmitter increased during the pandemic, suggesting that this sector has been used by the government as the central conduit for policy interventions to redirect capital resources in the economy. This aligns with the common view that the financial sector is rational in turbulent periods.

Some evidence emerged of switches from a net volatility transmitter (recipient) to a net volatility recipient (transmitter) in the consumer discretionary and technology sectors (consumer staples and real estate), suggesting the existence of disruptive shocks. These findings indicate that the pandemic not only increased the connectedness of the sectors but introduced wide and asymmetrical changes across sectors. Although several firms across different sectors faced huge losses, the pandemic did not have an equal impact on all sectors.

Whereas stock prices collapsed in some sectors, others may have benefited from the resulting lockdowns. Therefore, the roles as net recipients and transmitters are nonlinear, continuously changing in pattern and intensity. It is well known that household consumption priorities shift toward basic needs during a crisis. The pandemic has a significantly negative effect on luxury and non-essential goods. More specifically, because of its business dynamics, the real estate sector alternates between being a net recipient and a net transmitter of spillovers. The big change in the role of consumer discretionary from a net transmitter to a net recipient is inconsistent with the economic intuition that these stocks rely heavily on the business cycle and economic conditions. Within the consumer discretionary sector, the automobile industry, which was hard hit by the pandemic, changed the nature of its production lines by producing medical equipment. Other industry groups experienced a sharp increase in demand due to their online and e-commerce during the lockdowns. The consumer staples sector, although known for its defensive nature, shifted its role. This sector faced significant disruption in its supply chains and a reduction in consumption, explaining its role as a net transmitter during the pandemic. Finally, the technology sector benefited from the increased demand for specialized software needed to facilitate distance learning. The pandemic had a positive impact on this sector, as found by Al-Awadhi et al. (2020) and Mazur et al. (2021). Technology has become necessary, as the US economy is shifting to a service economy, explaining its inelastic demand.

Overall, our findings are important for portfolio and risk management because it is better to invest in sectors that are driving the market, rather than being driven by the market. A sector that is influenced by others can expose investors to much more risk. Moreover, it is better to invest in stable sectors, which have been less affected by the pandemic.

To further investigate the changes in the directional pairwise connectedness level, we use network representations in Fig. 2, in the periods before and during the pandemic. The results show several changes during the pandemic. For instance, in the period before the pandemic, t strong pairwise connectedness is found between utilities-consumer staples and utilities-real estate. However, during the pandemic, considerable concentration exists in pairwise connectedness to energy, namely, financials-energy, industrials-energy, and materials–energy. Energy is a fundamental input in industrial production and materials. The increasing importance of the energy sector is related to the finding by Zhang (2017) that oil can play a significant role when large shocks occur. Moreover, power and renewables companies maintained their assets by providing safe, reliable supplies of electricity and natural gas during the Covid-19 pandemic, explaining the increase in the linkage to the energy sector. Interestingly, the link between technology and utilities diminished during the pandemic.

3.1.2. Dynamic total connectedness index

To determine whether the connectedness between sectoral returns varied over time and how it was affected by the Covid-19 pandemic, Fig. 3 shows the timeline for the dynamic total connectedness index (TCI), which was relatively high during the entire period. We find that market interconnectedness decreased from the beginning of the period until 2017, reaching its trough in November 2016 (56.5%), before increasing steadily until 2020 (the outbreak of Covid). After the outbreak of Covid, in March 2020, the price of all indexes fell; this affected the interconnectedness of the market, which dropped to around 66 percent in November 2020. The reduction in connectedness levels could be attributed to vaccination and government stimulus efforts.

In March 2021, after this decline halted, market interrelationship increased again. This finding is somewhat consistent with Cepoi (2020) and Zhang et al. (2020), who find that dependence between stock markets remarkably increased during the health crisis.

3.1.3. Net total directional connectedness

Dynamic TCI shows the importance of investigating the time-varying behavior of connectedness measures in analyzing the transmission spillovers between stock markets, especially during critical periods. Thus, the next step is to look at the dynamics of the net total directional connectedness measures to see how persistently an asset is a net transmitter or a net recipient of shocks. The net total directional connectedness of the sectors over time is shown in Figs. 4 and 5 for the periods before and during the pandemic. Positive values mean net

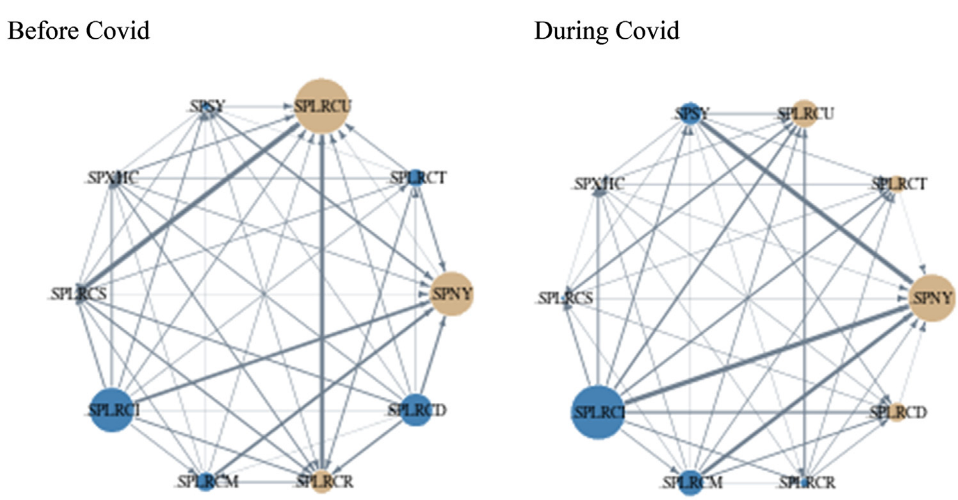


Fig. 2. Pairwise network connectedness. *Note*: blue (yellow) nodes illustrate net transmitter (recipient) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. Size of nodes represent weighted average net total directional connectedness. The arrow direction goes from the sector with positive net pairwise connectedness to its counterpart.

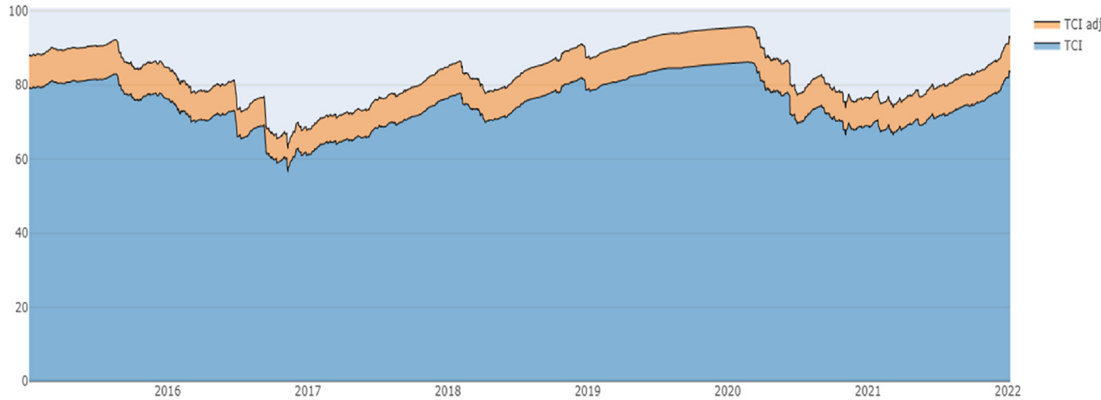


Fig. 3. Dynamic total connectedness. *Note*: the blue area represents TCI, and the orange area illustrates the TCI adjusted measure (for interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.).

transmission, and negative values mean net reception. This information is quite important, as a persistent net transmitter sector has a low number of sources of risk and is more attractive to investors. Moreover, we analyze the directional dynamic spillovers "to" and "from" connectedness for all US sectoral indexes, as shown in the Appendix.

Figs. 4 and 5 show that, during the pandemic, some sectors maintained their role from the period before Covid as persistent net recipients or net transmitters of connectedness, consistent with Costa et al. (2022). More specifically, SPLRCI (industrials) is a permanent net transmitter of shocks (in both periods) and increases its net transmission ability over time, which makes this sector more attractive to investors. SPLRCM (materials) has a prolonged period of net transmission, after 2016 and during the pandemic. SPSY (financials) has a period of net transmission during the pandemic, emphasizing the role of the financial sector in the transmission of contagion during turbulent periods. By contrast, SPNY (energy) and SPLRCU (utilities) are less attractive to investors, as they are permanent net recipients of shocks in both periods. Energy is a net recipient because oil prices are generally net recipients (Zhang, 2017).

However, SPLRCT (technology) and SPLRCD (consumer discretionary) are net transmitters of shocks before the pandemic but net recipients during it. The finding in the technology sector is consistent with Costa et al. (2022). However, Costa et al. (2022) find that consumer discretionary is a net transmitter during the pandemic, contrary to our findings. On another note, SPXHC (health care) plays a fluctuating role, changing from being a net recipient to a net transmitter several times before the pandemic. However, it becomes a net recipient during Covid, consistent with Costa et al. (2022). However, the fluctuating role of SPRCS (consumer staples) in the period before Covid turns more stable during Covid, as it becomes a net transmitter of shocks.

Thus, although the pandemic did not change the role of some sectors (energy, utilities, industrials, and materials), it had a significant impact on other sectors (technology, health care,

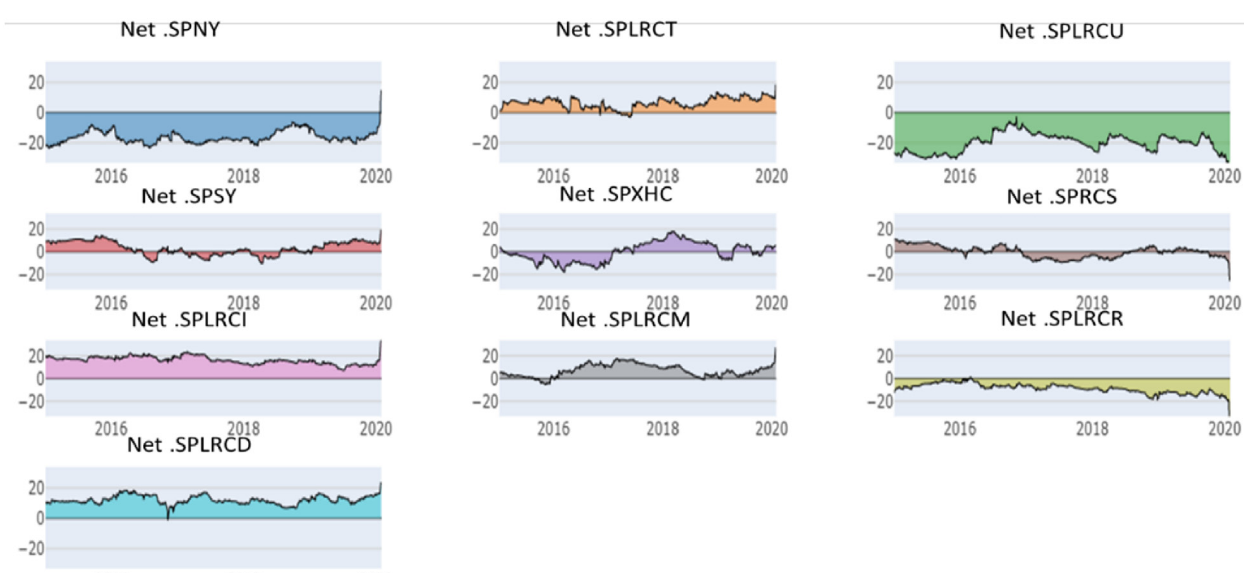


Fig. 4. Dynamic net total directional connectedness before Covid.

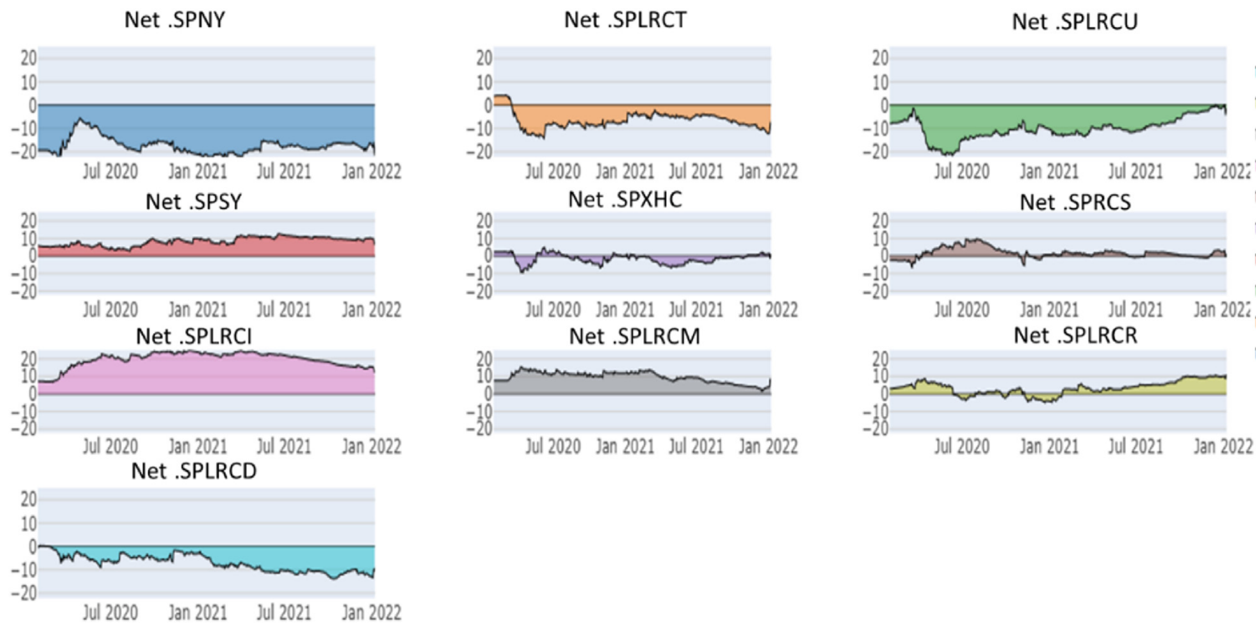


Fig. 5. Dynamic net total directional connectedness during Covid.

financials, consumer staples, consumer discretionary, real estate). More specifically, technology, health care, and consumer discretionary become net recipients during the pandemic, consumer staples, and real estate became net transmitters. During the pandemic, the role of financials in transmission increased.

Appendix A shows that the connectedness "from" is much flatter across sectors than the connectedness "to" connectedness, which supports Diebold and Yilmaz (2014), who analyzed the connectedness of 13 US financial institutions during the and Costa et al. (2022), who examined the connectedness of 10 US sectors during the pandemic. They conclude that the asymmetric size of US sectors leads to diversity in the responses to the spillovers of shocks to different sectors. Second, the "from" connectedness of all sectors during the pandemic has a similar pattern, whereas the "to" connectedness during the pandemic shows large fluctuation from one sector to another. Thus, the pandemic had a homogeneous and symmetrical effect across all sectors in terms of receiving spillovers, but a heterogeneous and asymmetric effect across sectors with respect to sending spillovers. This finding is also consistent with Costa et al. (2022).

3.2. Twitter sentiment index and sectoral connectedness

We now turn our attention to how crowd sentiment, as proxied by TEU and TMU indexes, affects interconnectedness among sectors. First, we estimate a standard OLS regression to estimate the impact of TEU/TMU on TCI, following other studies (Arouri et al., 2016; Azimli, 2020; Naeem et al., 2021; Youssef et al., 2021).

The standard OLS regression (see Table 3) yields similar coefficients for TEU and TMU during the pandemic, significant at the 1 percent level, providing initial evidence that, as uncertainty increases during turbulent periods, the spillover among sectoral returns increases. In the results for the period before the pandemic, the TEU coefficient is significant at 5 percent, but TMU loses its significance, suggesting that the impact of TUI on sectoral connectedness is more pronounced during the pandemic. It is well documented that periods of increased volatility as measured by TUI are characterized by increasing linkage. The results show evidence of the intensified impact of uncertainty on connectedness among the US equity sectors related to Covid-19, consistent with Shahzad et al. (2021). Market connectedness and spillovers are stronger during bearish markets (Bauмöhl & Shahzad, 2019; Shahzad, Hernandez, et al., 2018; Shahzad, Xiu, et al., 2018) and economic uncertainty (You et al., 2017). The role of uncertainty in dynamic connectedness is highlighted in several studies (Bouri et al., 2021; Sharif et al., 2020), showing that it is more pronounced during the pandemic. Thus, we can conclude that sentiment indicators are significant contributing factors to the connectedness of risky assets during stressful periods, such as that of the pandemic.

To provide a more robust alternative to the presence of outliers and to test the sensitivity of TCI in various quantiles, we perform a QR similar to that of Naeem et al. (2021). The results in Table 4 show that TCI is related to TUI. Specifically, we perform the estimations for the 10th, 25th 50th, 75th, and 90th quartiles. The results are consistent with those obtained from the OLS regressions. More specifically, the sign of the impact of TEU does not change direction across all quantiles and in both periods, remaining positive, but its magnitude and significance change. It is significant in all quantiles, except the lower quantiles before the pandemic (0.25 or below) and higher quantiles during the pandemic (0.90 or more). Thus, during the pandemic, any change in economic uncertainty affects TCI as long as it is not in the

Table 3
OLS regression (robust).

	Before				During			
	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value
TEU	0.0209048	0.011**			0.0098099	0.000***		
TMU			−0.001191	0.651			0.0098158	0.000***
R^2	4.23%		0.2%		8.69%		8.14%	
F-value	6.46	0.015**	2.30	0.056*	83.43	0.000***	20.55	0.000***

*, **, and *** denote significance at 1%, 5% and 10%, respectively.

Table 4
Quantile regression using TUI.

	Q10		Q25		Q50		Q75		Q90	
	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value
Panel A: full period										
TEU	0.0167586	0.000***	0.0061479	0.002***	0.009399	0.000***	0.005096	0.004***	0.0194618	0.000***
TMU	0.0016356	0.495	−0.0.0000	0.978	0.0082373	0.020**	0.0050536	0.000***	0.008424	0.001**
R^2 (TEU)	3.19%		0.83%		1.24%		0.73%		4.51%	
R^2 (TMU)	0.09%		0.01%		0.11%		0.44%		1.31%	
Panel B: before Covid										
TEU	0.0000	0.988	0.0160116	0.190	0.0472221	0.000***	0.0324873	0.000***	0.0298006	0.0000***
TMU	−0.0039	0.294	−0.008268	0.015**	−0.002389	0.386	0.0029724	0.283	0.0188599	0.000***
R^2 (TEU) (%)	0.001		0.041		4.57		6.48		12.06	
R^2 (TMU) (%)	0.33		0.40		0.03		0.19		2.31	
Panel C: during Covid										
TEU	0.009316	0.000***	0.011524	0.000***	0.0137102	0.000***	0.0103863	0.000***	0.002567	0.401
TMU	0.0000	0.998	0.0059234	0.199	0.0176649	0.000***	0.015737	0.000***	0.004708	0.061*
R^2 (TEU) (%)	3.58		5.25		7.73		7.86		1.4	
R^2 (TMU) (%)	0.01		1.22		6.10		12.01		2.73	

*, **, and *** denote significance at 1%, 5% and 10%, respectively.

Table 5
Impact of TUI on sectoral net connectedness (before and during Covid).

	Before Covid			During Covid		
	Coeff	P-value	R^2 (%)	Coeff	P-value	R^2 (%)
SPNY (energy)	−0.0004742	0.664	0.01	0.0039897	0.004***	3.65
SPLRCT (technology)	−0.0030382	0.125	0.065	−0.0085039	0.000***	13.34
SPLRCU (utilities)	0.0328514	0.007***	11.71	−0.0003187	0.844	0.02
SPSY (financials)	0.0049665	0.074*	0.41	−0.0083869	0.000***	29.02
SPXHC (health care)	0.0017533	0.578	0.02	0.003607	0.000***	4.27
SPLRCS (consumer staples)	−0.0071985	0.014**	1.24	−0.0001682	0.865	0.01
SPLRCI (industrials)	−0.0189097	0.015**	12.32	−0.0121994	0.000***	14.94
SPLRCM (materials)	0.0059427	0.002***	0.70	0.0109864	0.000***	19.00
SPLRCR (real estate)	0.0077134	0.021**	2.81	0.0043364	0.000***	4.56
SPLRCD (consumer discretionary)	−0.0245807	0.018**	14.26	0.0060935	0.000***	10.47

upper quantile. The results for TMU are different. During the pandemic, TMU increases TCI when TCI is at a moderate level (between 0.50 and 0.75), and TMU does not affect TCI at a low level of connectedness (0.25 or below) or a high level of connectedness (0.90 or above).

In the next step, we perform an OLS regression using the net connectedness of each sector as the dependent variable before and during Covid, following Youssef et al. (2021). The results in Table 5 show that, when measured by TEU, TUI has a positive effect on the net connectedness of materials and real estate in both periods. However, in other sectors, the impact of TEU depends on the period. Whereas TEU negatively affects consumer discretionary before the pandemic, it has a positive effects during the pandemic. During Covid, TEU has a positive impact on energy, health care, materials, real estate, and consumer discretionary, but it has a negative impact on technology, financials, and industrials. Thus, the Covid-19 pandemic had a multifold and differential impact on the sectors in the US stock market with various different reactions.

Table 6
Impact of TMU on sectoral net connectedness (before and during Covid).

Sector	TMU			
	Before Covid		During Covid	
	Coeff	P-value	Coeff	P-value
SPNY (energy)	0.0032736	0.009***	−0.000689	0.459
SPLRCT (technology)	−0.0011363	0.229	−0.0012103	0.426
SPLRCU (utilities)	0.0101025	0.000***	0.0054328	0.000***
SPSY (financials)	−0.0046994	0.000***	−0.0052705	0.000***
SPXHC (health care)	0.0020683	0.524	0.0032188	0.000***
SPLRCS (consumer staples)	−0.0061234	0.008***	−0.0043121	0.000***
SPLRCI (industrials)	−0.0040249	0.012**	−0.0121458	0.000***
SPLRCM (materials)	0.0067652	0.000***	0.0053732	0.000***
SPLRCR (real estate)	−0.0010833	0.130	0.003343	0.000***
SPLRCD (consumer discretionary)	−0.0048446	0.013**	0.0060748	0.000***

The results for TMU in Table 6 confirm that the impact of uncertainty during the pandemic is not homogeneous. Specifically, TMU negatively affects the net connectedness of the financials, consumer staples, and industrials in both periods and positively affects utilities and materials in both periods. However, the impact of TMU on other sectors varies depending on the period. Although TMU positively (negatively) affects the energy sector (consumer discretionary) before the pandemic, it negatively (positively) affects it during the pandemic. Finally, TMU does not have any impact on the tech sector in either period.

We also run a regression with the sectoral returns as the dependent variable. Although these results not reported here, we find that both TEU and TMU have an impact on all sectoral returns, which is consistent with several studies that investigate the impact of TUI on stock returns.

4. Conclusion

This paper investigates (1) the effect of the pandemic on connectedness among 10 US sectors: energy, technology, utilities, financials, health care, consumer staples, industrials, materials, real estate, and consumer discretionary and (2) the impact of TUI on the overall total connectedness index and the net connectedness of each of the ten sectors before and during the COVID pandemic. To do so, the study, first, adopts the TVP-VAR approach to examine changes in the magnitude and direction of spillovers before and during the pandemic in these 10 US sectors. Second, to contribute to the role of economic uncertainty on financial connectedness, we use regression and QR to examine the effect of crowd sentiment, proxied by TEU and TMU indexes, on interconnectedness among sectors, with the following three results. First, the findings concerning sectoral connectedness reveal that the main net transmitters of shocks industrials are the industrials and materials sectors, and the main recipients are utilities and energy. Second, TUI is positively associated with total connectedness at higher levels of connectedness but insignificant at a moderate level of connectedness. Third, the direction of the effect of the TUI on net connectedness varies from one sector to another, indicating that TUI can signal either good or bad news depending on the sector. Accordingly, policy makers, investors, portfolio managers, and researchers should consider TUI in their studies on financial interconnectedness.

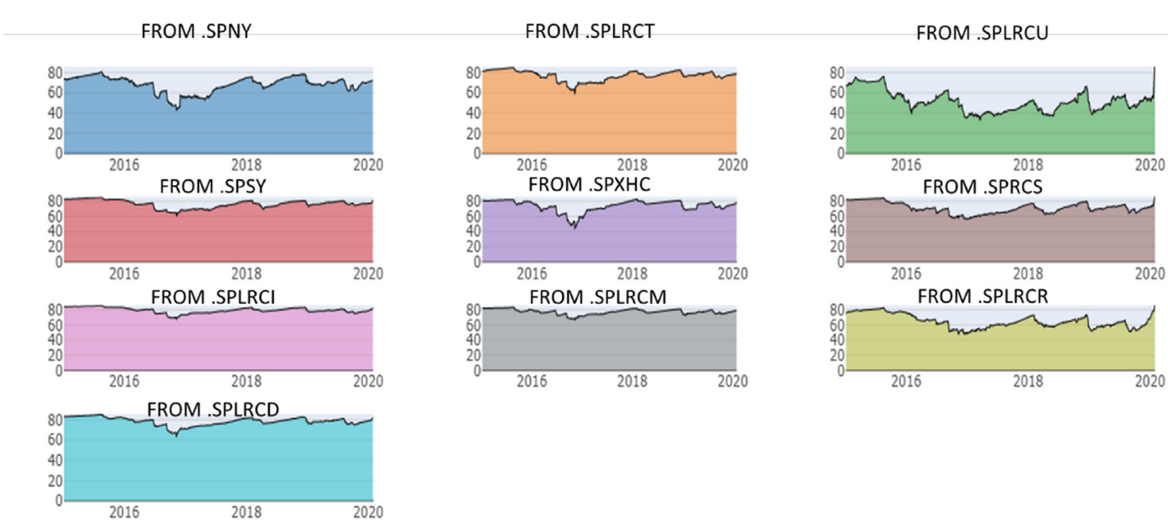
Various types of UI are proposed in the literature, such as monetary policy uncertainty and trade policy uncertainty. They lay a foundation for further research on the influence of different types of uncertainty on sectoral connectedness in the US and other markets.

Declaration of competing interest

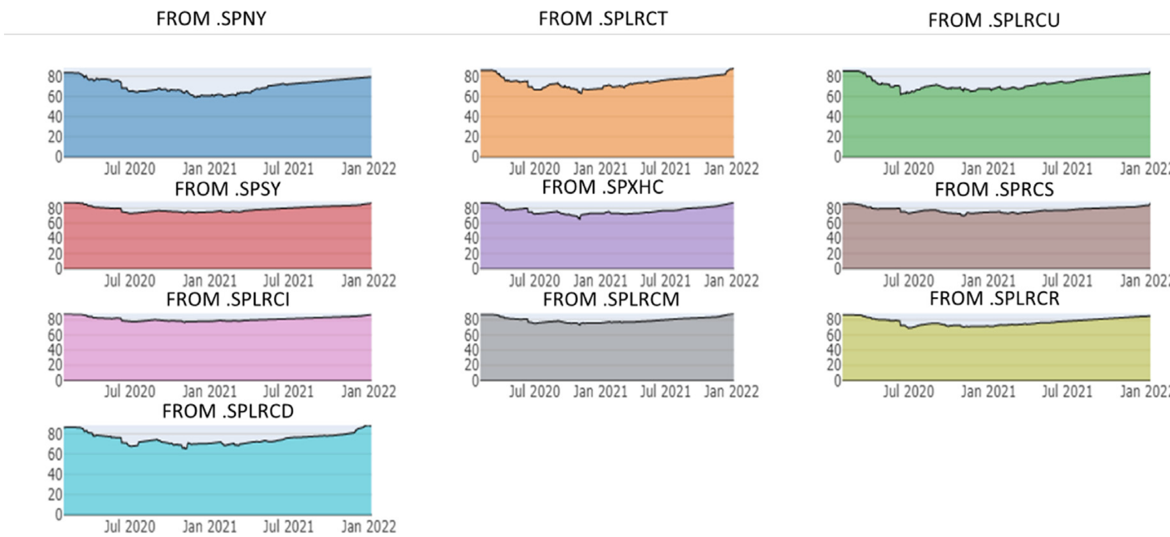
There are no competing interests to declare.

Appendix.

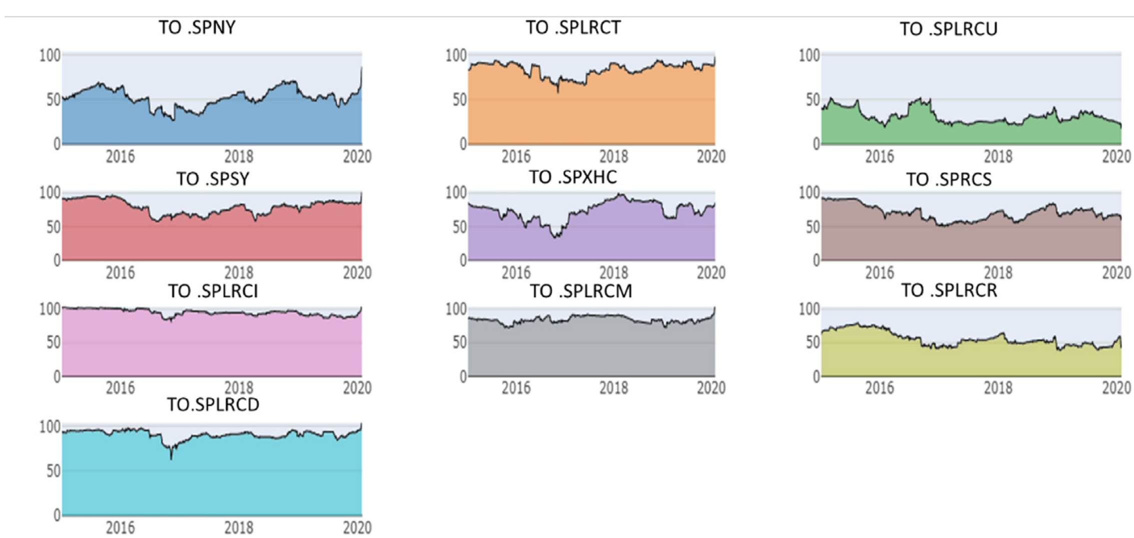
Appendix A.1. FROM connectedness during pre-covid



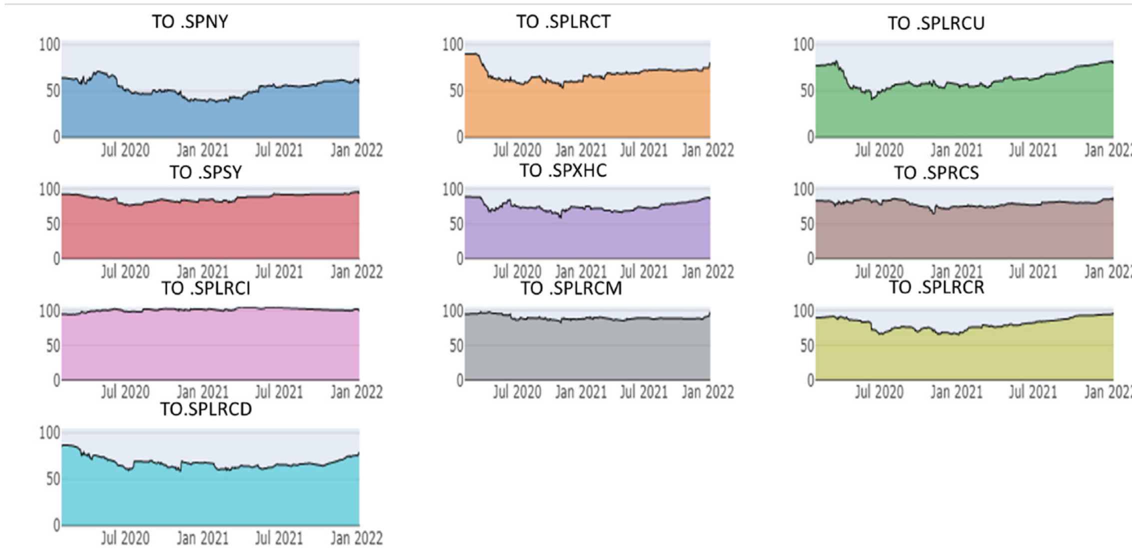
Appendix A.2. FROM connectedness during covid



Appendix A.3. TO connectedness during pre-covid



Appendix A.4. TO connectedness during covid



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